Food Purchasing Choices as Indicators of Stress and Mental Health: Insights from Italy During and After the COVID-19 Lockdown

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Food choices and response to public policies: new evidence on the behavioral dimension - ASSA 2025 Annual meeting,

December 2024 - preliminary version

Abstract

Existing literature highlights a connection between the overconsumption of certain foods and the risk of developing depression and declining mental health. Building on this, our study explores whether changes in the consumption patterns of specific foods serve as early indicators of psychological distress, potentially preceding mental health conditions that prompt the use of medications such as anxiolytics, antidepressants, and sedatives. To explore this relationship, we leverage the COVID-19 lockdown as a natural experiment, representing a period marked by heightened stress and anxiety that led to an increase in the use of mental health medications. Our analysis focuses on detecting shifts in the consumption of "emotional foods" during and after the lockdown and measuring their association with subsequent drug use. Using panel regression models applied to weekly purchase data from the YouGov Consumer Panel scanner dataset spanning three years (2019-2021), we find a significant increase in the consumption of unhealthy, comfort foods and drinks, with a corresponding association with the use of psycholeptic drugs.

1 Introduction

Coping with high levels of stress and anxiety often involves changes in food consumption patterns, particularly an increased reliance on unhealthy, emotional foods. More generally, emotional eating is defined as eating in response to negative emotions (Reichenberger et al., 2020). A growing body of literature highlights the link between dietary habits and mental health outcomes. For instance, consumption of ultra-processed foods (UPFs) has been associated with depressive symptoms (Contreras-Rodriguez et al., 2023; Gómez-Donoso et al., 2020). Some studies have identified a positive correlation between consumption of specific foods or ingredients and an elevated risk of developing depression, such as alcohol (Steptoe et al., 1998) and sugar (Navratilova et al., 2024). Furthermore, dietary habits such as snacking or binge drinking have been associated with psychological outcomes; for example, more frequent savoury snacking was associated with increased anxiety, while more frequent consumption of fruit has been linked to psychological well-being (Tuck et al., 2023), and binge drinking has been related to depression in adolescents (Theunissen et al., 2011). Nonetheless, the relationship between dietary choices and psychological well-being is complex, with causal mechanisms that are challenging to disentangle, as the two domains influence each other. Even without the pretense of uncovering causal patterns, establishing an association may help in the timely detection of mental health-related problems in population.

Building on this evidence, we formulate the hypothesis that (over-)consumption of specific foods and drinks can serve as a timely potential predictor of mental health issues and as an indicator of their prevalence within the population. We posit that individuals experiencing anxiety, depression, or stress may initially adopt emotional eating as a coping mechanism, which in some cases could progress to diagnosed mental health conditions. It follows that, in the presence of events that generate anxiety and stress in broad groups, there should be an increase in the prevalence of both mental health issues and emotional eating behavior. If this assumption holds, real-time food consumption data could offer valuable insights for public health policymaking, enabling targeted and timely interventions and prevention strategies.

Our study is based on the general idea that the COVID-19 pandemic and the related policy measures provide a natural setting where a population-wide stressful situation led to an increased prevalence of mental health issues. Numerous studies have explored the relationship between the recent pandemic and mental health. For instance, using weekly data on wholesale drug purchases by pharmacies in Germany, Kostev and Lauterbach (2020) identified a significant rise in the sales of psychotropic and neurological medications, including a notable 24% increase in tranquilizer purchases in the week preceding the German lockdown. In Italy, Marazzi et al. (2022) found that purchases of mental health-related drugs increased in 2020 compared to the previous year. The imposition of public health restrictions concerning social distancing and stay-at-home orders led part of the population to social isolation and a perceived limitation on personal freedom. Exposure to worrisome news and fear of the COVID-19's potential adverse health effects, coupled with insecurity about future economic and job conditions, are major contributors to psychological distress (Pfefferbaum and North, 2020). Accordingly, we focus on the COVID-19 pandemic period and the lockdown as major sources of stress and anxiety, which generally worsened mental health levels, as found in previous literature (Rania and Coppola, 2021; Brooks et al., 2020).

Hence, this study seeks to explore the relationship between diet and mental health based on secondary data, focusing on the potential of food purchasing behaviors as early warning signals of stress and mental health outcomes during critical societal events. Our empirical strategy is based on an operational definition of excess consumption, both for the sales of drugs for mental health care and for food groups that have been identified as candidates for emotional consumption. It is important to note that we are not suggesting that excess purchases of emotional foods are necessarily a direct predictor of current or future mental health issues for individuals within a specific household, as our data do not allow for such inferences. Rather, we hypothesize that, during times of stress and anxiety, the prevalence of excess purchases of emotional foods in the population is correlated with the prevalence of mental health issues, which in our study is captured by excess sales of psycholeptic drugs. For the purpose of our study, the key data source is a household consumption panel based on home scan data (YouGov Consumer Panel). Our dataset consists of a balanced panel of 4,985 households whose weekly purchases of any food are observed between January 2019 and December 2021. This extensive dataset allows us to model the evolution of consumption patterns during the pandemic year for individual households, thus enabling the creation of a regional indicator of the prevalence of excess consumption for various categories of emotional foods. We also exploit regional monthly data on sales of drugs for mental health care to estimate aggregate (regional) excess consumption during 24 months in 2020 and 2021, using a panel difference-in-differences model. Finally, we combine these monthly regional estimates of excess consumption of emotional foods and mental health drugs to test for potential associations. We do find a significant association during the pandemic, which confirms that high-frequency, rapidly available food consumption data might be used as an early warning indicator for outbreaks of mental health issues, also for sub-populations and/or targeted areas.

