arXiv:2109.10808v1 [cs.SI] 22 Sep 2021

Population-scale dietary interests during the COVID-19 pandemic

Kristina Gligorić[1], Arnaud Chiolero[2*], Emre Kıcıman[3], Ryen W. White[3], Robert West[1]

[1]School of Computer and Communication Sciences, EPFL, Lausanne, Switzerland
{kristina.gligoric, robert.west}@epfl.ch
[2]Population Health Laboratory, University of Fribourg, Fribourg, Switzerland
arnaud.chiolero@unifr.ch
[3]Microsoft Research, Redmond, Washington, United States
{emrek,ryenw}@microsoft.com

Abstract

The SARS-CoV-2 virus has altered people's lives around the world, not only through the coronavirus disease (COVID-19) it causes, but also through unprecedented non-pharmaceutical interventions such as full-scale national lockdowns. Here we document population-wide shifts in dietary interests in 12 countries in 2020, as revealed through timeseries of Google search volumes. We find that during the first wave of the COVID-19 pandemic there was an overall surge in food interest, larger and longer-lasting than the surge during typical end-of-year holidays. The changes were strongly associated with population-wide mobility patterns. Using a quasi-experimental regression discontinuity design, we estimate that the shock of decreased mobility manifested as a drastic increase in interest in consuming food at home, with interest in recipes and related entities increasing by 90% on average across countries, and a corresponding decrease in consuming food outside of home, with the interest in restaurants decreasing by 54% on average. We find that, in addition to the volume of searched foods, the nature of searched foods also changed. The most drastic (up to threefold) increases occurred for calorie-dense carbohydrate-based foods such as pastries, bakery products, bread, pies, and desserts. In terms of the relative share (rather than absolute volume) of search interest, the most prominent increases occurred for carbohydrate-based foods, whereas the share of interest in other food categories on average remained robust. The observed shifts in dietary interests have the potential to affect food consumption and health outcomes of people worldwide. These findings can inform governmental and organizational decisions regarding measures to mitigate the effects of the COVID-19 pandemic on diet and nutrition, and thus on population health. They provide an informed starting point for future studies aiming to understand populations' evolving dietary behaviors in times of a global pandemic.

1 Introduction

The coronavirus disease 2019 (COVID-19) pandemic has led to the implementation of unprecedented non-pharmaceutical interventions, including case isolation, social and physical distancing measures, business and school closures, travel restrictions, and full-scale national lockdowns [31]. For instance, in mid-May 2020, more than one third of the global population was under lockdown [51]. These interventions have caused important shifts in people's lives, which in turn created challenges that did not originate directly in the virus itself, but in the social, economic, and psychological implications of the population-scale measures taken to prevent the spread of the virus [13, 67], transforming education [28], exercise habits [20], mental health [77], online behaviors [29], labor markets [38], transport, and mobility [13, 26], to name a few. Identifying how the pandemic has broadly impacted human needs and interests [69, 76] is therefore critical.

A thorough understanding of changes in food-related interests is particularly pressing, as changes in diet can have important ramifications for health, and dietary monitoring can help improve the well-being of populations. Diets are suspected to have become less balanced during the COVID-19 pandemic

*Also affiliated with Institute of Primary Health Care (BIHAM), University of Bern, Bern, Switzerland, and School of Population and Global Health, McGill University, Montreal, Canada.

[44], and changes in diet and physical activity during the pandemic are known to increase the risk of cardiovascular disease [53] and are suspected to be associated with negative mood during lockdowns [43]. To make matters worse, the pandemic can negatively impact the diet especially of those populations and individuals who are already most vulnerable [47], such as those suffering from malnutrition [39, 58], eating disorders [39, 64], addictions [19], or obesity [10, 59]. Furthermore, in general, diet and nutrition are prominent factors in maintaining overall health and are important for developing a healthy immune response, which affects the speed of recovery and the probability of developing severe symptoms [42]. Public health and nutrition researchers and stakeholders have therefore issued a number of warnings about the potential nutritional public health crises that might emerge as a consequence, such as an alcohol misuse crisis [19] or an obesity crisis [48]. However, it is not clear which aspects of the many potential adverse impacts of confinement on diets are most pressing, and on which of the many potential public health crises to focus first.

Beyond health, the question of COVID-19-induced shifts in dietary interests is also of economic importance [73]. It is necessary to understand emerging consumer needs, subsequent market readjustments [21, 40], and supply chain issues [37] that impact global access to food and food security [24, 49]. Many emerging customer behaviors are of interest to retailers and business owners during lockdowns, such as stockpiling, online purchasing, and changes in shopping locations [11, 16, 66, 71, 80].

Early on in the course of the pandemic, anecdotal reports about changes in dietary habits during lockdowns emerged, e.g., about increased interest in baking [1, 2]. Existing research has studied the impact of COVID-19 stay-at-home orders on health behaviors and physical and mental health [52], finding initial evidence of increased sedentary behaviors and reduced physical activity [8, 45, 75, 81], less eating out, increased cooking and baking from scratch [30, 32, 61], and generally increased consumption of [9, 33], and interest in [50], food. Overall, food consumption and meal patterns were mostly found to be more unhealthy during confinement [32, 86], with the exception of a decrease in alcohol consumption [8, 86].

Current evidence, however, relies primarily on surveys, does not leverage passively collected large-scale observational data, and is focused on specific countries [16, 23, 25, 70]. It remains challenging to quantify shifts in food interests globally and holistically, across different types of food, and fundamental questions about food interests during confinement remain unanswered.

The present study aims to bridge this gap by asking the following guiding question: How did dietary interests shift during COVID-19-induced mobility restrictions in 2020? In order to address this question, we quantify what foods people are interested in more or less when they spend more time at home and how long the shifts in interests persist as mobility reverts to normal. The fact that—unlike most previous events that directly impacted so many lives worldwide—the COVID-19 pandemic unfolded in a time of widespread Internet access allows us to conduct a population-wide study by relying on passively sensed digital trace data. Specifically, we use timeseries capturing the popularity of Google search queries related to 1,432 foods (e.g., “bread”, “pizza”), as well as ways of accessing food (e.g., “recipe”, “restaurant”), obtained in aggregated form via the publicly available Google Trends tool,[1] in order to analyze changes in food-related interests across 12 countries (illustration in Figure 1a). Google is the world’s largest Web search engine, and Google Trends search volumes have been shown to be a powerful population-scale sensor for numerous human behaviors, including unemployment [17], trading decisions [60], and voting [74]. We thus add to a rich literature that, well before COVID-19, has begun to analyze health and nutrition behaviors using digital trace data [7, 36], such as search engine logs [78, 83], purchase logs [4, 15, 35], online recipes [65], reviewing platforms [18], social media such as Twitter [3, 22, 55, 84] or Instagram [57, 72], and geo-location signals [68].

Methodologically, drawing meaningful conclusions from the longitudinal Google search volume timeseries is challenging due to the presence of trends and seasonalities. We overcome these hurdles via quasi-experimental timeseries analyses (outlined in Figure 1a), isolating the effect of the 2020 discontinuity in mobility patterns on food interests and going beyond simple correlations by accounting for 2019 baseline trends. This study design lets us identify the immediate, short-term increases in interest in all food types, which is found to be stronger and longer-lasting than those that coincide with end-of-year holidays (Figure 1b). The increased food interest is not uniform across types of food. The most prominent increases, in absolute and relative terms, occur for calorie-dense carbohydrate-based foods such as pastries and bread. The identified shifts in interests, many of which persisted for months (Figure S13b), represent a potential danger for public health and should be taken into account to inform decisions made by stakeholders in efforts to mitigate the effects of the COVID-19 pandemic on diets worldwide.

[1] https://www.google.com/trends

2 Results

We curated a set of 1,432 entities related to specific foods (e.g., "bread", "pizza") grouped in 28 food categories (details in *Methods*, Figure 1a), which covered 95.7% of the global food search volume in 2019 and 2020. Table 1 summarizes the descriptions of food categories and contains examples of popular foods in each category. We also curated a set of 16 different entities related to ways of accessing food (e.g., "recipe", "restaurant"), grouped in four categories: entities can be related to consuming food at home or outside of the home, and orthogonally, entities can be related to consuming food prepared by persons from within the household or food prepared by a third party (Table 2). We refer to these four groups of entities as defined in *Methods*.

Search interest timeseries were collected for 12 countries: Australia, Brazil, Canada, France, Germany, India, Italy, Mexico, Spain, United Kingdom, United States, and Denmark. The countries were selected such that a diversity of geographic location is achieved, and such that the severity of lockdowns varies. The interest timeseries were collected from the Google Trends platform [17, 34] and calibrated with Google Trends Anchor Bank [82] (so timeseries for different search queries can validly be compared with one another).[2] The interest timeseries in the same regions in 2019 serve as baselines.

Note that, although different languages are spoken in the 12 studied countries, search queries did not need to be translated, as Google Trends allows language-independent entity descriptors from the Freebase knowledge base [12] as input. For instance, for the input "/m/09728", Google Trends will return the search interest for all queries related to the concept "bread" across languages.

2.1 Overall surge in food interest larger than during end-of-year holidays

We examine how the total interest in food entities evolved in 2019 and 2020 (Figure 1b). We monitor interest in all food entities, normalized by the 2019 mean and standard deviation (z-scores). We refer to this quantity as surplus of interest. Normalizing food interest allows us to quantify the surplus of food interest in a week, relative to the Christmas week 2019. In a given week, the surplus relative to the Christmas week is measured as the ratio between the z-score in the observed week and the z-score in the Christmas week.

First, note the peaks of food interest during the end-of-year holiday season in both 2019 and 2020. Second, note the increase in overall interest in food entities coinciding with the reduced mobility due to COVID-19 occurring in March 2020. These rises of food interest are larger in amplitude compared to the rises of interest during end-of-year holidays, and they last longer. For example, in the US alone, the surplus (compared to the 2019 mean) of food interest at its peak during the first wave of the COVID-19 pandemic equals the surplus of interest during the Christmas week of 2019, as well as that of the surplus of interest during the Thanksgiving week of 2019. In total, the surplus of food interest in the first six months of 2020 in the US is 9.0 times as high as the surplus of interest during the Christmas week of 2019, and 8.9 times as high as the surplus of interest during the Thanksgiving week of 2019.

We next compare the surplus of food interest at its peak during the first wave of the COVID-19 pandemic with the surplus of interest during the Christmas week of 2019, across countries. We exclude India, a country with a Hindu majority, where there are no prominent increases in food interest during the Christmas week (Figure 1b). When comparing to Christmas holidays, the surplus of food interest at its peak during the first wave of the COVID-19 pandemic is on average 1.6 times as high as the surplus of interest during the Christmas week, while the total surplus of interest in the first six months of 2020 is on average 13.5 as high as the surplus of food interest in the Christmas week of 2019. The increases in food interest are drastic in India, too, with food interest at the peak of mobility restrictions surpassing 10 pre-pandemic standard deviations. Note that Denmark, the country with the mildest mobility restrictions, contrary to all other studied countries, had no notable overall increase in food interest in 2020 (Figure 1b).

Next, similarly, in Figure 1c, we examine the temporal evolution of the interest in the four modes of accessing food reflecting whether they relate to consuming food at home or outside of home, and orthogonally, whether they are related to consuming food prepared by persons within the household or food prepared by a third party. In all countries, in 2020, there was a decrease in interest in food prepared by third party, consumed outside (in red) and an increase in interest in food prepared within

[2] Although absolute search volume—the number of issued queries—cannot be inferred, calibration can infer absolute search volume up to a constant multiplicative factor. This way, ratios of absolute search volumes can be validly estimated when working with calibrated Google Trends timeseries.

the household, consumed at home (in blue) coinciding with the onset of the first wave of the COVID-19 pandemic in the first half of 2020.

Comparing to the end-of-year holidays, the surplus of interest in food prepared within the household, consumed at home (recipes, cooking, baking, grocery stores, and supermarkets) was at the peak 1.5 times as high as the surplus during the Christmas week of 2019. In the first six months of 2020, it was, on average across countries (excluding India), in total 11.4 times as high as the surplus of interest during the Christmas week of 2019. The increases in interest in recipes, cooking, baking, grocery stores, and supermarkets relative to 2019 mean were large in India as well, surpassing 10 pre-pandemic standard deviations at the peak.

Additionally, we note large increases in interest in food prepared by third party, consumed at home (in green), where in the US, Brazil, and Denmark, the interest in food prepared by third party, consumed at home increased by more than 30 pre-pandemic standard deviations at the peak.

2.2 Changes in food interests are strongly associated with mobility

Next, we combine search interest timeseries with mobility data published by Google (described in Section 4) which captures the relative increase in time people spend indoors compared to a pre-pandemic baseline. We find that interest in different ways of accessing foods and interest in specific foods are strongly correlated with mobility patterns during the COVID-19 crisis (Figures 2a and 2b). Across weeks in 2020, we calculate the country-specific Spearman rank correlation between mobility timeseries and food interest timeseries. Here, in order to adjust for seasonal trends, the food interest for a given week of 2020 is expressed as the relative increase compared to the corresponding week of 2019.

We observe strong and significant associations between food interests and mobility. Interest in recipes (Figure 2b) is positively correlated with spending more time at home ($p < 0.05$ in all countries; Spearman's rank correlation coefficient ranging between 0.68 in the US and 0.95 in Mexico), and takeout is significantly and positively correlated in 10 out of the 12 studied countries (Spearman's rank correlation coefficient ranging between 0.37 in Mexico and 0.82 in Australia). Interest in restaurants, on the other hand, is negatively correlated with spending more time at home, significant in all studied countries (Spearman's rank correlation coefficient ranging between -0.72 in Australia and -0.97 in Italy).

Regarding food categories (Figure 2a), although there is some variation between countries, there are notable food categories that have a significant positive correlation with mobility in each of the studied countries, such as desserts (ranging between 0.53 in Denmark and 0.84 in Brazil) and bread and flatbread (ranging between 0.51 in Denmark and 0.89 in Italy).

In Table 2, the correlation between mobility and food interest normalized by the 2019 baseline is shown for individual entities. All entities related to consuming food at home are correlated positively on average over countries, whereas all entities related to consuming food outside of home are correlated negatively on average (except barbecue, likely due to the fact that barbecue food can be prepared at home). Among specific foods, the strongest positive correlation is found for pancake, bread, baking powder, biscuit, chicken meat, chocolate brownie, pasta, sourdough, chocolate, and sponge cake. The strongest negative (although much smaller) correlation is found for foods such as tapas and Korean barbecue that are typically eaten in social contexts taking place outside of home.

In the analyses so far, we have examined the response of the interest as the mobility changed by measuring correlation. Next, given the abrupt nature of the change in mobility, we isolate the effect of the shock of mobility decrease on food interest via a modeling approach.

2.3 More interest in home food, less interest in out-of-home food

As depicted in Figure 1a, to isolate the shock of the mobility decrease occurring in all studied countries in March 2020, we first automatically detect changes in the mobility timeseries caused by both government-mandated lockdowns or self-motivated social distancing measures (Section 4). We refer to these points as mobility changepoints (Figure S1).

In order to measure the effect of decreased mobility on food interest timeseries, we employ a quasi-experimental design where the impact of the mobility decrease shock (the discontinuity) is isolated, controlling for patterns occurring in the same weeks of 2019 when COVID-19-induced mobility restrictions did not occur (Figure 1a). The model of a given interest timeseries in a given country is given by the following regression discontinuity design (RDD) in quadratic form:

$$\begin{aligned}
\log y_{tT} = \alpha' & + \beta' \cdot t & + \gamma' \cdot t^2 \\
+ \alpha'' \cdot i_t & + \beta'' \cdot i_t t & + \gamma'' \cdot i_t t^2 \\
+ \alpha''' \cdot j_T & + \beta''' \cdot j_T t & + \gamma''' \cdot j_T t^2 \\
+ \alpha \cdot i_t j_T & + \beta \cdot i_t j_T t & + \gamma \cdot i_t j_T t^2,
\end{aligned} \tag{1}$$

where T is the year (2019 or 2020); t is the week in the year relative to the week in which the discontinuity occurred in 2020 (but not in 2019), for $t \in [-t_{\min}, t_{\max}]$; $t_{\min} = 10$, since it is the maximum number of weeks in 2020 before the cutoff, $t_{\max} = 30$, since it is the maximum number of weeks we can have so that across all the studied countries, the second mobility decrease shock is not included; y_{tT} is the calibrated (see above) search interest volume in week t of year T of an entity, or set of entities in the respective country; i_t is a binary variable equal to 1 if $t > 0$ and 0 otherwise; and j_T is 1 in 2020 and 0 in 2019. This way, for all weeks where $i_t = j_T = 1$, a unit is "treated", otherwise is not. Logarithmic outcomes are used in order to make the model multiplicative. The outcome is modeled as a separate quadratic function of time before and after the discontinuity in order to capture nonlinear temporal patterns. By comparing observations lying closely on either side of the temporal threshold, we estimate the treatment effect, minimizing potential bias from unobservable confounders.

The interaction coefficients α, β, γ model the effect of the discontinuity, controlling for baseline trends in 2019. The short-term increase in interest is captured by the fitted coefficient α, which estimates the short-term effect of the mobility decrease on search interest. The approach is described in more detail in Section 4 and outlined in Figure 1a.

We find that in all countries (Figure 3a), there was a significant short-term increase in interest in food prepared within the household, consumed at home, with short-term increase in interest (α) ranging between +34.2% in Denmark and +179.8% in India. In all countries except in Brazil, there was a significantly decreased interest in food prepared by third party, consumed outside, ranging between -32.1% in USA and -81.7% in France. There were major increases in interest in food prepared by third party, consumed at home, with more than a +100% increase in six of the 12 studied countries.

We next analyze the relationship between the amplitude of the short-term changes in dietary interest and the severity of lockdowns (Figure 3b), where the severity of a lockdown is defined as the percentage change of the fraction of time spent at home (with respect to the pre-pandemic baseline level) at the peak of reduced mobility, varying between +16.9% in Denmark and +31.6% in Italy. All peaks of mobility decrease occurred in March and April 2020.

We find that the more drastic the lockdown severity, the more drastic the change in dietary interests. Changes in interest in recipes and restaurants have a significant association with the severity of the lockdown: positive for food prepared within the household, consumed at home ($R = 0.81$, $p = 0.001$), and negative for consumption outside of home, i.e., food prepared by third party, consumed outside ($R = -0.6$, $p = 0.039$) and food prepared by third party, consumed at home ($R = -0.83$, $p = 0.001$). Here, the UK was excluded because it is a clear outlier—when not excluding the UK, we still observe a negative, but non-significant correlation ($R = -0.391$, $p = 0.209$). The discrepancy between the UK and the other countries might be linked to COVID-19 policies allowing congregation in open green spaces, including parks and beaches [46].

The fact that the effect of decreased mobility on the interest in recipes across countries rises linearly with the severity of lockdown adds to the evidence that interests changed after mobility decreased. If there were other confounding factors that could explain the changes in dietary interests, and those factors had nothing to do with the shock of the mobility decrease, we would not expect to find such a clear dose–response relationship. Instead, we would need to envisage a more complex and stronger effect of an unobserved factor that could impact both the strength of the lockdown in a country and cause changes in the population's dietary interests, in ways that have nothing to do with spending more time at home.

Although significant increases in interest in food prepared by third party, consumed outside also exist, they are not correlated with lockdown strength. Presumably other factors are at play, such as the response of the market, availability of delivery companies, or how quickly restaurants adapted to do deliveries.