Section 2 provides a brief summary of the evolution of the COVID-19 pandemic in Italy and the related public policy countermeasures, particularly the movement restrictions. The data used for the analysis and the empirical strategies are presented in Sections 3 and 4, respectively. Finally, the results are discussed in Section 5, and preliminary conclusions are drawn in Section 6.

2 COVID-19 evolution in Italy and effect on food and drink purchases

The spread of the COVID-19 disease has impacted people lives all over the world in many different ways. In 2020 only, the new coronavirus caused more than 1.8 million deaths, with over 83.5 millions registered infections worldwide (Dong et al., 2020). Government-imposed restrictions to curb the spread of the virus ranged from mild measures, such as social distancing and mandatory mask-wearing, to strict lockdowns involving the closure of workplaces, schools, and non-essential stores, as well as stay-at-home orders. Italy was the first European country to implement strict public health measures in response to a surge of COVID-19 clusters in its northern regions. The Italian government imposed a nation-wide lockdown on March 11, 2020[1]; the same day the WHO Director-General declared COVID-19 a global pandemic. This strict lockdown in Italy lasted for ten weeks, ending on May 18. In October, COVID-19 cases began to rise again, prompting the implementation of targeted regional restrictions. These restrictions varied in severity and were represented by a color-coded system (yellow, orange, and red, with increasing levels of strictness) based on various indicators, such as the basic reproduction number and the occupancy rate of intensive care unit beds. The color-coded system was introduced on November 6, 2020, with indicators continuously monitored and regional classifications reviewed weekly. Table 1 displays COVID-19 main regulations enacted in 2020 in Italy.

During the lockdown, the containment measures in place (e.g., stay-at-home orders, closure of schools and workplaces, and restaurant shutdowns) significantly altered the lifestyle of the entire population. Among other behaviors, dietary habits and food and drink consumption had to adapt to the new situation. The first and perhaps most significant factor that contributed to changes in food consumption patterns – particularly

[1]See `https://www.ecdc.europa.eu/en/covid-19/timeline-ecdc-response` for a timeline of European responses to COVID-19.

Table 1: COVID-19 main regulations timeline in 2020 in Italy

Period	Date	Regulation
Baseline	January, 31	First public information campaign, start of testing and contact tracing for suspected cases
	February, 21	Mandatory quarantine for COVID-19 tested positive
	February, 23	Lockdown in eleven municipalities of northern Italy
	March, 4	National school closure
	March, 8	Lockdown in 26 provinces of northern Italy
Lockdown	**March, 10**	National lockdown
	May, 4	Gathering small number of people allowed, stay at home requirement loosened, parks opened
Post-lockdown	**May, 18**	Shops, restaurants and museum opened, no restriction on gatherings
	May, 25	Gyms, swimming pools opened
	June, 3	No restriction on movements
	June, 15	Theatres and movie theatres opened
New restrictions	October, 14	Restrictions on bars and restaurants
	October, 23	Targeted restrictions on gatherings, shops, schools, gyms and theatres, and curfew
	November, 6	National curfew at 10pm and regional colour zoning system implemented
	December, 24-27,31	Italy red zone

for certain socio-economic groups – was the substitution for out-of-home consumption. While food and drink stores were considered essential businesses and remained open during the lockdown, restaurants and bars, where on-site consumption posed a higher risk for virus transmission, were either closed or open with restrictions for nearly half of 2020. As a result, all potential dining-out occasions had to be replaced by home-cooked meals during the lockdown. Furthermore, the negative impact of the pandemic on restaurant utilization persisted even after restrictions were eased (Yenerall et al., 2022). This led to a substantial increase in food and drink purchases for at-home consumption. To grasp the scale of this increase and lifestyle change, according to 2019 data nearly half of people aged 25-34 (48.7%) typically had lunch outside of the home (ISTAT, 2019), not to mention children eating lunch in school canteens, or the dining occasions related to tourism and leisure activities.

Furthermore, the increased time available due to reduced commuting and the cancellation of leisure events temporarily changed food habits, which in turn influenced food purchases. Some of the extra time was spent on cooking, as evidenced by the significant rise in purchases of flour, yeast, and other cooking ingredients. We observed that the lockdown led to a shift toward purchasing raw ingredients, while there was a decrease in the purchase of ready meals and convenience foods.