2.4 Drastic increases in interest for calorie-dense, carbohydrate-based foods

Having established the link between the sudden decrease in mobility and the shifting interests in ways of accessing food, we next examine how exactly the interest in specific types of food varied (Figure 4).

Is the observed increase in food interest uniform across all food types, with all foods increasing interest proportionally, or does interest in certain foods increase more? We apply the modeling approach (Figure 1a) on timeseries capturing interest in the 28 food categories in the 12 countries, and first measure the short-term effect of decreased mobility.

Overall, we find that there was a significant momentary increase of total food interest (gray bands in Figure S11), ranging between +24.6% in Denmark and +99.4% in Spain. Similarly, there was an increase in interest in most of the individual food categories (Figure 4). The biggest increases, however, occurred for calorie-dense, processed, carbohydrate-based foods: pastry and bakery products, bread and flatbread, pie, and dessert. These effects are significant in most of the countries. Especially strong cases (with increases of over 200%) include pastry and bakery products in Spain, France, and Canada; bread and flatbread in Spain, France, and Italy; and pie in Spain.

We observe smaller increases for other categories, including fresh produce (fruit, vegetable, salad, herb), meat and fish dishes (chicken, pork, beef, fish, lamb dishes), and wine, beer, liquor and cocktail, which saw an increase in some of the countries. These conclusions and the relative ranking between categories are robust to specific modeling choices (Supplementary Material, Table S3).

In the Supplementary Material (Figure S9), we additionally provide an alternative analysis where the outcome variable is the relative volume share (i.e., the fraction of the total weekly food interest that is allocated to the respective search queries), rather than absolute volume as analyzed above. This way, we control for the overall increased food interest. In terms of the share of interest, the most prominent increases indeed occurred for pastry and bakery products (over 50% increase in share fraction in nine of the 12 countries) and bread and flatbread (over 50% increase in share faction in six of the 12 countries), whereas the share of interest in other food categories remained robust.

In Table S2, we show the effects at the entity level. Although most food categories saw increased interest in most countries, there are specific foods with a negative effect, where interest decreased as mobility decreased, such as tapas and cotton candy.

We next measure the time it took for search interest to revert to normal, illustrated in Figure 1a for the example of Brazil. We measure how many weeks after the mobility decrease it takes until the modeled interest in 2020 is no longer significantly different from the counterfactual prediction based on 2019 (based on non-overlapping 95% CI). In addition to being drastic in amplitude, we observe that the numerous shifts in interests lasted for months. For instance, the shortest duration of increased interest in food prepared within the household, consumed at home was 17 weeks (in Denmark; Figure 5a), and the shortest duration of increased interest in specific food categories, nine weeks (wine, beer, and liquor in France; Figure 5b). Most of the changes in interest in specific groups of food entities are transient, and the interest came back to normal within 30 weeks.

In cases where interest did not go back to normal within the 30 weeks after the mobility decrease, we measure (in Figure S13) how elevated the interest remains at the end of the modeled period, 30 weeks after the mobility decrease, compared to the interest in the same week in 2019 (illustrated in Figure 1a using the example of Australia). While most interests come back to normal within 30 weeks, there are some notable exceptions of more permanent changes (Figure S13): the interest in food prepared by third party, consumed at home permanently increased in Italy, Canada, US, Australia and Denmark, while the interest in food prepared within the household, consumed at home also remained modified in Spain, UK, US, and Australia.

2.5 Second wave had less impact on food interests

Finally, we explore the effect of the "second wave of the pandemic", which occurred between October and December 2020 in the UK, Canada, Italy, US, France, and Spain. In Figure S12a, we observe much smaller effects in the second wave compared to the first wave of mobility decrease. No significant increases in interest in food prepared within the household, consumed at home are observed. While mobility saw large changes in some countries, such as France and Italy (in Figure S1, the second wave is comparable to the first wave), no drastic changes in food interests occurred.

Notable exception are France and Italy, where food prepared by third party, consumed at home saw large increases in interest in the second wave. We observe significant decreases in interest in restaurants in the UK, Italy, and France, but smaller effects compared to the first wave. Finally, no notable surges in interests in bread, pastry, baking, and desserts as in the first wave are observed in the second wave. The second wave brought on less drastic mobility decreases and was less of a disruption. Additionally, populations adapt, and might have acquired new skills. As a consequence, there might be less of a need to search for recipes anymore.

3 Discussion

In order to formulate policies and allocate resources for mitigating the adverse nutritional impacts of the COVID-19 pandemic, governments, organizations, non-governmental organizations, and other stakeholders need reliable and timely data regarding the circumstances faced by affected populations. The results presented here provide documentation of the impacts of confinement on nutritional interests. As the pandemic continues to unfold, warnings about many potential public health crises emerge. In this study, we aim to point out prominent emerging behaviors by quantifying initial developments and providing a broad grounding for future studies.

Implications for public health. From a public-health perspective, the emerging surge in food interest during confinement is concerning. During the first wave of the COVID-19 pandemic, there was an overall surge in food interest, stronger and longer-lasting compared to the end-of-year holiday season of 2019 (Figure 1b). Since Christmas and Thanksgiving are known to be disruptive to dietary habits and a hazard to balanced diets [41], and the effects of confinement on food interests are comparable in amplitude, and last longer, there is a pressing need for understanding them.

In addition to the overall volume, the nature of the food interest changed as well. After the shock of the mobility decrease, there was a large immediate increase in interest in consuming food at home and a decrease in consuming food outside of home. In nine of the 12 studied countries, as mobility decreased, the interest in preparing and consuming food at home momentarily increased by more than 50% (Figure 3a), and the interest in baking and pastries more than doubled (Figure 4). Since such modified interests persisted for a prolonged period (at least nine weeks, Figure 5) and since frequent consumption of meals prepared away from home is significantly associated with an increased risk of all-cause mortality [27], preparing more meals at home is a potentially positive side of the shifts in interest and should be understood further from public-health perspective.

However, the sharply increased interest in potentially unhealthy foods is worrisome. Overall, we find that the most drastic increases in interest are in baking and desserts, i.e., carbohydrate-rich foods. These surges are not matched by proportional increases in interest in fresh produce, meat meals, vegetables, or fruit. Such shifts represent a danger of developing potentially unhealthy eating habits favoring processed and calorie-dense foods, at times when physical activity is reduced. This is particularly concerning from a population-scale well-being and mental health point of view. These results call for developing a deeper understanding of the exact mechanisms how stress, boredom, and emotional eating associated with the lockdown, together with changed availability, may have contributed to the observed effects [14, 56, 85].

Implications for consumer behavior. Figure S13 hints at permanent small increases in interests in certain foods. While the interest in restaurants came back to normal in the studied countries except India and Mexico within 30 weeks after the shock of the mobility decrease, interest in takeout remained increased in Italy, Canada, US, Australia, Denmark, and interest in recipes in Spain, UK, US, Australia also remained increased.

Future work should determine if these are new permanent habits brought by the pandemic, or they will fall back to normal at a point in the future. These findings are particularly important to take into account in efforts to understand market readjustments.

Comparison to surveys. Our results confirm and refine what is known from survey-based research. A meta-analysis [86] of 12 preliminary articles studying the impact of COVID-19 confinement on dietary habits revealed a sharp rise of carbohydrate consumption, especially of foods with a high glycemic index (e.g., homemade pizza, bread, cake, and pastries), as well as more frequent snacking. A high consumption of fruits and vegetables, as well as protein sources, particularly pulses, was also recorded, although there was no clear peak of increase in the latter. A decrease in alcohol intake and of fresh fish and seafood was further observed.

Whereas surveys are potentially a more accurate reflection of consumption, our findings, which were derived from passively sensed data, provide a complementary view. Search interest timeseries capture fine-grained temporal dynamics within the contrasted periods. Additionally, search interest timeseries capture true interest and are not subject to reporting biases. By relying on them, we account for behavioral changes beyond subjective impressions. Finally, search interest timeseries provide insights at a population scale.

Contrary to previous concerns about the danger of alcohol abuse during confinement [19], on a population level, we do not observe important surges in interest. In fact, consistent with survey-based research [8, 86], we observe a significant negative correlation between seasonality-adjusted interest in alcoholic drinks and mobility in some of the studied countries (cocktail -0.44, $p < 0.05$ in Italy, -0.33,

$p < 0.05$ in Spain, and wine, beer, and liquor in -0.61, $p < 0.05$ France and -0.34, $p < 0.05$ Denmark), meaning that more interest in alcohol is associated with more time spent outside of home, not less. Additionally, the relative share of interest in alcoholic drinks (Figure S9) decreased because the increase in other foods was not mirrored by the increase of interest in alcoholic drinks.

It is important to keep in mind that these findings are based on aggregate population-level interests, and that specific subpopulations of users might still be susceptible to alcohol misuse. Future work should study search logs and alternative digital traces [5] of individual users in a longitudinal user-level study to understand what pre-pandemic user characteristics are predictive of behaviors emerging during confinement.

Limitations. When interpreting our results, several additional considerations should be kept in mind. First, searching for a food is not tantamount to consuming the food. Users may search but not consume, and vice versa. Also, search interest might not be an equally good sensor for real behavior in different countries.

Note, however, that several factors nonetheless render our findings consequential:

1. In other contexts, digital traces of nutritional behavior have been shown to be valid proxies of actual behavior; e.g., calories estimated from social media posts correlate with population-level obesity [3].

2. Major shifts in search interest have the potential to impact actual food consumption, even if traces are imperfect proxies. In that sense, search interest can lead to consumption.

3. Search interest is one of the few global signals that are publicly accessible to researchers and policymakers.

Second, while we make no claims of causal identification based on our statistical analyses, our regression discontinuity-based design alleviates the effect of unobserved covariates by exploiting the sudden shock in mobility and accounting for seasonal variation. The observed dose-response relationship supports this, as does the fact that search interest in ways of accessing foods behaves as one would expect if those interests were causally affected by mobility.

Third, the data collection capacities limited the number of studied countries such that interest data could feasibly be collected. We believe results from the countries studied here are indicative of shifts in interests in neighboring countries. Still, our results are not representative beyond the 12 studied countries.

Finally, beyond people's shifting habits, interests, and emotional responses, other internal and external factors brought by the pandemic, most notably food product availability, price, and expected shelf life [54] or populations' present level of cooking skill and willingness and ability to learn to cook [62] can play a role, and should be kept in mind when interpreting our the observed shifts in dietary interests.

Implications beyond COVID-19. Outside of the ongoing COVID-19 pandemic, spending more time at home due to enforced lockdowns is a naturally occurring implicit dietary intervention encouraging people to eat at home. By documenting the impacts on people's interests and measuring how lasting the effects are we learn something about the kinds of foods in which people become interested when staying at home in general. This has implications for designing interventions outside of COVID-19, and future work should compare effects on diet of staying at home due to COVID-19 lockdown measures to the impacts of staying at home due to other, more frequent external circumstances, such as extreme weather or air pollution.

We study and document the impacts of a single event (COVID-19 crisis), but we observe similar impacts across culturally and geographically different countries. The observed impacts are therefore general to a certain extent, applying to different kinds of populations, in varying intensity depending on the intensity of the treatment.

When confined, people are interested in carbohydrates and calorie-dense foods (Figure 4), likely due to changes in preferences [14, 85], on the one hand, and changes in accessibility and price of foods [54], on the other hand. These effects are consistent across countries, which is a demonstration that they occur across cultures and economic conditions. While this study quantified initial developments during the pandemic, future studies aiming to understand the impacts of the pandemic and the related mobility restrictions on diet will continue to be important for designing policies and programs to tackle adverse health impacts.

4 Methods

4.1 Search interest timeseries

Our analyses rely on a curated and calibrated set of interest timeseries collected from Google Trends,[3] an important tool for researchers [17, 34] that makes aggregate statistics about the popularity of search queries in Google search engine publicly available. We collect timeseries of search interest in entities related to foods or ways of accessing foods. Search queries may be specified as plain text (e.g., "Cookie") or as entity identifiers (e.g., "/m/021mn") from the Freebase knowledge base [12]. We use Freebase identifiers to conduct a multilingual study of interest since they allow for grouping various surface forms relating to the same topic. For instance, the entity "Cookie" ("/m/021mn") captures "cookies", "cookie", "Cookie", or "cookie jar", etc., while the entity "Recipe" ("/m/0p57p") captures all recipe queries, across languages.

Google Trends provides timeseries of search interest for the specified input queries. Since search interest is not returned in terms of absolute search volume, but normalized by time and location, and rounded to integer precision, we use Google Trends Anchor Bank (G-TAB) [82] to calibrate the timeseries. The benefit of calibration is that the interest is expressed on the same scale up to bounded precision, and the combined interest in a set of entities can be estimated by adding up the interest in individual entities.

We collect interest data for two types of freebase food entities: (1) entities related to the ways how people access food (such as "recipe", "restaurant"), and (2) specific food entities (such as "cookie", "pizza").

1. Modes entities: we curate entities that reflect ways of accessing food, starting from seed entities (recipe, take-out, restaurant, picnic), and inspecting related entities. Mode entities are aggregated into four groups. Entities can be related to consuming food at home or outside of the home; orthogonally, entities can be related to consuming food prepared by persons within the household or food prepared by a third party (see Table 2 for details about individual entities). We refer to the four groups of entities related to food:

   (a) **prepared within the household, consumed at home**: recipe, cooking, baking, grocery store, supermarket

   (b) **prepared by third party, consumed at home**: food delivery, take-out, drive-in

   (c) **prepared within the household, consumed outside**: picnic, barbecue, lunchbox

   (d) **prepared by third party, consumed outside**: restaurant, cafeteria, cafe, diner, food festival

2. Foods entities: we start from extracted mids of food entities from freebase. These are entities of type "food", "dish", "beverage", or "ingredient". Food entities are aggregated into categories. Category creation: we enrich Freebase entities with Wikidata knowledgebase [79] properties using Wikidata query API. For each Freebase entity id, we query wikidata with the mid to get its "instance of" or "subclass of" properties. We derive a taxonomy of 28 categories based on "subclass of" and "instance of" relations. To ensure that the food classes are general and representative, we keep all classes with at least ten entities. Note that not all entities have a "subclass of" or "instance of" field available in Wikidata and therefore cannot be automatically categorized. To achieve higher coverage, we manually annotate a set of popular entities. We monitor global timeseries of all food entities in 2019–2020. We select the top entities that covered 95.7% of global food search volume and annotate all such entities that do not already have a category derived based on Wikidata. This process resulted in a set of N=1432 entities, categorized either based on Wikidata or manually. Categories are presented in Table 1. An author who is a professional epidemiologist specialized in nutrition assessed and refined the entities and the corresponding categorization.

Overall, we collect timeseries of $N = 1432$ food entities and $N = 16$ modes entities in 12 regions, spanning from the beginning of 2019, until the end of 2020, at weekly granularity. The goal to achieve global coverage and include countries with varying severity of mobility restrictions.

The food entities ($N = 1432$) are categorized into 28 food categories, and the mode entities ($N = 16$) are categorized into four groups. We obtain country-specific timeseries for 28 food categories, and four aggregate modes by adding up timeseries of respective individual entities.

[3] https://www.google.com/trends

4.2 Mobility timeseries and COVID-19-induced mobility decreases

To capture variation in the mobility of the populations in the 12 studied countries, we use mobility reports [6] published by Google,[4] which capture population-wide movement patterns based on cellphone location signals. The mobility reports specify, for each day, by what percentage the time spent in residential areas differed from a pre-pandemic baseline period in early 2020.

We chose to rely on mobility data and not the official start of lockdown dates. The problem with employing the official start of lockdown date in statistical analyses is that it is not guaranteed that they would impact movement patterns across different countries homogeneously (e.g., it could be that for some of the countries people stayed more at home even before the lockdown was enacted). Similarly, the official lockdown date might vary within a country.

We automatically detect changes in the mobility timeseries caused by both government-mandated lockdowns as well as self-motivated social distancing measures [63]. We refer to these points as mobility changepoints. We use mobility changepoints as heuristic dates for when people started or stopped spending substantially more time in their homes. Unlike choosing one of the official dates of lockdown implementation or relaxation, this leads to a meaningful onset of decreased mobility across different countries.

Figure S1 depicts three important mobility changepoints dates that occur at different moments throughout 2020 in the studied countries:

1. The first sharp mobility decrease occurring in March 2020 when people started to spend substantially more time at home.

2. The eventual mobility increase occurring between May and October 2020, when people stopped spending substantially more time at home.

3. The second mobility decrease that occurs between October and December 2020 (occurs in some of the studied countries), when people started spending substantially more time at home during the second wave of the pandemic.

We detect the three changepoints for each country independently by smoothing and thresholding: we consider the weekly rolling average mobility. We monitor the percentage of time spent at home. The first date when time spent at home increased by 10% is the start of reduced mobility in the first wave. We repeat the same to detect the onset of the second wave. In this way, the period when percentage of time spent at home consistently stays above 10% compared to pre-pandemic baseline (defined as pre-pandemic mobility levels by Google) is a period of decreased mobility, in the first, or in the second wave.

The three changepoint dates are marked in Figure S1 in the 12 studied countries. The first mobility decrease, and the second mobility decrease (in case it occurs) serve as cutoff dates in our modelling approach. The date of the eventual mobility increase serves to limit the possible duration of the studied period with decreased mobility.

4.3 Modeling approach

To estimate the potential effects of the sudden mobility changes on food interest timeseries, we devise a regression discontinuity design (RDD) with a local regression in time. Additionally, we incorporate fake discontinuity separating before vs. after the cutoff date in 2019, the year before the pandemic, to account for seasonal trends. The model of a given interest timeseries in a given country has the general quadratic form described in Equation 1.

With this form of the model, we measure the time-dependent trends because the model is expressive enough (i.e., quadratic terms capture the temporal evolution, see illustrations in Figure S5). We also provide the main results with the constant and linear model in Supplementary material.

Bandwidth choices are made in the following way: $t_{\min} = 10$, since it is the maximum number of weeks in 2020 before the cutoff, $t_{\max} = 30$, since it is the maximum number of weeks we can have so that across all the studied countries, the second mobility decrease shock is not included. We investigated the impact of the choice of the bandwidth (see Supplementary Material).

The interaction coefficients α, β, γ model the effect of discontinuity, controlling for trends in 2019. We are primarily interested in α, the magnitude of the initial increase at the discontinuity.

[4] `https://www.google.com/covid19/mobility/`. We use country-wise mobility data from February to the end of December 2020.

In our analyses, we fit a model of this general form (Equation 1) to interest timeseries, separately for each studied entity or groups of entities, in each of the studied countries. We use the modeling approach to investigate three key quantities illustrated on the example of *Pastry and bakery product* interest in Brazil, and Australia, in Figure 1a:

1. **Short-term increase in interest**. It is captured with fitted coefficient α. The model is multiplicative due to the logarithm. After fitting the model (Equation 1) with OLS, the relative increase over the baseline is then calculated by converting back to the linear scale the fitted coefficient α, $e^{\alpha} - 1$; the 95% CI also appropriately converted back to linear scale; The 95% CI approximated with two standard errors.

2. **Time it takes for the interest to revert to normal**. We measure how many weeks after the mobility decrease within the $t_{\max} = 30$ weeks, the modeled interest in 2020 is no longer significantly different from the counterfactual prediction based on 2019 (based on non-overlapping 95% CI).

3. **Long-term increase in interest**. In case the interest did not go back to normal within the 30 weeks after the mobility decrease, we measure how elevated the interest remains at the end of the modelled period, 30 weeks after mobility decrease, compared to the interest in the same week in 2019.

Acknowledgements

We thank Gorjan Popovski, Manoel Horta Ribeiro, and Maxime Peyrard for help with data collection, as well as Eric Horvitz for helpful feedback.

References

[1] Why banana bread is the official comfort food of the coronavirus quarantine. `https://www.thekitchn.com/banana-bread-official-comfort-food-coronavirus-23021239`. Accessed: 2021-03-01.

[2] Sourdough baking sees rise in popularity during covid-19 pandemic. `https://www.cbc.ca/news/canada/north/sourdough-popular-covid-19-1.5529649`. Accessed: 2021-03-01.

[3] Sofiane Abbar, Yelena Mejova, and Ingmar Weber. You tweet what you eat: Studying food consumption through twitter. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI)*, pages 3197–3206, 2015.

[4] Luca Maria Aiello, Rossano Schifanella, Daniele Quercia, and Lucia Del Prete. Large-scale and high-resolution analysis of food purchases and health outcomes. *EPJ Data Science*, 8(1):14, 2019.

[5] Luca Maria Aiello, Daniele Quercia, Rossano Schifanella, and Lucia Del Prete. Tesco grocery 1.0, a large-scale dataset of grocery purchases in london. *Scientific data*, 7(1):1–11, 2020.

[6] Ahmet Aktay et al. Google covid-19 community mobility reports: Anonymization process description, 2020.

[7] Tim Althoff, Hamed Nilforoshan, Jenna Hua, and Jure Leskovec. How food environment impacts dietary consumption and body weight: A country-wide observational study of 2.3 billion food logs. *medRxiv*, 2020.

[8] Achraf Ammar, Michael Brach, Khaled Trabelsi, Hamdi Chtourou, Omar Boukhris, Liwa Masmoudi, Bassem Bouaziz, Ellen Bentlage, Daniella How, Mona Ahmed, et al. Effects of covid-19 home confinement on eating behaviour and physical activity: results of the eclb-covid19 international online survey. *Nutrients*, 12(6):1583, 2020.

[9] Laura Batlle-Bayer, Rubén Aldaco, Alba Bala, Rita Puig, Jara Laso, María Margallo, Ian Vázquez-Rowe, Josep Maria Antó, and Pere Fullana-i Palmer. Environmental and nutritional impacts of dietary changes in spain during the covid-19 lockdown. *Science of the Total Environment*, 748: 141410, 2020.

[10] Matthew J Belanger, Michael A Hill, Angeliki M Angelidi, Maria Dalamaga, James R Sowers, and Christos S Mantzoros. Covid-19 and disparities in nutrition and obesity. *New England Journal of Medicine*, 383(11):e69, 2020.

[11] Tarek Ben Hassen, Hamid El Bilali, and Mohammad S Allahyari. Impact of covid-19 on food behavior and consumption in qatar. *Sustainability*, 12(17):6973, 2020.

[12] Kurt Bollacker, Colin Evans, Praveen Paritosh, Tim Sturge, and Jamie Taylor. Freebase: a collaboratively created graph database for structuring human knowledge. In *Proceedings of the 2008 ACM SIGMOD international conference on Management of data*, pages 1247–1250, 2008.

[13] Giovanni Bonaccorsi et al. Economic and social consequences of human mobility restrictions under covid-19. *Proceedings of the National Academy of Sciences*, 2020.

[14] Abel Brodeur, Andrew E Clark, Sarah Fleche, and Nattavudh Powdthavee. Covid-19, lockdowns and well-being: Evidence from google trends. *Journal of public economics*, 193, 2021.

[15] David L Buckeridge, Katia Charland, Alice Labban, and Yu Ma. A method for neighborhood-level surveillance of food purchasing. *Annals of the New York Academy of Sciences*, 1331(1):270–277, 2014.

[16] Lauren Chenarides, Carola Grebitus, Jayson L Lusk, and Iryna Printezis. Food consumption behavior during the covid-19 pandemic. *Agribusiness*, 37(1):44–81, 2021.

[17] Hyunyoung Choi and Hal Varian. Predicting the present with google trends. *Economic record*, 88: 2–9, 2012.

[18] Martin J Chorley, Luca Rossi, Gareth Tyson, and Matthew J Williams. Pub crawling at scale: tapping untappd to explore social drinking. In *Proceedings of the 10th International AAAI Conference on Web and Social Media (ICWSM)*, 2016.

[19] James M Clay and Matthew O Parker. Alcohol use and misuse during the covid-19 pandemic: a potential public health crisis? *The Lancet Public Health*, 5(5):e259, 2020.

[20] Rachel C Colley, Tracey Bushnik, and Kellie Langlois. Exercise and screen time during the covid-19 pandemic. *Health Reports*, 2020.

[21] Peter Dannenberg, Martina Fuchs, Tim Riedler, and Cathrin Wiedemann. Digital transition by covid-19 pandemic? the german food online retail. *Tijdschrift voor economische en sociale geografie*, 111(3):543–560, 2020.

[22] Munmun De Choudhury, Sanket Sharma, and Emre Kıcıman. Characterizing dietary choices, nutrition, and language in food deserts via social media. In *Proceedings of the 19th ACM conference on computer-supported cooperative work & social computing (CSCW)*, pages 1157–1170, 2016.

[23] Melanie Deschasaux-Tanguy, Nathalie Druesne-Pecollo, Younes Esseddik, Fabien Szabo de Edelenyi, Benjamin Alles, Valentina A Andreeva, Julia Baudry, Helene Charreire, Valerie Deschamps, Manon Egnell, et al. Diet and physical activity during the covid-19 lockdown period (march-may 2020): Results from the french nutrinet-sante cohort study. *MedRxiv*, 2020.

[24] Stephen Devereux, Christophe Béné, and John Hoddinott. Conceptualising covid-19's impacts on household food security. *Food Security*, 12(4):769–772, 2020.

[25] Laura Di Renzo, Paola Gualtieri, Francesca Pivari, Laura Soldati, Alda Attinà, Giulia Cinelli, Claudia Leggeri, Giovanna Caparello, Luigi Barrea, Francesco Scerbo, et al. Eating habits and lifestyle changes during covid-19 lockdown: an italian survey. *Journal of translational medicine*, 18: 1–15, 2020.

[26] Annie Doubleday, Youngjun Choe, Tania Busch Isaksen, Scott Miles, and Nicole A Errett. How did outdoor biking and walking change during covid-19?: A case study of three us cities. *PLoS one*, 16 (1):e0245514, 2021.

[27] Yang Du, Shuang Rong, Yangbo Sun, Buyun Liu, Yuxiao Wu, Linda G. Snetselaar, Robert B. Wallace, and Wei Bao. Association between frequency of eating away-from-home meals and risk of all-cause and cause-specific mortality. *Journal of the Academy of Nutrition and Dietetics*, 2021.

[28] Thomas Favale, Francesca Soro, Martino Trevisan, Idilio Drago, and Marco Mellia. Campus traffic and e-learning during covid-19 pandemic. *Computer Networks*, 2020.

[29] Anja Feldmann et al. The lockdown effect: Implications of the covid-19 pandemic on internet traffic. *arXiv*, 2020.

[30] Emily W Flanagan, Robbie A Beyl, S Nicole Fearnbach, Abby D Altazan, Corby K Martin, and Leanne M Redman. The impact of covid-19 stay-at-home orders on health behaviors in adults. *Obesity*, 29(2):438–445, 2021.

[31] Seth Flaxman et al. Report 13: Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries. Report, 2020.

[32] Sarah Gerritsen, Victoria Egli, Rajshri Roy, Jill Haszard, Charlotte De Backer, Lauranna Teunissen, Isabelle Cuykx, Paulien Decorte, Sara Pabian Pabian, Kathleen Van Royen, et al. Seven weeks of home-cooked meals: changes to new zealanders' grocery shopping, cooking and eating during the covid-19 lockdown. *Journal of the royal society of new zealand*, pages 1–19, 2020.

[33] Davide Giacalone, Michael Bom Frøst, and Celia Rodríguez-Pérez. Reported changes in dietary habits during the covid-19 lockdown in the danish population: the danish covidiet study. *Frontiers in nutrition*, 7:294, 2020.

[34] Jeremy Ginsberg, Matthew H Mohebbi, Rajan S Patel, Lynnette Brammer, Mark S Smolinski, and Larry Brilliant. Detecting influenza epidemics using search engine query data. *Nature*, 457(7232): 1012–1014, 2009.

[35] Kristina Gligorić, Ryen W. White, Emre Kiciman, Eric Horvitz, Arnaud Chiolero, and Robert West. Formation of social ties influences food choice: A campus-wide longitudinal study. *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW1), April 2021.

[36] Samuel L Groseclose and David L Buckeridge. Public health surveillance systems: recent advances in their use and evaluation. *Annual Review of Public Health*, 38:57–79, 2017.

[37] Dabo Guan, Daoping Wang, Stephane Hallegatte, Steven J Davis, Jingwen Huo, Shuping Li, Yangchun Bai, Tianyang Lei, Qianyu Xue, D'Maris Coffman, et al. Global supply-chain effects of covid-19 control measures. *Nature human behaviour*, pages 1–11, 2020.

[38] Sumedha Gupta et al. Effects of social distancing policy on labor market outcomes. Technical report, National Bureau of Economic Research, 2020.

[39] Derek Headey, Rebecca Heidkamp, Saskia Osendarp, Marie Ruel, Nick Scott, Robert Black, Meera Shekar, Howarth Bouis, Augustin Flory, Lawrence Haddad, et al. Impacts of covid-19 on childhood malnutrition and nutrition-related mortality. *The Lancet*, 396(10250):519–521, 2020.

[40] Kristina Heinonen and Tore Strandvik. Reframing service innovation: Covid-19 as a catalyst for imposed service innovation. *Journal of Service Management*, 2020.

[41] Holly R Hull, Duncan Radley, Mary K Dinger, and David A Fields. The effect of the thanksgiving holiday on weight gain. *Nutrition journal*, 5(1):1–6, 2006.

[42] Mohammed Iddir, Alex Brito, Giulia Dingeo, Sofia Sosa Fernandez Del Campo, Hanen Samouda, Michael R La Frano, and Torsten Bohn. Strengthening the immune system and reducing inflammation and oxidative stress through diet and nutrition: considerations during the covid-19 crisis. *Nutrients*, 12(6):1562, 2020.

[43] Joanne Ingram, Greg Maciejewski, and Christopher J Hand. Changes in diet, sleep, and physical activity are associated with differences in negative mood during covid-19 lockdown. *Frontiers in psychology*, 11:2328, 2020.

[44] Ranil Jayawardena and Anoop Misra. Balanced diet is a major casualty in covid-19. *Diabetes & Metabolic Syndrome*, 2020.

[45] Peng Jia, Lei Zhang, Wanqi Yu, Bin Yu, Meijing Liu, Dong Zhang, and Shujuan Yang. Impact of covid-19 lockdown on activity patterns and weight status among youths in china: the covid-19 impact on lifestyle change survey (coinlics). *International Journal of Obesity*, pages 1–5, 2020.

[46] Thomas F Johnson, Lisbeth A Hordley, Matthew P Greenwell, and Luke C Evans. Effect of park use and landscape structure on covid-19 transmission rates. *Science of The Total Environment*, page 148123, 2021.

[47] Anna Josephson, Talip Kilic, and Jeffrey D Michler. Socioeconomic impacts of covid-19 in low-income countries. *Nature Human Behaviour*, pages 1–9, 2021.

[48] Michail Katsoulis, Laura Pasea, Alvina G Lai, Richard JB Dobson, Spiros Denaxas, Harry Hemingway, and Amitava Banerjee. Obesity during the covid-19 pandemic: both cause of high risk and potential effect of lockdown? a population-based electronic health record study. *Public health*, 191: 41–47, 2021.

[49] David Laborde, Will Martin, Johan Swinnen, and Rob Vos. Covid-19 risks to global food security. *Science*, 369(6503):500–502, 2020.

[50] Laura Laguna, Susana Fiszman, Patricia Puerta, C Chaya, and Amparo Tárrega. The impact of covid-19 lockdown on food priorities. results from a preliminary study using social media and an online survey with spanish consumers. *Food quality and preference*, 86:104028, 2020.

[51] Adam Liverpool et al. Covid-19 news: Coronavirus restrictions to ease slightly in England, 2020.

[52] Kathryn E Mansfield, Rohini Mathur, John Tazare, Alasdair D Henderson, Amy R Mulick, Helena Carreira, Anthony A Matthews, Patrick Bidulka, Alicia Gayle, Harriet Forbes, et al. Indirect acute effects of the covid-19 pandemic on physical and mental health in the uk: a population-based study. *The Lancet Digital Health*, 3(4):e217–e230, 2021.

[53] Anna V Mattioli, Susanna Sciomer, Camilla Cocchi, Silvia Maffei, and Sabina Gallina. Quarantine during covid-19 outbreak: Changes in diet and physical activity increase the risk of cardiovascular disease. *Nutrition, Metabolism and Cardiovascular Diseases*, 30(9):1409–1417, 2020.

[54] Dave Mead, Karen Ransom, Stephen B Reed, and Scott Sager. The impact of the covid-19 pandemic on food price indexes and data collection. *Monthly Lab. Rev.*, 143:1, 2020.

[55] Yelena Mejova, Sofiane Abbar, and Hamed Haddadi. Fetishizing food in digital age:# foodporn around the world. In *Tenth International AAAI Conference on Web and Social Media (ICWSM)*, 2016.

[56] Andrew B Moynihan, Wijnand AP Van Tilburg, Eric R Igou, Arnaud Wisman, Alan E Donnelly, and Jessie B Mulcaire. Eaten up by boredom: Consuming food to escape awareness of the bored self. *Frontiers in psychology*, 6:369, 2015.

[57] Ferda Ofli, Yusuf Aytar, Ingmar Weber, Raggi Al Hammouri, and Antonio Torralba. Is saki# delicious?: The food perception gap on instagram and its relation to health. In *Proceedings of the 26th International Conference on World Wide Web (WWW)*, pages 509–518, 2017.

[58] Saskia Osendarp, Jonathan Kweku Akuoku, Robert E Black, Derek Headey, Marie Ruel, Nick Scott, Meera Shekar, Neff Walker, Augustin Flory, Lawrence Haddad, et al. The covid-19 crisis will exacerbate maternal and child undernutrition and child mortality in low-and middle-income countries. *Nature Food*, pages 1–9, 2021.

[59] Angelo Pietrobelli, Luca Pecoraro, Alessandro Ferruzzi, Moonseong Heo, Myles Faith, Thomas Zoller, Franco Antoniazzi, Giorgio Piacentini, S Nicole Fearnbach, and Steven B Heymsfield. Effects of covid-19 lockdown on lifestyle behaviors in children with obesity living in verona, italy: a longitudinal study. *Obesity*, 28(8):1382–1385, 2020.

[60] Tobias Preis, Helen Susannah Moat, and H Eugene Stanley. Quantifying trading behavior in financial markets using google trends. *Scientific reports*, 3(1):1–6, 2013.

[61] Giulia Pullano, Eugenio Valdano, Nicola Scarpa, Stefania Rubrichi, and Vittoria Colizza. Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the covid-19 epidemic in france under lockdown: a population-based study. *The Lancet Digital Health*, 2(12):e638–e649, 2020.

[62] Pengyu Patrick Ren, Zhenyu Cheryl Qian, and Jung Joo Sohn. Learn to cook for yourself: Employing gamification in a recipe app design to promote a healthy living experience to young generation. In *International Conference on Human-Computer Interaction*, pages 458–470. Springer, 2020.

[63] Manoel Horta Ribeiro, Kristina Gligorić, Maxime Peyrard, Florian Lemmerich, Markus Strohmaier, and Robert West. Sudden attention shifts on wikipedia following covid-19 mobility restrictions. *arXiv preprint arXiv:2005.08505*, 2020.

[64] Rachel F Rodgers, Caterina Lombardo, Silvia Cerolini, Debra L Franko, Mika Omori, Matthew Fuller-Tyszkiewicz, Jake Linardon, Philippe Courtet, and Sebastien Guillaume. The impact of the covid-19 pandemic on eating disorder risk and symptoms. *International Journal of Eating Disorders*, 53(7):1166–1170, 2020.

[65] Markus Rokicki, Christoph Trattner, and Eelco Herder. The impact of recipe features, social cues and demographics on estimating the healthiness of online recipes. In *Proceedings of the 12th International AAAI Conference on Web and Social Media (ICWSM)*, 2018.

[66] E Romeo-Arroyo, M Mora, and L Vázquez-Araújo. Consumer behavior in confinement times: Food choice and cooking attitudes in spain. *International Journal of Gastronomy and Food Science*, 21: 100226, 2020.

[67] Benjamin J. Ryan, Damon Coppola, Deon V. Canyon, Mark Brickhouse, and Raymond Swienton. COVID-19 Community Stabilization and Sustainability Framework. *Disaster Medicine and Public Health Preparedness*, 2020.

[68] Adam Sadilek, Stephanie Caty, Lauren DiPrete, Raed Mansour, Tom Schenk, Mark Bergtholdt, Ashish Jha, Prem Ramaswami, and Evgeniy Gabrilovich. Machine-learned epidemiology: real-time detection of foodborne illness at scale. *npj Digital Medicine*, 1(1):36, 2018.

[69] Koustuv Saha, John Torous, Eric D Caine, and Munmun De Choudhury. Psychosocial effects of the covid-19 pandemic: Large-scale quasi-experimental study on social media. *J Med Internet Res*, 22 (11):e22600, Nov 2020.

[70] Federico Scarmozzino and Francesco Visioli. Covid-19 and the subsequent lockdown modified dietary habits of almost half the population in an italian sample. *Foods*, 9(5):675, 2020.

[71] Claudia Schmidt, Stephan Goetz, Sarah Rocker, and Zheng Tian. Google searches reveal changing consumer food sourcing in the covid-19 pandemic. *Journal of Agriculture, Food Systems, and Community Development*, 9(3):1–8, 2020.

[72] Sanket S Sharma and Munmun De Choudhury. Measuring and characterizing nutritional information of food and ingestion content in instagram. In *Proceedings of the 24th International Conference on World Wide Web (WWW)*, pages 115–116, 2015.

[73] Jagdish Sheth. Impact of covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, 117:280–283, 2020.

[74] Seth Stephens-Davidowitz. The cost of racial animus on a black candidate: Evidence using google search data. *Journal of Public Economics*, 118:26–40, 2014.

[75] Stephanie Stockwell, Mike Trott, Mark Tully, Jae Shin, Yvonne Barnett, Laurie Butler, Daragh McDermott, Felipe Schuch, and Lee Smith. Changes in physical activity and sedentary behaviours from before to during the covid-19 pandemic lockdown: a systematic review. *BMJ Open Sport & Exercise Medicine*, 7(1):e000960, 2021.

[76] Jina Suh, Eric Horvitz, Ryen W White, and Tim Althoff. Population-scale study of human needs during the covid-19 pandemic: Analysis and implications. *arXiv*, 2020.

[77] Takanao Tanaka and Shohei Okamoto. Increase in suicide following an initial decline during the covid-19 pandemic in japan. *Nature human behaviour*, 5(2):229–238, 2021.

[78] Simeon Vosen and Torsten Schmidt. Forecasting private consumption: survey-based indicators vs. google trends. *Journal of Forecasting*, 30(6):565–578, 2011.

[79] Denny Vrandečić and Markus Krötzsch. Wikidata: a free collaborative knowledgebase. *Communications of the ACM*, 57(10):78–85, 2014.

[80] Erpeng Wang, Ning An, Zhifeng Gao, Emmanuel Kiprop, and Xianhui Geng. Consumer food stockpiling behavior and willingness to pay for food reserves in covid-19. *Food Security*, 12(4): 739–747, 2020.

[81] André O Werneck, Danilo R Silva, Deborah C Malta, Crizian Saar Gomes, Paulo RB Souza-Júnior, Luiz O Azevedo, Marilisa BA Barros, and Célia L Szwarcwald. Associations of sedentary behaviours and incidence of unhealthy diet during the covid-19 quarantine in brazil. *Public health nutrition*, 24 (3):422–426, 2021.

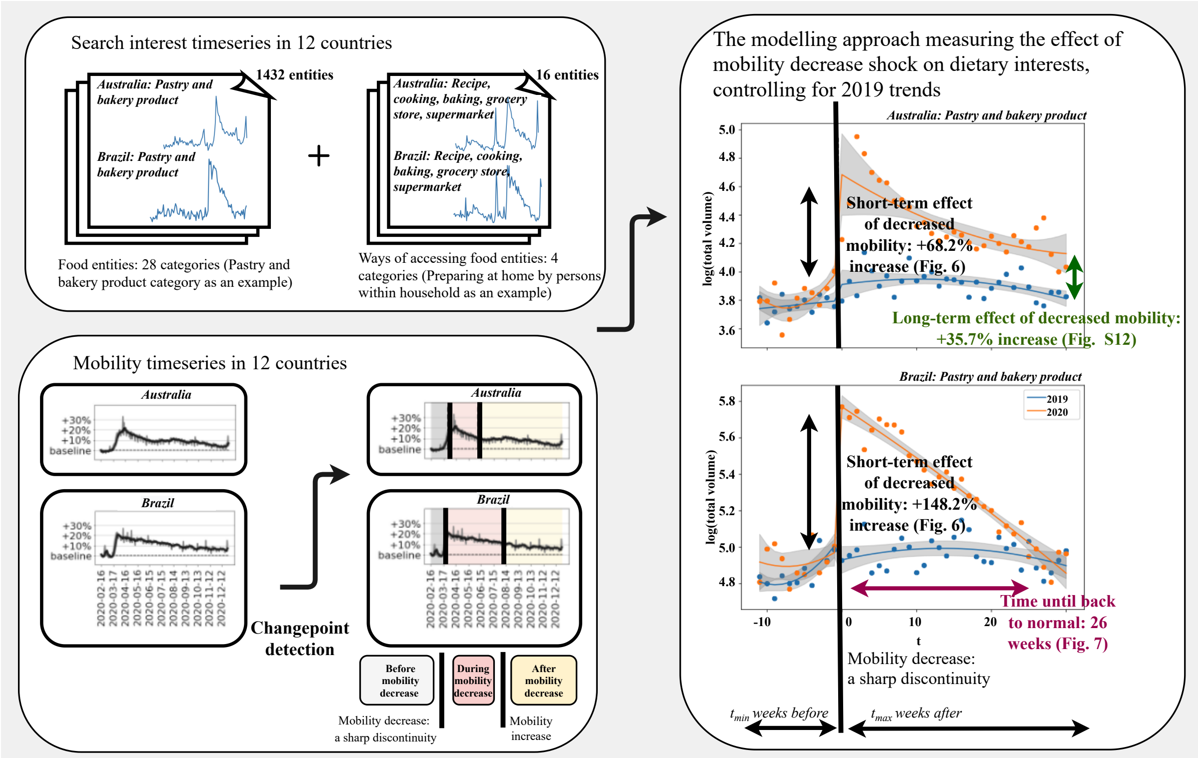
[82] Robert West. Calibration of google trends time series. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pages 2257–2260, 2020.

[83] Robert West, Ryen W. White, and Eric Horvitz. From cookies to cooks: Insights on dietary patterns via analysis of web usage logs. In *Proceedings of the 22nd International Conference on World Wide Web (WWW)*, pages 1399–1410, 2013.

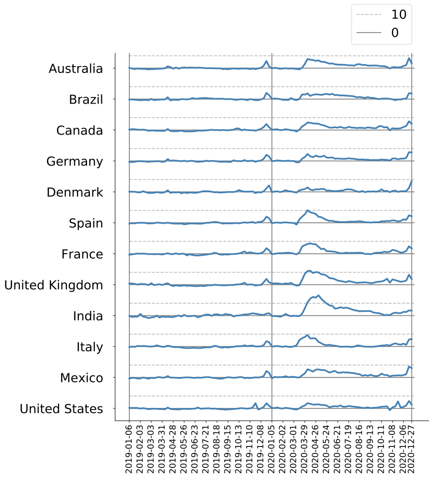
[84] Michael J Widener and Wenwen Li. Using geolocated twitter data to monitor the prevalence of healthy and unhealthy food references across the us. *Applied Geography*, 54:189–197, 2014.

[85] Jian Zhang, Yumei Zhang, Shanshan Huo, Yidi Ma, Yalei Ke, Peiyu Wang, and Ai Zhao. Emotional eating in pregnant women during the covid-19 pandemic and its association with dietary intake and gestational weight gain. *Nutrients*, 12(8):2250, 2020.

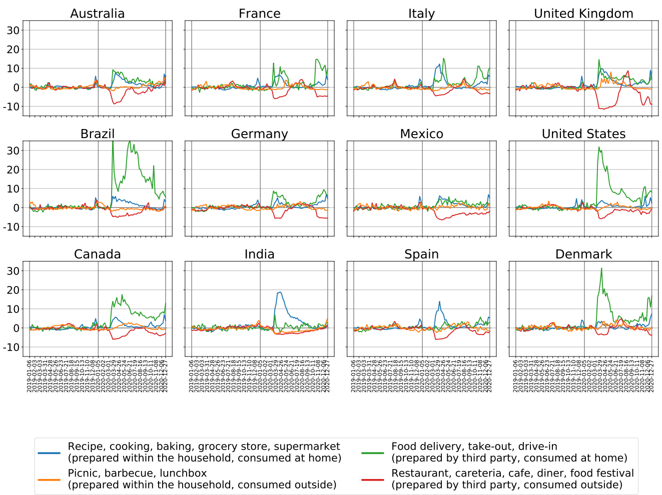
[86] Roberta Zupo, Fabio Castellana, Rodolfo Sardone, Annamaria Sila, Vito Angelo Giagulli, Vincenzo Triggiani, Raffaele Ivan Cincione, Gianluigi Giannelli, and Giovanni De Pergola. Preliminary trajectories in dietary behaviors during the covid-19 pandemic: a public health call to action to face obesity. *International Journal of Environmental Research and Public Health*, 17(19):7073, 2020.



(a) Study design. We start from interest timeseries in 12 countries, capturing search interest in food entities and in entities about the ways of accessing food. In order to measure the effect of the changes in mobility timeseries on interest, we first detect mobility changepoints: the abrupt mobility decrease and the eventual mobility increase via changepoint detection. Then, we illustrate the modelling approach on an the example of interest in pastry and bakery products in Australia and Brazil, where on the x-axis is the week relative to the week of the mobility decrease, and on the y-axis is search interest. The modelling approach measures the effect of the shock of mobility decrease on dietary interests, controlling for pre-pandemic trends. With this model, we measure the three key quantities: the short-term effect of decreased mobility (black arrow), the time until interest reverts back to normal (purple arrow), and the long-term effect of increased mobility (green arrow).

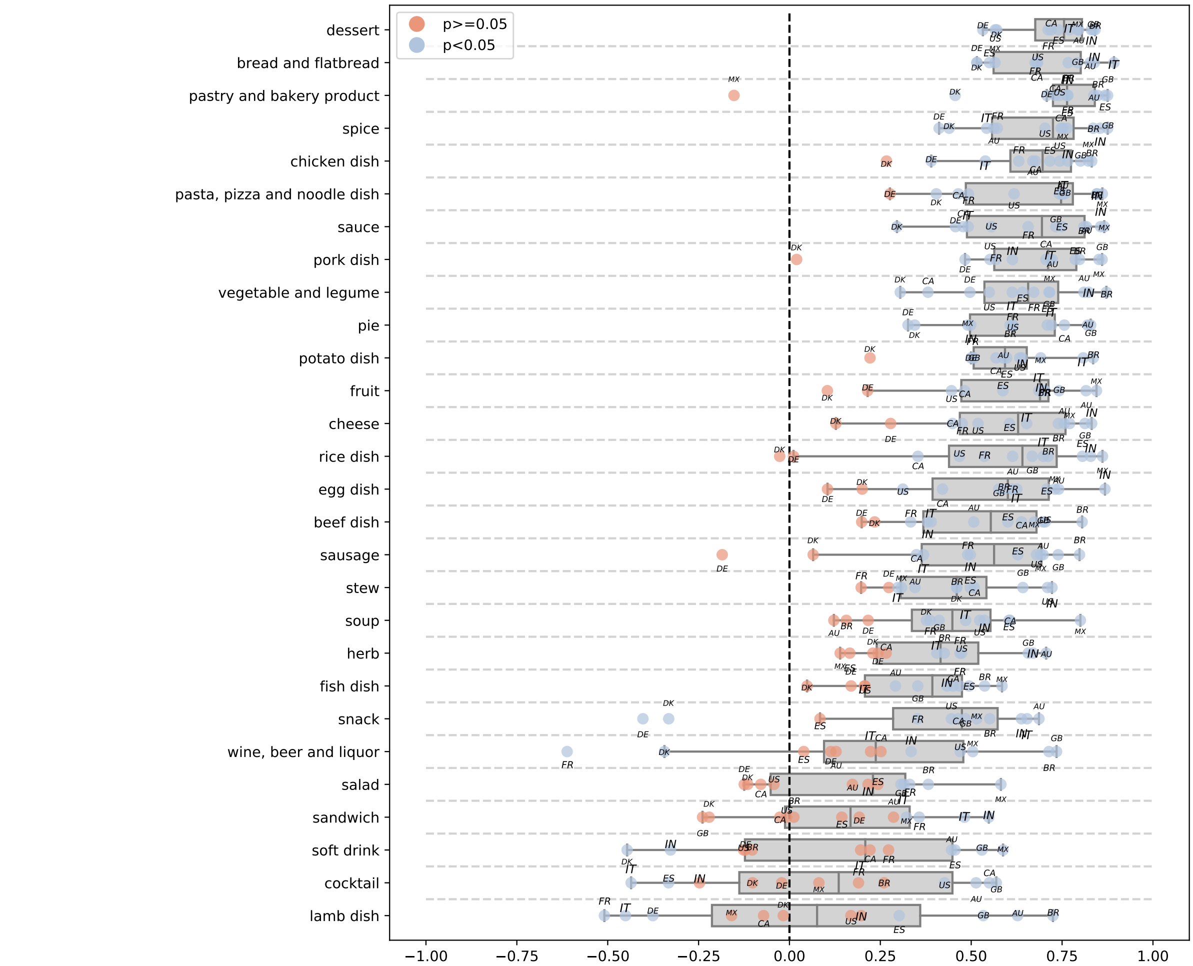


(b) Total interest in food entities (z-scores), 2019-2020.

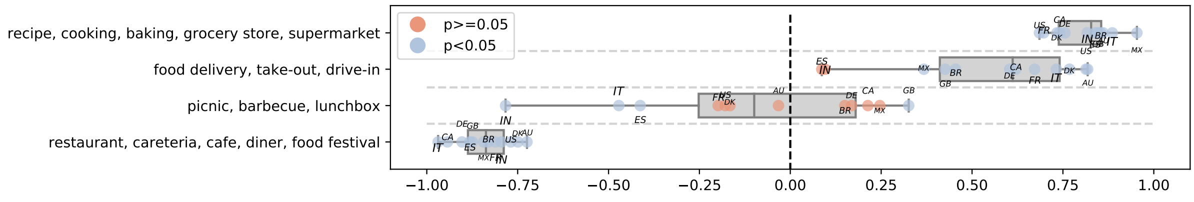


(c) Interest in ways of accessing food (z-scores), 2019-2020.

Figure 1: In (a), Study design. In (b) and (c), interest timeseries, standardized by 2019 mean and standard deviation. In (b), total interest in specific food entities. Dashed line marks 10 standard deviations above the 2019 mean. In (c), interest in ways of accessing food.

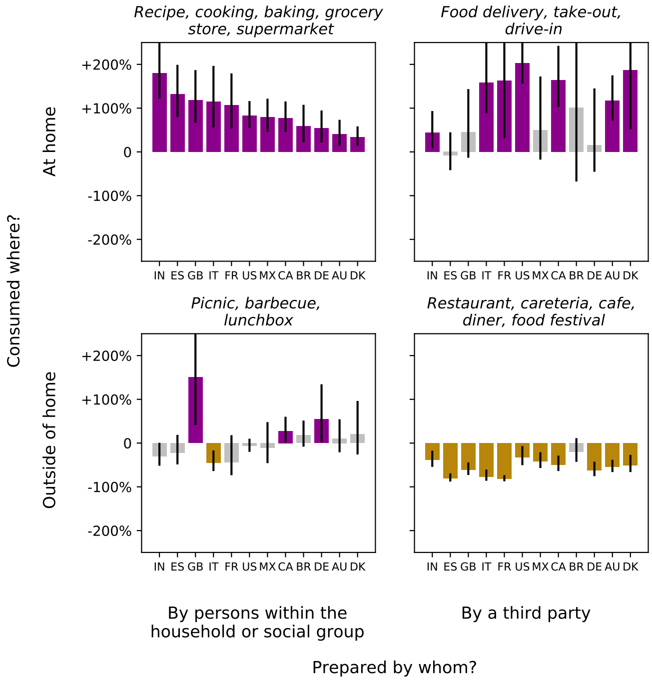


(a) Categories of food entities.

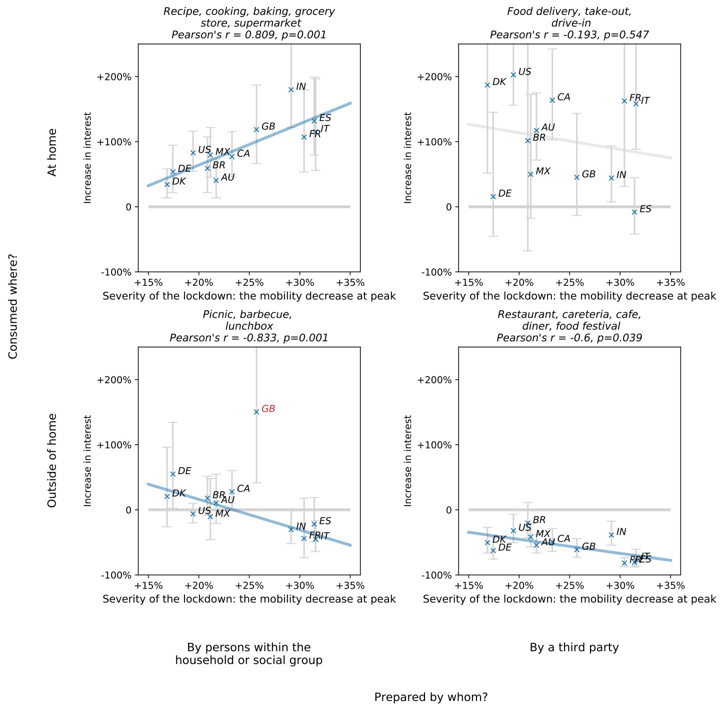


(b) Entities about ways of accessing food.

Figure 2: Spearman rank correlation coefficient between mobility and interest volume, in (a) for categories of food entities, and in (b), for ways of accessing food. For each group, 12 values represent correlation, and the boxplot summarizes the value across 12 countries. Significant correlations ($p < 0.05$) are marked in blue, and not significant in orange.



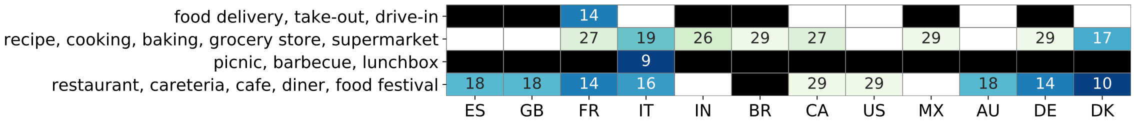
(a) The short-term effect of the shock of mobility decrease on interest in accessing food, estimated with our RDD-based model, with 95% confidence intervals. Purple marks significant positive ($p < 0.05$), yellow significant negative ($p < 0.05$), and grey marks non-significant effects. Fitted coefficients and statistics are presented in Table S1.



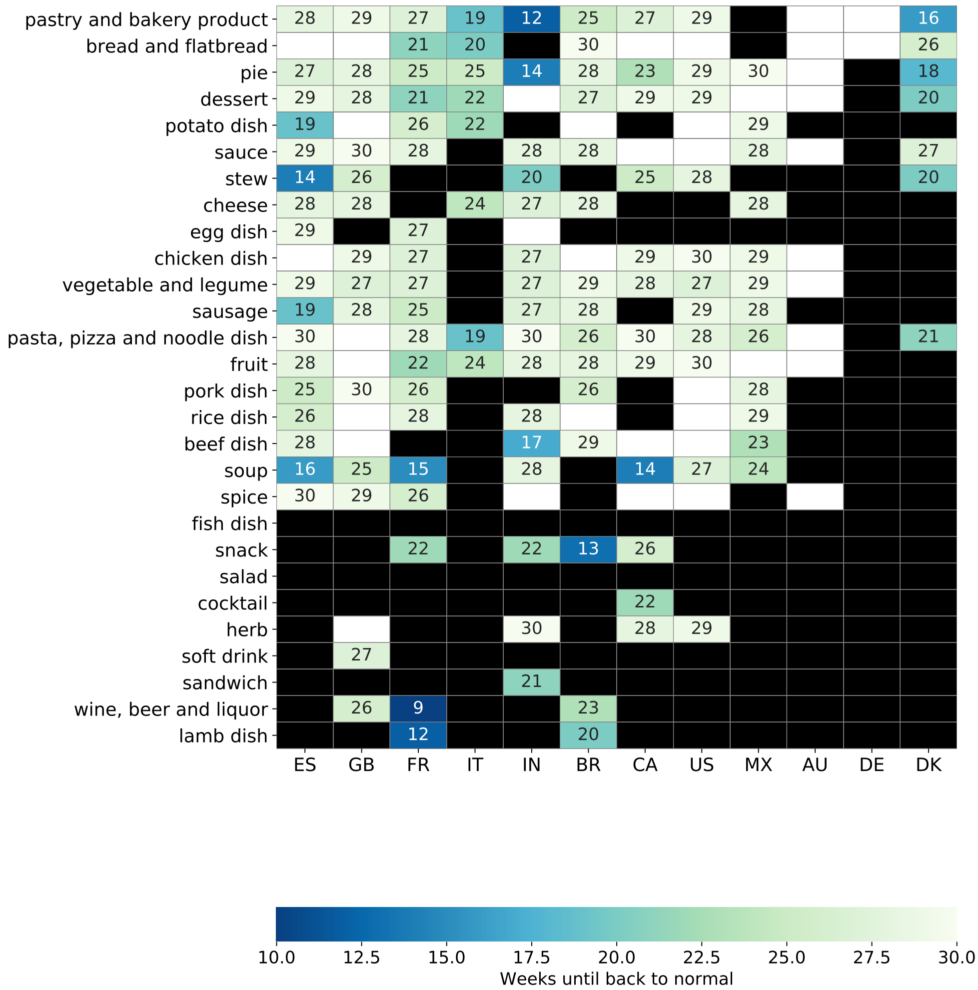
(b) The relationship between the severity of the lockdown, measured as the increase in the percentage of time spent at home at the peak of reduced mobility (x-axis), and the estimated short-term effect on interest (y-axis), across four groups of entities about ways of accessing food. The straight line is a least square fit.

Figure 3: The short-term effect of mobility decrease on interest in accessing food.

Figure 4: The short-term effect of the shock of mobility decrease on interest in categories of food entities (described in Table 1), estimated with our RDD-based model, with 95% confidence intervals. Purple marks significant positive ($p < 0.05$), yellow significant negative ($p < 0.05$), and grey marks non-significant effects. Fitted coefficients and statistics are presented in Table S1. Food categories are sorted by average effect across countries.



(a) Entities about ways of accessing food.



(b) Categories of food entities.

Figure 5: Number of weeks until food interest goes back to normal, in (a) for ways of accessing food, and in (b) for food categories. The number of weeks is determined by measuring how many weeks after the mobility decrease, the modeled interest in 2020 is no longer significantly different from the counterfactual prediction based on 2019 interest, based on non-overlapping 95% CI. Black marks that there are no significant differences in 2020 compared to 2019, and white marks that the interests did not go back to normal, until the end of 2020.

Table 1: Summary of the 28 food entity categories. For each category, we present the category description, the number of entities in the category, and category size that is the fraction of search interest covered by the category, on average, in the 12 studied countries in 2019 and 2020. Additionally, for each category, we show top 10 individual entities by the rank of the volume in average across 12 studied countries, in 2019 and 2020.

Category	Description	Number of entities	Category size
beef dish	food preparation based on beef	51	3.6%
Top 10 entities:	*Hamburger, Beef, Steak, Meatball, Meatloaf, Beef Stroganoff, Beef mince, Fajita, Sirloin steak, Big Mac*		
chicken dish	food preparation based on chicken	37	3.4%
Top 10 entities:	*Chicken meat, Chicken nugget, Fried chicken, Chicken curry, Hendl, Chicken soup, Butter chicken, Chicken tikka masala, Cordon bleu, Crispy fried chicken*		
pork dish	food preparation based on pork	45	2.2%
Top 10 entities:	*Pork, Ham, Hot dog, Bacon, Pork chop, Pork belly, Gyro, Pork tenderloin, Pulled pork, Ham hock*		
lamb dish	food preparation based on lamb	17	0.5%
Top 10 entities:	*Lamb and mutton, Doner kebab, Shawarma, Méchoui, Rogan josh, Sfiha, Kokoretsi, Çiğ köfte, Pasanda, Arrosticini*		
fish dish	type of dish comprised of fish	57	1.7%
Top 10 entities:	*Cod, Caviar, Tuna, Salmon, Squid, Catfish, Tempura, Sardine, Smoked salmon, Crayfish*		
sausage	food usually made from ground meat with a skin around it	16	0.7%
Top 10 entities:	*Sausage, Salami, Chorizo, Mortadella, Black pudding, Bratwurst, 'Nduja, Boudin, Sujuk, Andouille*		
pasta, pizza and noodle dish	Italian food made from flour, eggs and water and shaped in different forms, usually cooked and served with a sauce, or a dish made with pasta, or type of staple food made from some type of unleavened dough	95	7.3%
Top 10 entities:	*Pizza, Pasta, Spaghetti, Lasagne, Carbonara, Noodle, Gnocchi, Macaroni, Penne, Ravioli*		
potato dish	type of food based on potatoes	27	1.2%
Top 10 entities:	*Mashed potato, French fries, Gratin, Baked potato, Tortilla de patatas, Potato, Potato pancake, Patatas bravas, Tater Tots, Sunday roast*		
rice dish	a type of dish made of rice	49	3.3%
Top 10 entities:	*Rice, Sushi, Risotto, Fried rice, Paella, Basmati, Pilaf, Bento, Biryani, White rice*		
egg dish	a type of dish made of eggs	22	2.6%
Top 10 entities:	*Egg, Boiled egg, Omelette, Quiche, Scrambled eggs, Poached egg, Frittata, Eggs Benedict, Deviled egg, Egg roll*		
stew	combination of solid food ingredients that have been cooked in liquid and served in the resultant gravy	24	0.4%
Top 10 entities:	*Stew, Ratatouille, Jambalaya, Dolma, Gumbo, Cassoulet, Sambar, Blanquette de veau, Irish stew, Pot-au-feu*		
soup	primarily liquid food	55	2.2%
Top 10 entities:	*Soup, Broth, Ramen, Miso, Pho, French onion soup, Hot pot, Goulash, Minestrone, Cream of mushroom soup*		
bread and flatbread	staple food prepared from a dough	31	2.8%
Top 10 entities:	*Bread, Pita, Bagel, Sourdough, Baguette, Naan, Pretzel, Focaccia, Bruschetta, White bread*		
sandwich	two slices of bread with filling in between them	20	0.5%
Top 10 entities:	*Sandwich, Panini, Corn dog, Croque-monsieur, Tuna fish sandwich, BLT, Peanut butter and jelly sandwich, Filet-O-Fish, Bocadillo, Cucumber sandwich*		
salad	dish consisting of a mixture of small pieces of food, usually vegetables or fruit	24	1.9%
Top 10 entities:	*Salad, Lettuce, Potato salad, Pasta salad, Caesar salad, Tabbouleh, Greek salad, Insalata Caprese, Egg salad, Olivier salad*		
cheese cheese	yellow or white, creamy or solid food made from the pressed curds of milk	90	3.2%
Top 10 entities:	*Cheese, Mozzarella, Cream cheese, Parmigiano-Reggiano, Ricotta, Feta, Fondue, Cheddar cheese, Mascarpone, Cottage cheese*		
sauce	liquid, creaming or semi-solid food served on or used in preparing other foods	60	3.8%
Top 10 entities:	*Sauces, Pesto, Mayonnaise, Dip, Mustard, Béchamel sauce, Tomato sauce, Soy sauce, Bolognese sauce, Gravy*		
snack	portion of food, often smaller than a regular meal	20	1.8%
Top 10 entities:	*Peanut, Popcorn, Hummus, Guacamole, Cashew, Pistachio, Tapas, Nachos, Cracker, Edamame*		
vegetable and legume	edible plant or part of a plant, involved in cooking	85	9.5%
Top 10 entities:	*Vegetable, Tomato, Sweet potato, Onion, Cucumber, Spinach, Eggplant, Cauliflower, Cabbage, Zucchini*		
fruit	food, edible in the raw state	63	9.0%
Top 10 entities:	*Apple, Lemon, Pineapple, Avocado, Grape, Cherry, Watermelon, Mango, Banana, Fruit*		
herb	plant part used for flavoring, food, medicine, or perfume	29	1.9%
Top 10 entities:	*Lavender, Basil, Rosemary, Herb, Celery, Coriander, Parsley, Eucalyptus, Peppermint, Sage*		
spice	dried seed, fruit, root, bark, or vegetable substance primarily used for flavoring, coloring or preserving food	38	4.1%
Top 10 entities:	*Garlic, Table salt, Ginger, Chili pepper, Spice, Turmeric, Vanilla, Cinnamon, Common Fig, Black pepper*		
soft drink	non-alcoholic drink, often carbonated (sparkling)	27	1.9%
Top 10 entities:	*Coca-Cola, Juice, Soft drink, Cola, Lemonade, Orange juice, Tonic water, Energy drink, Iced tea, Apple juice*		
wine, beer and liquor	alcoholic drink, alcoholic drink typically made from grapes, or alcoholic beverage that is produced by distilling	46	8.1%
Top 10 entities:	*Vodka, Wine, Beer, Rum, Gin, Alcoholic beverage, Tequila, Champagne, Red Wine, Sake*		
cocktail	alcoholic mixed drink	142	1.5%
Top 10 entities:	*Cocktail, Mojito, Martini, Sour, Gin and tonic, Margarita, Spritz, Piña colada, Mimosa, Bloody Mary*		
pie	baked dish	20	1.4%
Top 10 entities:	*Tart, Pie, Apple pie, Cottage pie, Pumpkin pie, Tarte Tatin, Meat pie, Börek, Lemon meringue pie, Banoffee pie*		
pastry and bakery product	various baked products made of dough	40	1.3%
Top 10 entities:	*Baking powder, Baker's yeast, Pastry, Brioche, Puff pastry, Samosa, Filo, Ice cream cone, Cannoli, Beignet*		
dessert	course that concludes a meal; usually very sweet	202	18.0%
Top 10 entities:	*Cake, Chocolate, Ice cream, Honey, Pancake, Biscuit, Cookie, beigne, Cupcake, Muffin*		

Table 2: Entity-level Spearman rank correlation (* marks $p < 0.05$) between seasonality adjusted interest and mobility. For modes all entities are shown. For foods, top 10 entities most and least correlated across countries on average are shown. Entities related to consuming food **at home** are marked in blue if food is prepared by persons within the household, or in teal if food is prepared by a third party. On the other hand, entities related to consuming food **outside of home** home are marked in orange if food is prepared by persons within the household or social group, or in red if food is prepared by a third party. All entities related to consuming food at home are correlated positively on average, all entities related to consuming food outside of home are correlated negatively on average, except barbecue.

Mode entity (N=16)	**Avg**	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
On average positively correlated													
Recipe	0.8	0.88*	0.87*	0.73*	0.74*	0.73*	0.8*	0.72*	0.85*	0.82*	0.85*	0.95*	0.68*
Baking	0.67	0.88*	0.8*	0.71*	0.55*	0.28	0.63*	0.42*	0.88*	0.91*	0.46*	0.79*	0.77*
Cooking	0.67	0.75*	0.67*	0.6*	0.39*	0.23	0.87*	0.61*	0.88*	0.84*	0.75*	0.82*	0.62*
Take-out	0.58	0.8*	0.66*	0.64*	0.55*	0.73*	0.1	0.62*	0.33*	0.31*	0.79*	0.49*	0.88*
Grocery store	0.31	0.15	0.32*	0.64*	0.4*	0.32*	0.12	-0.29*	0.64*	0.8*	0.46*	-0.28	0.39*
Supermarket	0.18	-0.21	0.58*	0.38*	-0.01	0.25	0.48*	-0.44*	0.02	0.01	0.63*	0.23	0.28
Food delivery	0.1	0.51*	-0.12	0.4*	0.07	-0.25	-0.08	-0.05	0.27	-0.12	0.36*	-0.33*	0.52*
Barbecue	0.04	0.04	0.61*	0.23	-0.01	-0.2	0.11	-0.01	0.4*	-0.81*	-0.05	0.31*	-0.2
Drive-in	0.03	-0.44*	0.25	-0.14	0.42*	0.51*	-0.24	0.47*	0.09	-0.27	-0.21	-0.17	0.09
On average negatively correlated													
Picnic	-0.19	-0.41*	-0.44*	-0.16	0.13	0.08	-0.53*	-0.22	0.31*	-0.78*	-0.48*	0.06	0.19
Lunchbox	-0.44	-0.69*	-0.18	-0.59*	-0.67*	-0.14	-0.18	-0.34*	-0.56*	-0.44*	-0.36*	-	-0.66*
Cafeteria	-0.47	-0.49*	-0.37*	-0.56*	-0.78*	-0.5*	-0.41*	-0.86*	-0.29	-0.5*	-0.1	0.0	-0.81*
Food festival	-0.42	-0.4*	-0.39*	-0.52*	-0.69*	-0.03	-0.24	-0.29	-0.63*	-0.72*	-0.32*	-0.18	-0.69*
Diner	-0.39	-0.41*	-0.03	-0.83*	-0.71*	-0.12	-0.04	-0.46*	-0.79*	-0.15	-0.38*	-0.08	-0.62*
Cafe	-0.82	-0.65*	-0.86*	-0.94*	-0.86*	-0.72*	-0.86*	-0.8*	-0.86*	-0.9*	-0.85*	-0.74*	-0.82*
Restaurant	-0.82	-0.71*	-0.81*	-0.9*	-0.84*	-0.72*	-0.88*	-0.8*	-0.86*	-0.93*	-0.95*	-0.78*	-0.64*
Food entity (N=1432)	**Avg**	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
Top 10, on average positively correlated													
Pancake (dessert)	0.67	0.72 *	0.87 *	0.62 *	0.64 *	0.53 *	0.67 *	0.61 *	0.57 *	0.74 *	0.8 *	0.72 *	0.62 *
Bread (bread and flatbread)	0.67	0.81 *	0.74 *	0.69 *	0.5 *	0.37 *	0.54 *	0.58 *	0.77 *	0.92 *	0.81 *	0.56 *	0.71 *
Baking powder (pastry and bakery product)	0.65	0.61 *	0.73 *	0.76 *	0.6 *	0.16	0.56 *	0.6 *	0.82 *	0.89 *	0.8 *	0.7 *	0.63 *
Biscuit (dessert)	0.65	0.7 *	0.7 *	0.74 *	0.39 *	0.05	0.73 *	0.69 *	0.82 *	0.74 *	0.68 *	0.77 *	0.73 *
Chicken meat (chicken dish)	0.64	0.64 *	0.83 *	0.63 *	0.47 *	0.26	0.76 *	0.61 *	0.75 *	0.73 *	0.4 *	0.83 *	0.75 *
Chocolate brownie (dessert)	0.63	0.65 *	0.89 *	0.63 *	0.44 *	0.22	0.43 *	0.73 *	0.84 *	0.7 *	0.58 *	0.78 *	0.65 *
Pasta (pasta, pizza and noodle dish)	0.63	0.72 *	0.51 *	0.6 *	0.4 *	0.19	0.68 *	0.61 *	0.74 *	0.77 *	0.83 *	0.78 *	0.69 *
Sourdough (bread and flatbread)	0.61	0.66 *	0.8 *	0.57 *	0.42 *	0.43 *	0.64 *	0.77 *	0.78 *	0.5 *	0.48 *	0.59 *	0.7 *
Chocolate (dessert)	0.6	0.58 *	0.67 *	0.71 *	0.12	0.34 *	0.7 *	0.59 *	0.82 *	0.54 *	0.77 *	0.67 *	0.7 *
Sponge cake (dessert)	0.59	0.68 *	0.69 *	0.33 *	0.48 *	0.5 *	0.79 *	0.29 *	0.83 *	0.81 *	0.61 *	0.42 *	0.62 *
Top 10, on average negatively correlated													
Tapas (snack)	-0.43	-0.51 *	-0.05	-0.49 *	-0.76 *	-0.45 *	-0.89 *	-0.83 *	-0.77 *	0.09	-0.18	0.41 *	-0.7 *
Korean barbecue (beef dish)	-0.32	-0.62 *	0.02	-0.69 *	-0.5 *	-0.17	-0.17	-0.47 *	-0.6 *	0.09	-0.06	0.03	-0.73 *
Hot pot (soup)	-0.21	-0.54 *	-0.17	-0.45 *	-0.22	0.02	-0.33 *	-0.26	0.24	0.08	-0.18	0.11	-0.79 *
Sushi (rice dish)	-0.2	-0.33 *	-0.1	-0.36 *	-0.43 *	-0.15	0.02	-0.07	-0.12	-0.16	-0.43 *	0.15	-0.42 *
Agnolotti (pasta, pizza and noodle dish)	-0.2	-0.19	-0.21	-0.32 *	-0.25	0.03	-0.28	-0.15	-0.58 *	0.14	0.2	-0.29	-0.44 *
Mochi (dessert)	-0.19	-0.02	-0.35 *	-0.21	-0.22	0.05	-0.25	-0.26	-0.08	-0.41 *	-0.17	-0.19	-0.11
Bento (rice dish)	-0.18	-0.29	0.15	-0.35 *	-0.12	-0.27	-0.03	-0.37 *	-0.54 *	-0.22	0.05	-0.18	-0.05
Dim sum food (pasta, pizza and noodle dish)	-0.18	-0.1	-0.1	-0.53 *	-0.05	0.0	0.05	-0.26	-0.46 *	0.29	-0.16	-0.18	-0.72 *
Jackfruit (fruit)	-0.18	-0.05	-0.17	-0.42 *	-0.1	-0.09	-0.11	-0.29 *	-0.28	0.26	-0.41 *	-0.16	-0.39 *
Burrata (cheese)	-0.18	-0.02	0.18	-0.36 *	-0.15	0.25	-0.48 *	-0.28	-0.27	0.06	-0.33 *	-0.12	-0.63 *

Supplementary material

1.1 Supplementary information, design choices and robustness checks

In Figure S1, we present the detected mobility decreases and increases in the 12 countries. We list all fitted coefficients and statistics of our main model in Table S1, and in Table S2, we present a variant of Table 2 where the short term increase in interest in individual entities is estimated with a quadratic model. We provide correlation plots with Pearson correlation coefficient, instead of Spearman rank correlation coefficient in Figure S2. Next, we provide our main results obtained with the RDD model with varying design choices and confirm that the qualitative interpretations of the effects remain stable under a number of robustness checks.

The impact of model order. We show our main results with a linear model in Figures S3a and S3b, and in Figures S4a and S4b with a constant model, instead of a quadratic model. While quadratic and linear models let us estimate the short-term effect (as illustrated in Figure 1a), with the constant model we estimate the average effect in the entire period, from the discontinuity, until the bandwidth (K_2) weeks after discontinuity. The estimates of the effect with the constant model are then lower because the weeks when the effect diminishes are taken into account to calculate the average (see illustration in Figure S7). While the nature and the amplitude of the estimated effect vary (i.e., whether the immediate short-term boost of average boost is captured), most of the conclusions are robust to this choice.

Additionally, for each category of food items, we fit a slightly different model pulling the interest volume across different countries similar to Equation 1, but with an added country-specific offset, that lets us measure effect across all countries. In Table S3, as a robustness check, we show the food categories ranked by effect size pulled across countries, estimated with a constant, linear, and quadratic model. The rank between categories is strongly correlated (Spearman rank correlation $0.95\,(p < 10^{-14})$ between constant and linear, $0.91\,(p < 10^{-10})$ between constant and quadratic, and $0.96\,(p < 10^{-15})$ between linear and quadratic models.

In Figure S5, we show how the quadratic model fits the temporal evolution in the case of pastry and bakery category, in 12 countries. We also show linear (Figure S6) and constant fit (Figure S7) for comparison.

The impact of bandwidth. In Figure S8, we study the impact of the choice of the bandwidth $\max(t_{\min}, t_{\max}) = 30$ and the choice of the degree of the model. We observe that for a sufficiently large bandwidth, all four models estimate a similar effect, and the choice of bandwidth does not matter as the estimates converge.

Modelling interest share. We show our main results with the same model, but the dependent variable being the weekly share of interest in Figures S9a and S9b. This way, we control for overall increased interest in all categories. This analysis provides an alternative view. We see that the share of volume decreases significantly for foods whose growth is not proportional to the growth of the foods that experience major surges of interest.

1.2 Supplementary analyses

We perform supplementary analyses that support our main conclusions or provide complementary insights. In Figure S10, we show interest in ways of accessing food normalized by 2019 baseline by week, with mobility periods indicated in the background. We take the value of the interest in each 2020 week and calculate the relative difference compared to the value in 2019 in the corresponding week.

In Figure S11 we show short-term effects estimated with quadratic model, grouped by country. In each country, the gray line represents the overall country-specific short-term effect, that is the increase in interest in all food entities. Finally, we explore the effect of the second mobility decrease in Figure S12, and we present the long-term effects in Figure S13.

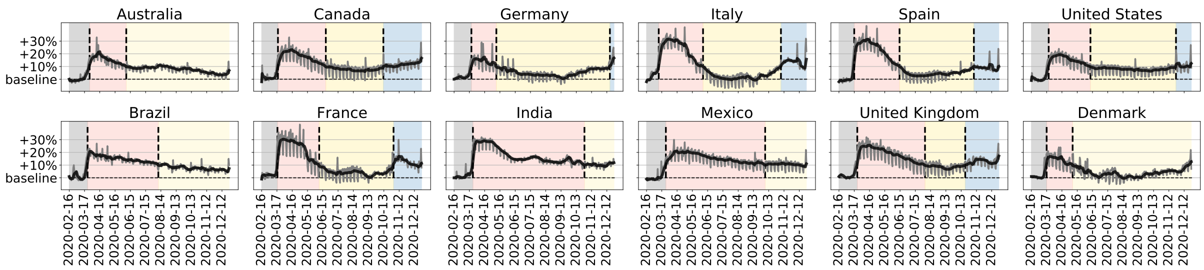


Figure S1: Mobility in 12 studied countries. Mobility changepoints (mobility decrease, mobility increase, and the second mobility decrease in case it occurs) are marked with vertical dashed lines.

Table S1: Main quadratic model: fitted coefficient alpha, standard error in brackets, and R^2 statistic. Entities Recipe, Food delivery, Restaurant, and Picnic mark the sets of entities described in Figure 3a.

Ways of accessing	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
Recipe	0.34[0.11], 0.9	0.46[0.13], 0.9	0.57[0.1], 0.87	0.43[0.12], 0.77	0.29[0.08], 0.77	0.84[0.13], 0.9	0.73[0.15], 0.81	0.78[0.14], 0.94	1.03[0.12], 0.95	0.77[0.16], 0.87	0.58[0.11], 0.93	0.6[0.08], 0.91
Food delivery	0.78[0.12], 0.9	0.7[0.92], 0.93	0.97[0.13], 0.95	0.15[0.38], 0.85	1.05[0.32], 0.9	-0.09[0.23], 0.66	0.96[0.35], 0.57	0.37[0.26], 0.86	0.37[0.15], 0.24	0.95[0.16], 0.7	0.4[0.3], 0.65	1.11[0.08], 0.96
Restaurant	-0.78[0.15], 0.86	-0.23[0.17], 0.88	-0.68[0.17], 0.87	-0.98[0.21], 0.84	-0.7[0.19], 0.75	-1.65[0.23], 0.93	-1.7[0.19], 0.92	-0.95[0.18], 0.84	-0.49[0.15], 0.97	-1.45[0.26], 0.88	-0.54[0.15], 0.93	-0.39[0.16], 0.82
Picnic	0.1[0.17], 0.7	0.16[0.13], 0.85	0.24[0.11], 0.97	0.44[0.21], 0.7	0.19[0.24], 0.55	-0.25[0.21], 0.75	-0.58[0.37], 0.77	0.92[0.29], 0.87	-0.36[0.18], 0.92	-0.6[0.21], 0.72	-0.11[0.25], 0.49	-0.06[0.08], 0.84
Food categories	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
beef dish	0.16[0.08], 0.79	0.35[0.06], 0.82	0.24[0.08], 0.63	0.26[0.1], 0.4	0.16[0.15], 0.39	0.59[0.13], 0.7	0.38[0.15], 0.68	0.55[0.12], 0.77	0.23[0.11], 0.64	0.17[0.13], 0.39	0.2[0.1], 0.66	0.41[0.11], 0.66
bread and flatbread	0.39[0.15], 0.91	0.6[0.11], 0.96	1.08[0.17], 0.9	0.48[0.11], 0.93	0.69[0.17], 0.88	1.41[0.21], 0.91	1.36[0.19], 0.9	0.67[0.25], 0.96	0.64[0.13], 0.8	1.37[0.28], 0.86	0.13[0.11], 0.92	0.84[0.09], 0.92
cheese	0.37[0.11], 0.74	0.45[0.09], 0.85	0.35[0.11], 0.68	0.18[0.1], 0.8	0.26[0.21], 0.52	0.64[0.18], 0.65	0.44[0.15], 0.6	0.62[0.12], 0.76	0.6[0.11], 0.89	0.41[0.18], 0.64	0.62[0.12], 0.66	0.27[0.08], 0.66
chicken dish	0.25[0.09], 0.84	0.28[0.06], 0.91	0.3[0.09], 0.81	0.31[0.12], 0.77	0.19[0.13], 0.65	0.77[0.14], 0.87	0.52[0.16], 0.67	0.57[0.11], 0.82	0.38[0.13], 0.79	0.5[0.17], 0.81	0.34[0.07], 0.91	0.29[0.07], 0.83
cocktail	0.25[0.16], 0.73	0.35[0.21], 0.73	0.29[0.09], 0.8	0.06[0.12], 0.84	-0.18[0.21], 0.79	0.09[0.22], 0.74	0.26[0.16], 0.77	0.7[0.2], 0.72	-0.23[0.19], 0.4	0.5[0.23], 0.79	-0.1[0.14], 0.51	0.31[0.1], 0.66
dessert	0.44[0.12], 0.79	0.41[0.08], 0.89	0.56[0.11], 0.83	0.34[0.12], 0.71	0.32[0.12], 0.69	0.99[0.15], 0.9	0.74[0.18], 0.81	1.01[0.16], 0.85	0.51[0.19], 0.76	0.66[0.18], 0.85	0.27[0.09], 0.88	0.37[0.1], 0.72
egg dish	0.82[0.27], 0.74	0.24[0.17], 0.61	0.23[0.17], 0.58	0.29[0.15], 0.66	0.14[0.19], 0.47	0.73[0.18], 0.79	0.58[0.19], 0.81	0.55[0.18], 0.81	0.55[0.12], 0.9	0.33[0.29], 0.73	0.34[0.1], 0.82	0.21[0.2], 0.56
fish dish	0.12[0.17], 0.44	0.36[0.36], 0.38	0.14[0.1], 0.66	0.24[0.14], 0.5	0.33[0.23], 0.22	0.65[0.17], 0.55	0.27[0.12], 0.57	0.29[0.09], 0.79	0.08[0.08], 0.68	0.11[0.16], 0.31	0.38[0.21], 0.61	0.16[0.08], 0.85
fruit	0.36[0.07], 0.87	0.21[0.04], 0.8	0.33[0.07], 0.9	0.2[0.09], 0.79	0.05[0.06], 0.61	0.6[0.11], 0.83	0.64[0.12], 0.77	0.65[0.08], 0.94	0.28[0.1], 0.83	0.33[0.1], 0.78	0.35[0.07], 0.93	0.19[0.06], 0.89
herb	0.03[0.09], 0.78	0.05[0.05], 0.95	0.21[0.07], 0.91	0.16[0.12], 0.93	0.45[0.18], 0.66	0.16[0.08], 0.81	0.19[0.14], 0.87	0.58[0.1], 0.91	0.17[0.08], 0.92	0.27[0.14], 0.76	-0.18[0.13], 0.71	0.14[0.06], 0.92
lamb dish	0.18[0.14], 0.82	0.61[0.14], 0.71	-0.04[0.17], 0.35	0.05[0.11], 0.75	0.13[0.45], 0.22	-0.31[0.55], 0.08	-0.32[0.15], 0.4	0.31[0.26], 0.59	-0.14[0.14], 0.47	-0.37[0.24], 0.5	-0.11[0.45], 0.18	0.11[0.21], 0.34
pasta, pizza and noodle dish	0.22[0.08], 0.8	0.43[0.08], 0.78	0.28[0.07], 0.82	0.17[0.07], 0.63	0.25[0.08], 0.4	0.66[0.14], 0.77	0.34[0.1], 0.65	0.37[0.1], 0.91	0.5[0.12], 0.88	0.61[0.15], 0.72	0.3[0.11], 0.77	0.27[0.06], 0.68
pastry and bakery product	0.52[0.17], 0.86	0.91[0.09], 0.93	1.26[0.25], 0.81	0.96[0.15], 0.87	0.43[0.2], 0.55	1.45[0.25], 0.86	1.32[0.27], 0.82	1.1[0.23], 0.93	1.05[0.24], 0.74	1.08[0.33], 0.84	-0.0[0.1], 0.32	1.06[0.22], 0.83
pie	0.37[0.16], 0.88	0.49[0.15], 0.87	0.8[0.19], 0.79	0.3[0.31], 0.45	0.58[0.19], 0.5	1.14[0.22], 0.79	0.74[0.18], 0.77	0.75[0.14], 0.83	0.31[0.13], 0.44	0.84[0.28], 0.84	0.65[0.26], 0.63	0.66[0.26], 0.75
pork dish	0.19[0.1], 0.85	0.32[0.06], 0.88	0.35[0.12], 0.59	0.23[0.13], 0.43	0.31[0.1], 0.28	0.42[0.12], 0.69	0.34[0.13], 0.76	0.56[0.1], 0.85	0.19[0.11], 0.83	0.4[0.13], 0.53	0.49[0.1], 0.81	0.34[0.12], 0.61
potato dish	0.33[0.13], 0.72	0.46[0.15], 0.87	0.53[0.19], 0.58	0.47[0.11], 0.77	0.01[0.26], 0.59	0.61[0.13], 0.72	0.59[0.15], 0.82	0.66[0.11], 0.78	0.63[0.09], 0.93	0.47[0.19], 0.83	1.11[0.28], 0.67	0.44[0.12], 0.73
rice dish	0.17[0.1], 0.75	0.4[0.07], 0.74	0.16[0.09], 0.66	0.1[0.1], 0.73	0.24[0.11], 0.5	0.63[0.12], 0.68	0.37[0.13], 0.75	0.28[0.09], 0.87	0.61[0.09], 0.89	0.21[0.16], 0.54	0.32[0.09], 0.85	0.23[0.06], 0.85
salad	0.18[0.15], 0.84	0.11[0.09], 0.61	0.04[0.06], 0.9	0.16[0.12], 0.81	-0.08[0.22], 0.79	0.54[0.15], 0.89	0.41[0.16], 0.85	0.6[0.17], 0.81	0.35[0.11], 0.39	0.24[0.13], 0.8	0.24[0.11], 0.64	0.02[0.09], 0.85
sandwich	0.25[0.1], 0.48	0.04[0.11], 0.4	-0.13[0.09], 0.5	0.17[0.14], 0.31	-0.09[0.24], 0.28	0.26[0.18], 0.25	0.25[0.22], 0.46	0.14[0.13], 0.49	0.33[0.13], 0.69	0.34[0.24], 0.41	0.18[0.13], 0.5	-0.18[0.11], 0.36
sauce	0.38[0.08], 0.84	0.43[0.06], 0.86	0.31[0.08], 0.8	0.26[0.12], 0.72	0.36[0.15], 0.6	0.71[0.12], 0.81	0.49[0.13], 0.69	0.6[0.09], 0.86	0.71[0.15], 0.9	0.52[0.14], 0.57	0.46[0.09], 0.84	0.33[0.08], 0.85
sausage	0.33[0.18], 0.72	0.29[0.09], 0.77	0.18[0.11], 0.54	-0.01[0.18], 0.47	0.15[0.26], 0.22	0.77[0.12], 0.73	0.36[0.11], 0.75	0.55[0.1], 0.8	0.81[0.18], 0.56	0.38[0.17], 0.44	0.27[0.12], 0.75	0.34[0.05], 0.77
snack	0.28[0.1], 0.56	0.3[0.06], 0.75	0.26[0.08], 0.78	0.02[0.09], 0.64	-0.11[0.15], 0.34	0.13[0.12], 0.45	0.37[0.11], 0.67	0.57[0.09], 0.72	0.43[0.13], 0.8	0.18[0.16], 0.58	0.08[0.09], 0.39	0.32[0.08], 0.72
soft drink	0.27[0.11], 0.54	-0.05[0.05], 0.59	-0.02[0.07], 0.48	0.09[0.06], 0.82	-0.04[0.18], 0.46	0.47[0.15], 0.61	0.04[0.09], 0.57	0.32[0.11], 0.72	-0.13[0.09], 0.64	0.53[0.13], 0.41	0.15[0.13], 0.49	-0.02[0.06], 0.56
soup	-0.11[0.11], 0.92	0.5[0.18], 0.68	0.27[0.11], 0.91	0.12[0.11], 0.87	0.22[0.12], 0.85	0.5[0.1], 0.74	0.34[0.14], 0.88	0.29[0.1], 0.94	0.34[0.09], 0.63	0.23[0.15], 0.83	0.31[0.11], 0.56	0.25[0.09], 0.96
spice	0.28[0.08], 0.84	0.14[0.07], 0.94	0.27[0.08], 0.85	0.09[0.07], 0.78	0.03[0.06], 0.57	0.49[0.1], 0.78	0.45[0.15], 0.77	0.49[0.09], 0.85	0.42[0.08], 0.95	0.09[0.1], 0.34	0.16[0.09], 0.89	0.29[0.06], 0.82
stew	0.23[0.14], 0.86	0.55[0.2], 0.58	0.48[0.16], 0.89	0.41[0.16], 0.52	0.59[0.26], 0.54	0.57[0.19], 0.78	0.08[0.14], 0.84	0.43[0.13], 0.87	0.55[0.13], 0.83	0.39[0.3], 0.3	0.5[0.27], 0.25	0.61[0.13], 0.94
vegetable and legume	0.29[0.08], 0.9	0.21[0.07], 0.94	0.28[0.09], 0.86	0.22[0.15], 0.71	0.34[0.12], 0.46	0.51[0.12], 0.86	0.69[0.14], 0.79	0.57[0.11], 0.89	0.53[0.07], 0.92	0.27[0.16], 0.73	0.4[0.09], 0.81	0.3[0.07], 0.84
wine, beer and liquor	0.13[0.05], 0.68	0.19[0.08], 0.85	0.1[0.05], 0.59	0.02[0.07], 0.82	-0.04[0.11], 0.68	0.06[0.14], 0.64	-0.29[0.05], 0.78	0.33[0.08], 0.78	0.18[0.13], 0.55	-0.16[0.1], 0.53	0.33[0.1], 0.52	0.13[0.05], 0.45

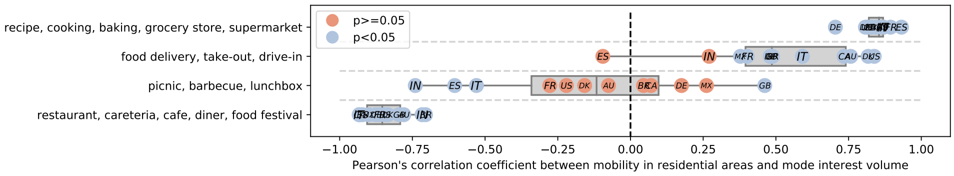
Table S2: Entity-level short-term effects of decreased mobility on interest. For modes, all entities are shown; for foods, the top 10 entities with the largest and the smallest effect across countries by median are shown. Food entities with an average weekly volume of at least 0.3 threshold compared to the reference query are considered, to reduce the impact of outlier entities with very little interest. Entities related to consuming food **at home** are marked in blue if food is prepared by persons within the household, or in teal if food is prepared by a third party. On the other hand, entities related to consuming food **outside of home** home are marked in orange if food is prepared by persons within the household or social group, or in red if food is prepared by a third party.

Mode entity (N=16)	**Median**	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
Median effect positive													
Take-out	+154.59%	+146.02%*	+265.64%	+201.39%*	+54.52%	+365.72%*	+2.57%	+145.19%*	+37.96%	+87.29%*	+163.16%*	+256.26%*	+354.73%*
Drive-in													
+85.15%	-	-	-	-	-	-	-	-	-	-	+85.15%*		
Recipe	+88.18%	+59.63%*	+77.33%*	+84.56%*	+54.3%*	+36.72%*	+157.9%*	+140.41%*	+170.7%*	+180.0%*	+122.57%*	+80.65%*	+91.8%*
Food delivery	+87.17%	+27.28%	+834.23%	+106.0%*	+90.29%	-100.0%*	-22.33%	+14883.59%	+84.05%	+27.49%	+204.11%	+241821.81%	+65.38%*
Baking	+84.23%	+68.69%*	+148.33%*	+72.61%*	+84.22%*	+16.2%	+393.1%*	+47.5%	+175.09%*	+225.34%*	+85.96%*	+78.53%*	+84.24%*
Cooking	+59.38%	+30.67%*	+42.13%*	+34.99%*	+33.81%	+75.92%	+80.46%*	+44.1%*	+92.22%*	+66.79%*	+68.71%*	+92.29%*	+51.97%*
Barbecue	+29.53%	+17.47%	+123.02%*	+26.18%	+26.49%	+17.76%	+68.91%	+32.57%	+214.48%*	-37.69%*	+54.3%	+58.46%	-6.18%
Grocery store	+17.96%	-42.84%*	-47.67%	+106.98%*	+38.93%	+46.56%	-22.64%	-43.37%*	+30.65%	+264.01%*	+5.26%	-5.06%	+82.61%*
Supermarket	+9.76%	-63.28%*	-12.72%	+55.76%*	+4.63%	-37.53%	+58.57%	-38.61%	-44.47%	+76.76%*	+96.05%	+14.88%	+24.99%
Median effect negative													
Picnic	-27.31%	-23.24%	-31.39%	+54.43%	+87.66%*	-99.47%	-49.93%*	-49.04%	+5.38%	-21.7%	-66.24%*	-43.38%	+5.59%
Diner	-33.1%	-36.83%	-29.37%	-25.75%	-41.73%	+112.79%	+113.85%	-99.35%	-51.91%	-45.03%	-99.91%	+1347.27%	-23.28%
Lunchbox	-38.31%	-19.8%	-38.31%	-2.09%	-38.56% *	-14.94%	-21.41%	-56.24%	-43.82% *	-43.56% *	-69.78% *	-	-34.35% *
Cafeteria	-47.45%	-40.04%	-34.67%	-28.59%	-76.58%*	-100.0%*	-92.77%	-81.69%*	+16.73%	-11.05%	-99.98%	+1419.97%	-54.86%*
Restaurant	-53.06%	-55.12%*	-21.81%	-48.61%*	-58.24%*	-51.0%*	-81.38%*	-82.39%*	-59.12%*	-35.03%*	-77.73%*	-43.89%*	-30.88%*
Cafe	-56.24%	-53.19%*	+0.88%	-58.22%*	-75.5%*	-57.06%*	-79.72%*	-61.92%*	-69.49%*	-55.42%*	-35.09%*	-28.34%*	-45.66%*
Food festival	-73.3%	-	+332.43%	-99.49%	-100.0%*	-100.0%*	-98.02%	-	-57.84%*	-55.12%	-100.0%*	-	-88.76%*
Food entity (N=1432)	**Median**	AU	BR	CA	DE	DK	ES	FR	GB	IN	IT	MX	US
Top 10 by median effect													
Baking powder (pastry and bakery product)	+306.6%	+84.51%*	+86.78%*	+317.21%*	+117.29%*	+59.88%	+1182.77%*	+1136.0%*	+377.81%*	+997.34%*	+1131.21%*	+295.99%*	+253.09%*
Sourdough (bread and flatbread)	+234.62%	+116.27%*	+133.27%*	+748.77%*	+179.79%*	+67.76%	+649.08%*	+1579.6%*	+276.11%*	-98.99%	+249.87%	-	+219.36%*
Turnip (vegetable and legume)	+232.55%	+1688.95%*	+107.67%	+228.78%*	+236.32%*	-	+224.23%*	+101.81%*	+529.55%*	+54.36%*	-33.77%	+457.63%*	+506.32%*
Chocolate chip cookie (dessert)	+162.26%	+117.41%*	+95.09%	+266.66%*	+162.33%*	+370.66%	+162.18%	+1369.27%	+375.18%*	+65.2%	+35.79%	+130.06%	+242.94%*
Empanada (pasta, pizza and noodle dish)	+147.74%	+710.44%*	+96.9%*	+113.72%*	+102.71%	+1630.79%	+200.52%*	+252.69%*	-30.97%	-99.99%	+341.31%*	+181.76%*	+45.76%*
Brioche (pastry and bakery product)	+146.62%	+43.04%	+150.58%*	+169.03%*	+20.63%	-36.17%	+90.99%	+383.91%*	+142.65%*	+6246.21%	+334.91%*	+162.64%	+47.78%*
Apple pie (pie)	+140.75%	+150.37%*	+138.11%*	+143.0%*	+73.35%*	+138.5%	+680.17%*	+167.56%*	+130.43%*	+276.11%*	+95.72%	+427.91%*	+102.56%*
Powdered sugar (dessert)	+138.7%	+132.34%*	+62.89%	+267.23%*	+210.19%*	-93.21%	+762.12%*	+384.95%*	+629.02%*	+59.68%	+137.88%*	+132.19%	+139.53%*
Crêpe (dessert)	+129.32%	+92.1%*	+40.57%*	+160.76%*	+32.94%*	+171.37%	+260.0%*	+175.82%*	+172.6%*	+104.72%*	+153.92%*	+58.54%*	+56.71%*
Bread (bread and flatbread)	+128.14%	+39.74%*	+77.92%*	+221.15%*	+56.06%*	+20.14%	+294.93%*	+295.71%*	+77.68%	+193.17%*	+372.36%*	+11.8%	+178.37%*
Bottom 10 by median effect													
Tapas (snack)	-39.76%	-41.02%	+284.01%*	-77.24%*	-65.98%*	-52.68%*	-71.2%*	-79.11%*	-38.49%	+44.82%	-10.61%	+7.13%	-36.25%*
Cotton candy (dessert)	-28.95%	-42.46%	-34.61%*	+8.3%	-31.85%	-94.91%	-68.19%	-18.33%	+258.52%*	-32.71%	-26.05%	-18.04%	+9.95%
Jackfruit (fruit)	-27.15%	-30.47%	-23.84%	-30.49%	+91.13%	+4675.13%	-73.95%	-52.86%	-17.13%	-9.74%	-85.1%*	+35.67%	-32.84%*
Absinthe (wine, beer and liquor)	-21.63%	-16.57%	-38.14%	-26.69%	+11.81%	+12914.16%	-48.51%	+-0.37%	-40.42%	-56.23%*	-28.4%	+28100.37%	+17.72%
Edamame (snack)	-19.21%	+34.85%	-7.55%	-19.24%	-47.25%*	+26.35%	-56.26%	-23.31%	+171.87%*	-29.34%	-19.17%	+24.24%	-27.48%*
Champagne (wine, beer and liquor)	-18.8%	-3.35%	+24.15%	-35.5%	-19.53%	-27.06%	-27.1%	-35.9%*	+13.11%	+43.02%	-6.18%	-37.63%*	-18.06%
Common sage (herb)	-17.6%	-47.23%*	-46.9%	+15.06%	+32.52%	-88.26%	+18.16%	-10.25%	+55.97%*	-24.95%	+9.03%	-99.58%	-33.82%*
Persimmon (fruit)	-15.27%	-67.1%	-17.29%	+40.24%	-	-98.8%	-10.08%	-50.47%	+24.92%	-1.62%	-98.93%	-19.93%	-13.26%
Kale (vegetable and legume)	-13.2%	+6096.07%	-100.0%*	+18.07%	+9.81%	+72.32%	-63.09%*	-20.91%	+58.97%	-5.49%	-74.3%	-21.74%	-29.69%
Cola (soft drink)	-8.71%	+19.41%	+254.36%	-24.24%	-11.71%	-30.99%	-15.1%	-65.93%*	+45.46%*	-5.7%	+20.3%	+67.35%	-26.41%*

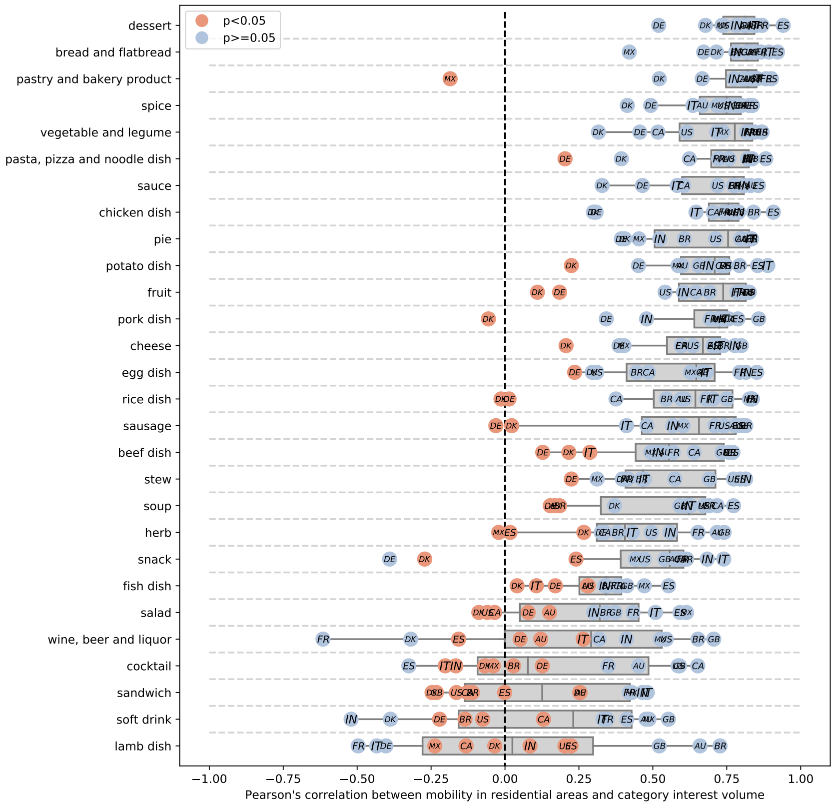
Draft

Table S3: Food categories, ranked by short-term effect sizes in decreasing order, estimated with a constant, linear, and quadratic model.

Rank	**Constant model**	**Linear model**	**Quadratic model**
1	pastry and bakery product	pastry and bakery product	pastry and bakery product
2	bread and flatbread	bread and flatbread	bread and flatbread
3	pie	pie	pie
4	dessert	dessert	dessert
5	sauce	potato dish	potato dish
6	chicken dish	sauce	sauce
7	stew	chicken dish	cheese
8	fruit	stew	stew
9	vegetable and legume	vegetable and legume	egg dish
10	egg dish	pasta, pizza and noodle dish	chicken dish
11	rice dish	fruit	vegetable and legume
12	potato dish	cheese	pasta, pizza and noodle dish
13	cheese	egg dish	fruit
14	pasta, pizza and noodle dish	pork dish	sausage
15	spice	rice dish	pork dish
16	herb	beef dish	beef dish
17	pork dish	sausage	rice dish
18	beef dish	spice	soup
19	fish dish	fish dish	spice
20	sausage	herb	salad
21	salad	snack	fish dish
22	soup	soup	snack
23	snack	salad	cocktail
24	lamb dish	sandwich	herb
25	sandwich	cocktail	sandwich
26	cocktail	soft drink	soft drink
27	soft drink	wine, beer and liquor	wine, beer and liquor
28	wine, beer and liquor	lamb dish	lamb dish



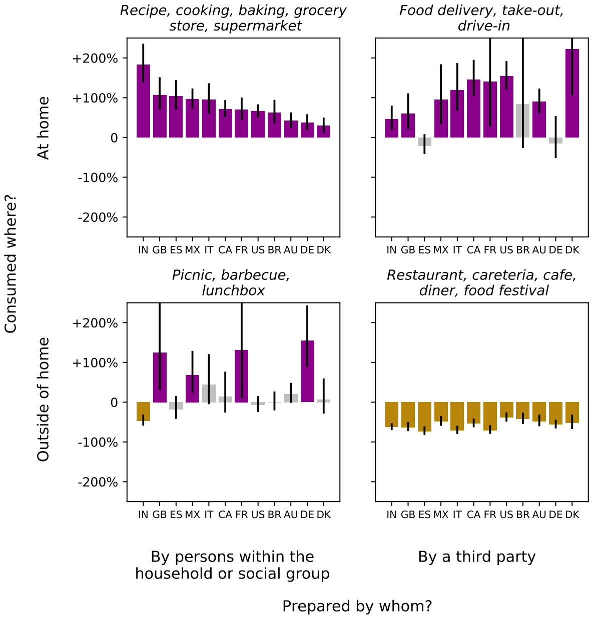
(a) Caption.



(b) Caption.

Figure S2: Pearson's correlation coefficient between mobility and interest volume, in (a) for categories of food entities, and in (b), for ways of accessing food. For each group, 12 values represent correlation, and the boxplot summarizes the value across 12 countries. Significant correlations ($p < 0.05$) are marked in blue, and not significant in orange.

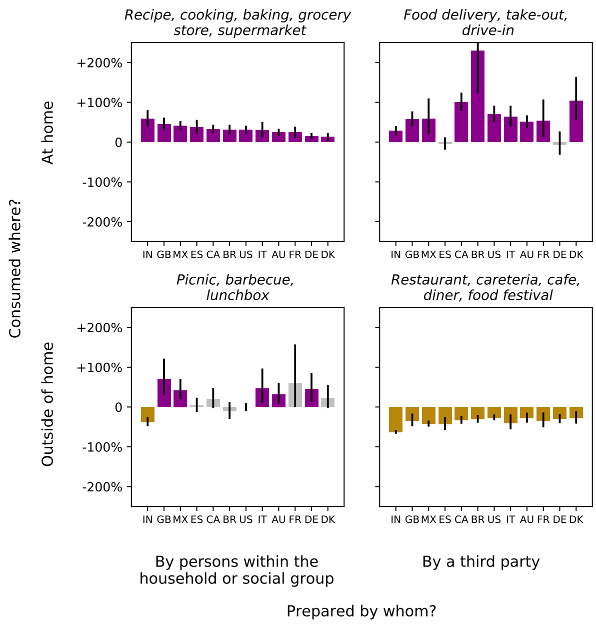
Draft



(a)

(b)

Figure S3: Short-term effects estimated with a linear model.



(a)

(b)

Figure S4: Short-term effects estimated with a constant model.

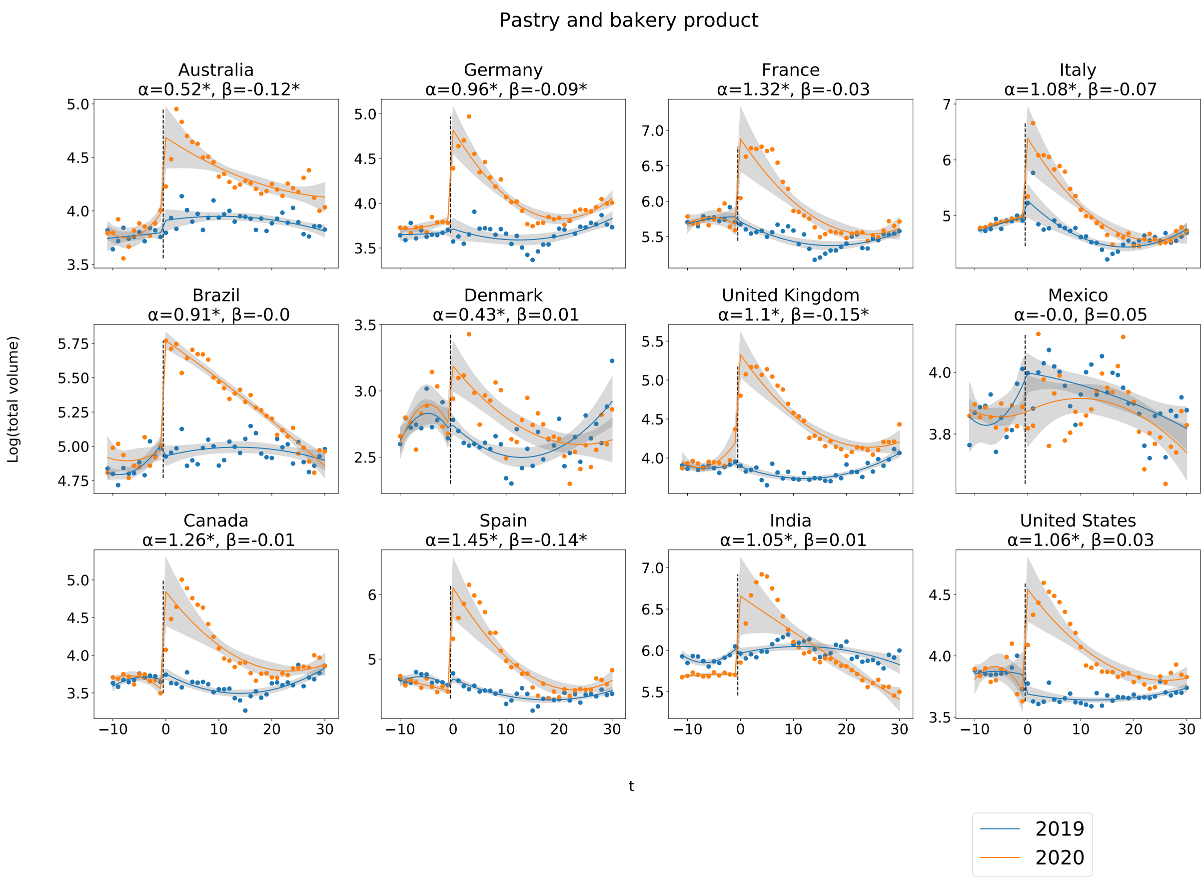


Figure S5: Example of the quadratic model fit. On x-axis weeks, relative to the week of mobility decrease, on y-axis the interest volume. Note the varying y-scales.

Draft

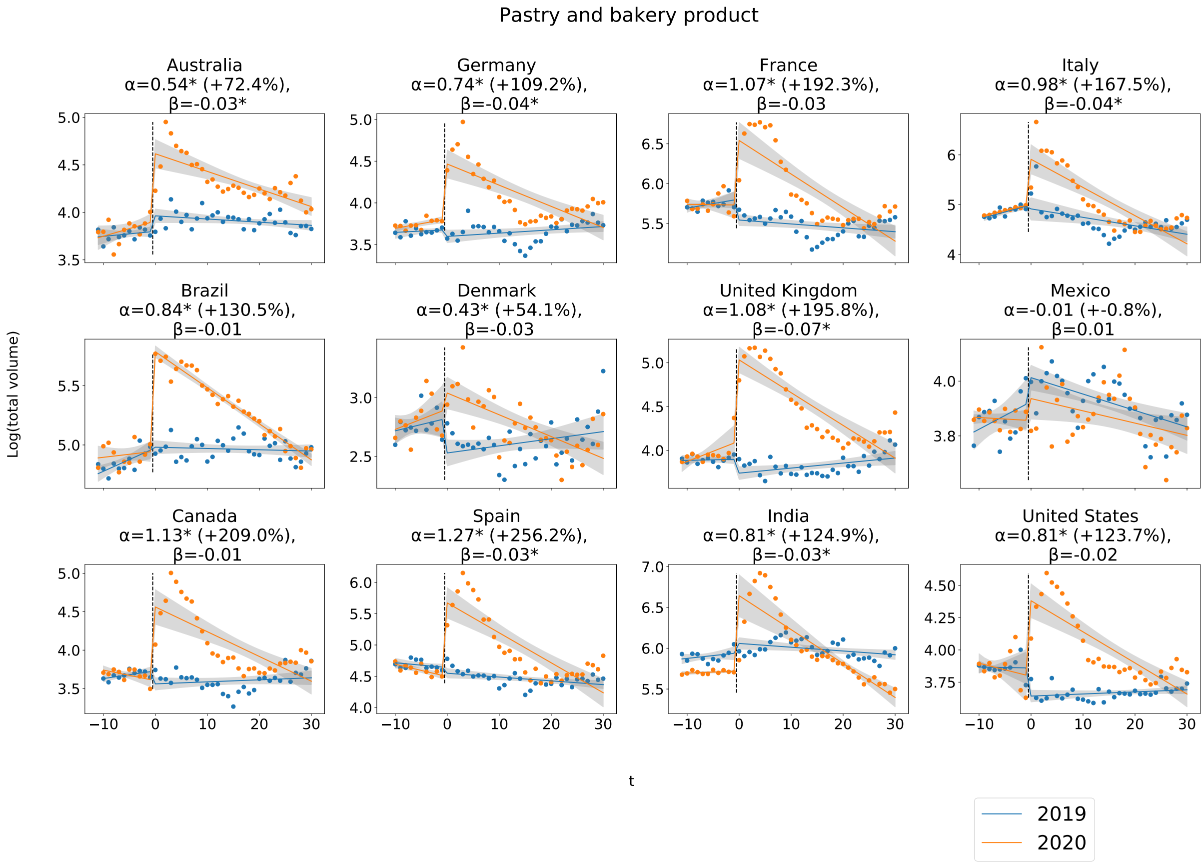


Figure S6: Example of the linear model fit. On x-axis weeks, relative to the week of mobility decrease, on y-axis the interest volume. Note the varying y-scales.

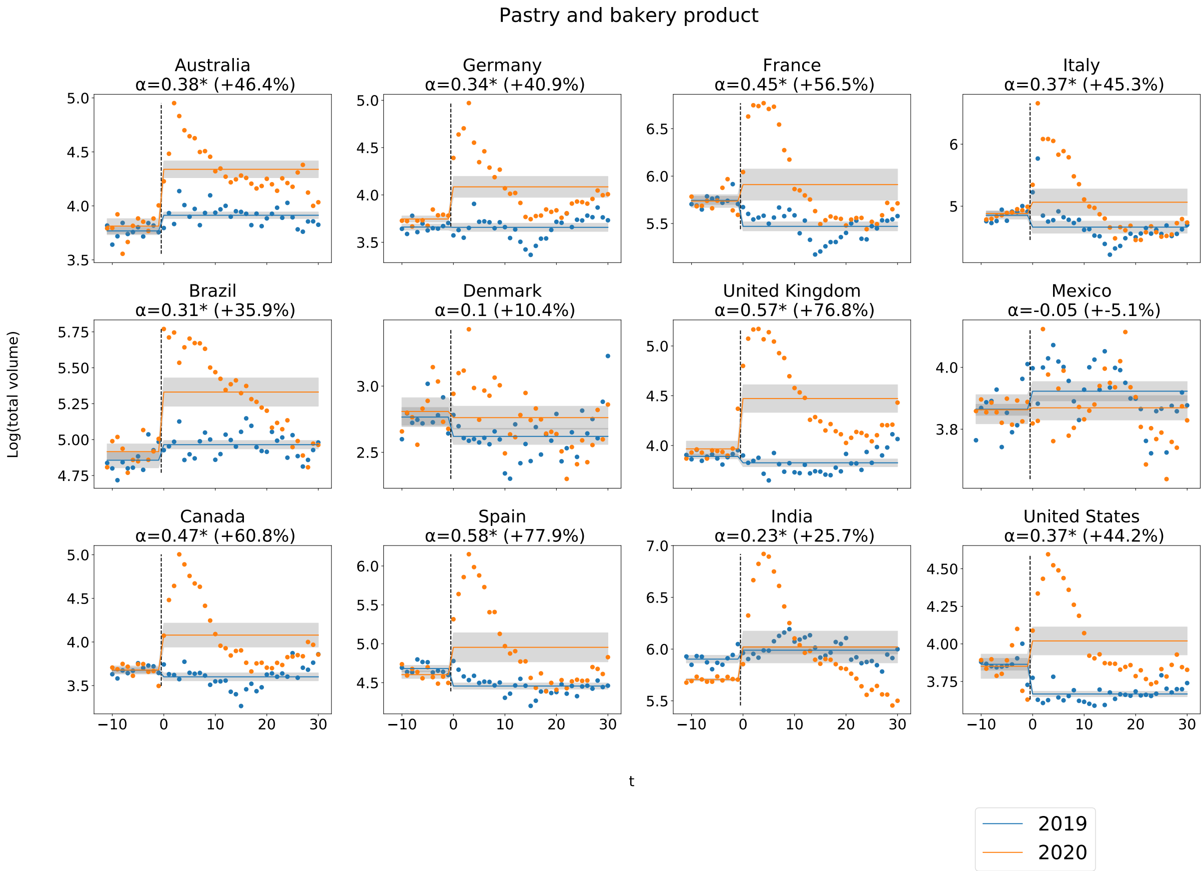


Figure S7: Example of the constant model fit. On x-axis weeks, relative to the week of mobility decrease, on y-axis the interest volume. Note the varying y-scales.

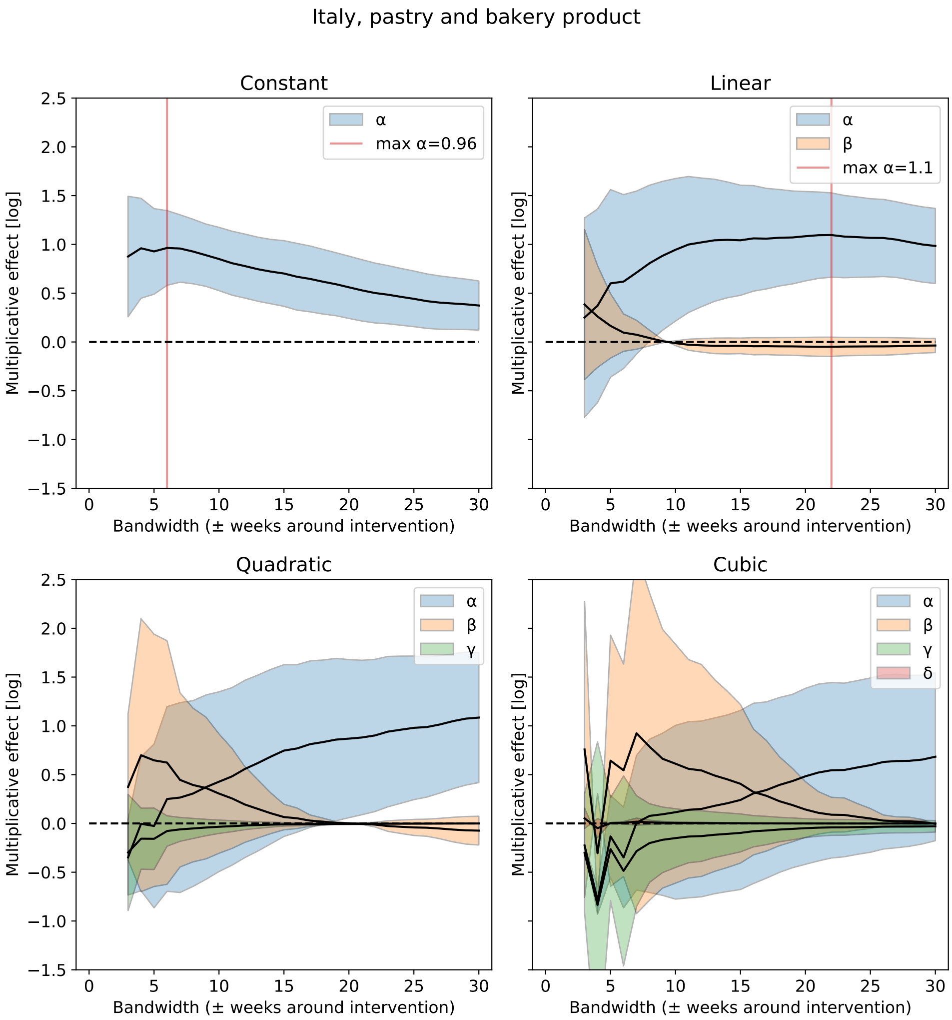
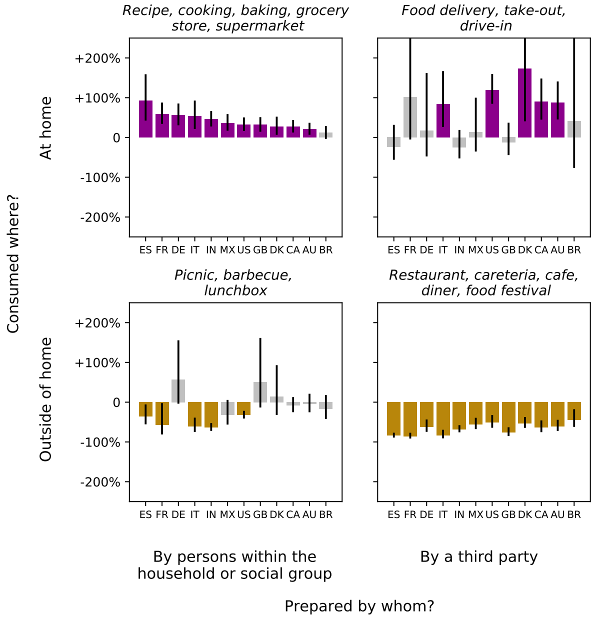


Figure S8: Estimating the impact of the bandwidth (on x axis) on the fitted coefficients for constant, linear, quadratic, and cubic model.

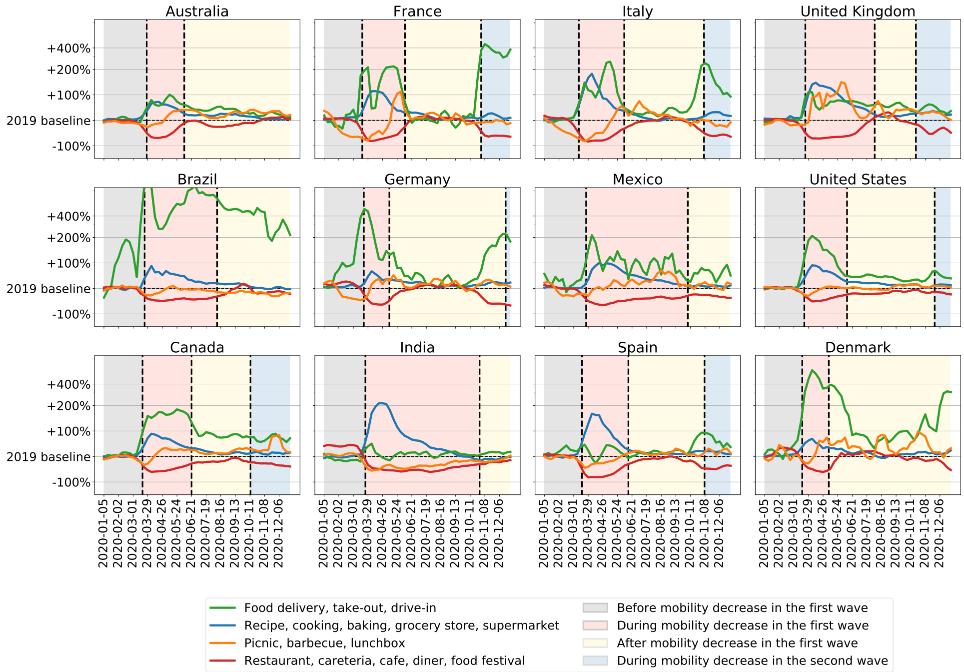


(a)

(b)

Figure S9: Short-term effects on the **share of interest**, estimated with a quadratic model.

Draft



(a)

Figure S10: Timeseries representing the temporal evolution of interest in ways of accessing food in 2020, normalized by the weekly 2019 baseline.

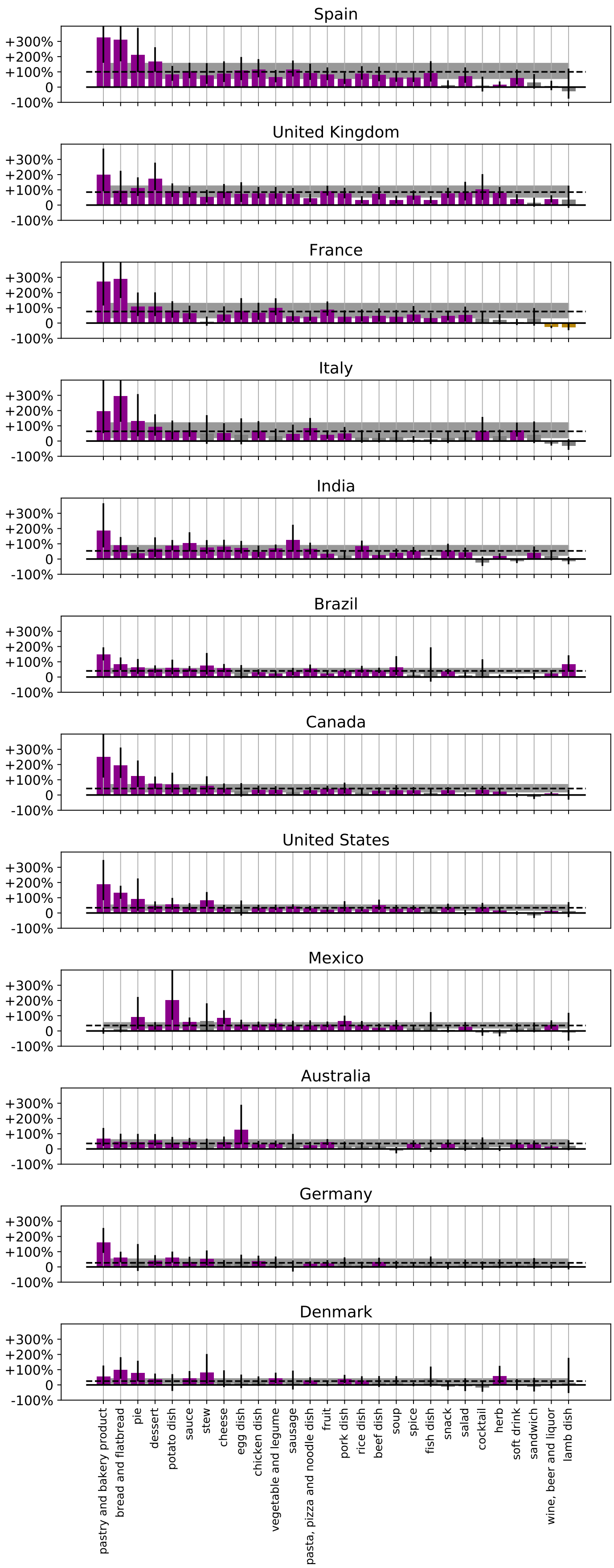
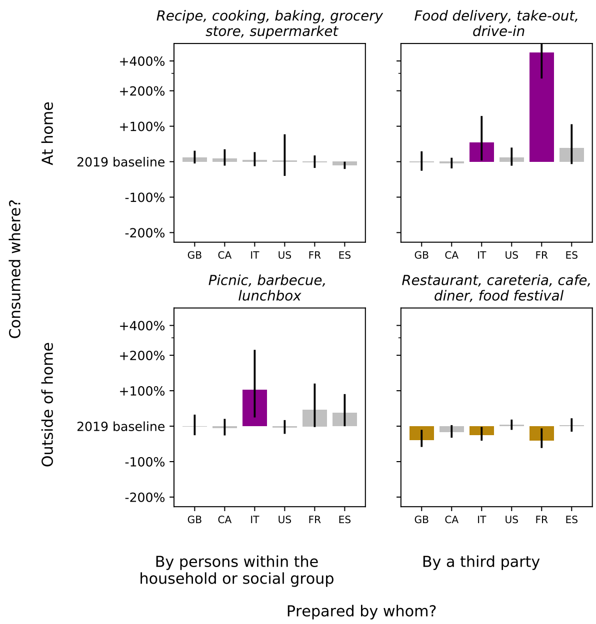
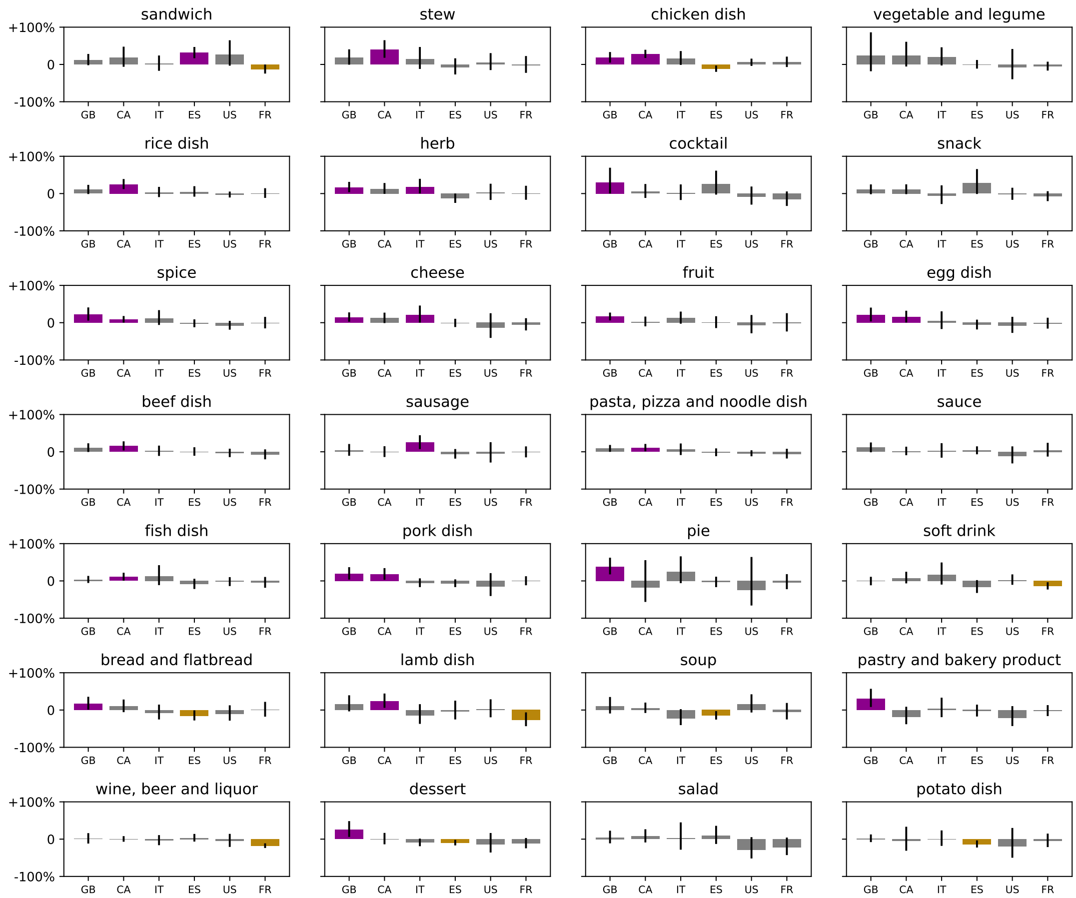


Figure S11: Short-term effects across food categories, grouped by country. The gray band marks the 95% CI of the effect on the country-specific total interest in all food entities.



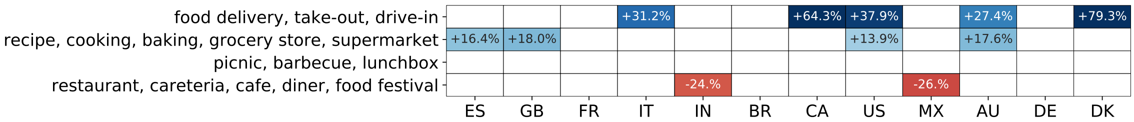
(a)



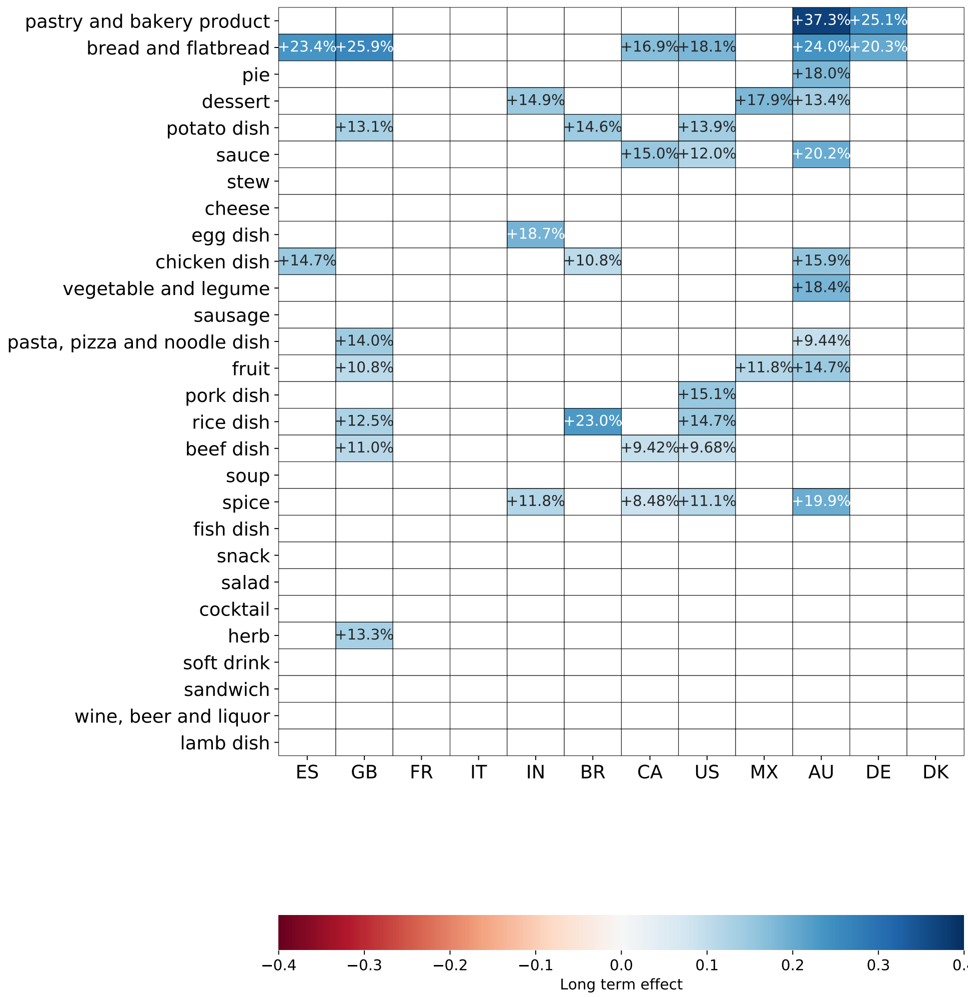
(b)

Figure S12: Short-term effects estimated with a quadratic model, in the second wave.

Draft



(a) Modes.



(b) Categories.

Figure S13: Long-term effect of mobility decrease on food interests. In case the interest did not go back to normal within the 30 weeks after the mobility decrease, we measure how elevated the interest remains at the end of the modelled period, 30 weeks after mobility decrease, compared to the interest in 2019. White marks absence of long term effect when the interest eventually comes back to normal.