3 Data

We use two distinct data sources to examine associations between the prevalence of mental health issues and the excess consumption of emotional foods during the COVID-19 pandemic in Italy. As a proxy for the population's mental health status, we rely on data from the Italian Medicines Agency (AIFA) on pharmaceutical purchases by pharmacies and hospitals. Data on food purchases come from home-scanner household purchase data provided by the YouGov Consumer Panel, as detailed below.

3.1 Drug purchases

The AIFA dataset provides consumption data for medical drugs, including the volume (number of packages) of drugs purchased for pharmaceutical assistance under approved care regimes and by healthcare facilities managed by the Italian National Health Service (NHS) between January 2016 and December 2021. The publicly accessible dataset includes monthly regional volumes classified by Anatomical Therapeutic Chemical (ATC) code. Specifically, our target variable is the volume of psycholeptic drug sales (ATC level 2, code N05). This category includes antipsychotic drugs, anxiolytics, hypnotics and sedatives, antidepressants, psychostimulants, ADHD agents, and nootropics.

We extend the 2019-2020 analysis of anxiolytic sales at the provincial level by Marazzi et al. (2022) to include additional pre-COVID years and a broader set of drugs (all those in the psycholeptic category). We adopt a regional aggregation level and include a placebo drug in our modeling approach to account for stockpiling, supply shortages, trade disruptions, and other lockdown effects unrelated to mental health (e.g., adjustments related to the reallocation of hospital beds during the pandemic). Our placebo strategy uses the sales of drugs for bone diseases (ATC level 1, code M) as a control, as this class of drugs requires continuous treatment and is less likely to be affected by changes in treatment during lockdowns. To obtain comparable regional purchase volumes, we divide them by the average regional population figures provided by the Italian National Institute of Statistics (ISTAT).

Figure 1 shows the log sales for both drug categories between 2019 and 2021. The two patterns remain relatively stable in 2019 until the onset of the pandemic, at which point they diverge sharply. Sales of psycholeptic drugs rise markedly in March and April 2020, while sales of bone disease drugs decline substantially in April and May 2020. Notably,

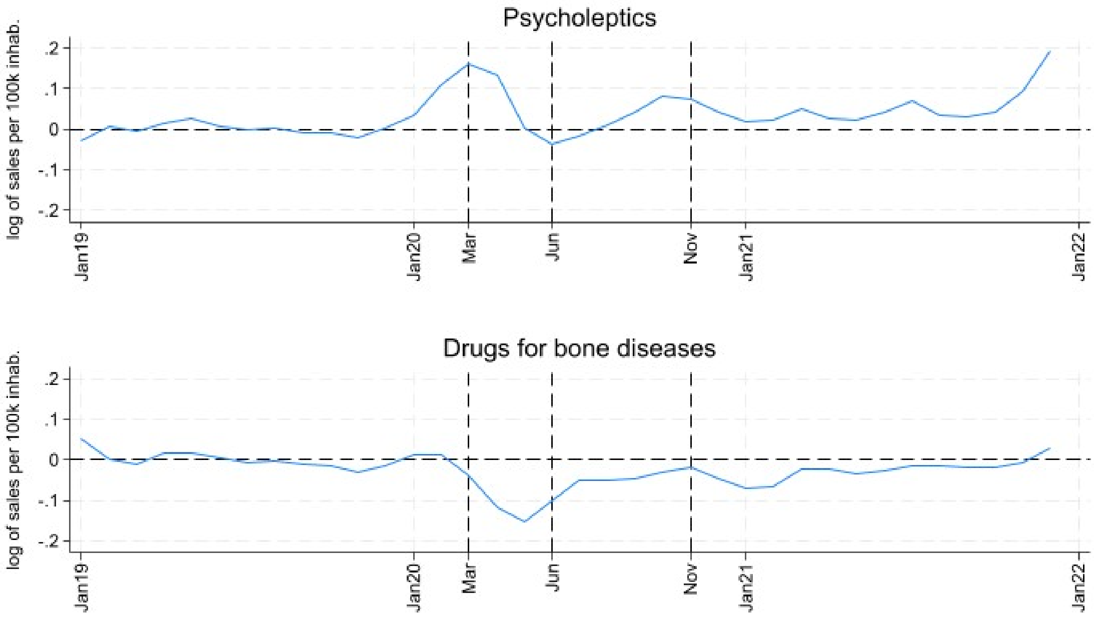

Figure 1: Per capita sales of psycholeptic and bone disease drugs (natural logarithms), 2019-2021. Source: Our processing of data from the Italian Medicines Agency (AIFA). Data were subject to lowess smoothing (bandwidth 0.15) and seasonal adjustment.

this sharp decrease is common across nearly all drugs in the AIFA dataset. In fact, sales of psycholeptic drugs also decreased in May 2020 relative to the previous months. While the sales trends for these two drug categories reacted differently in the first two months of the lockdown, they later converged, resembling the pre-pandemic patterns.

3.2 Food and drink purchases

Our data on food and drink purchases consist of household-scanner recorded purchases made by a representative sample of households in Italy from 2019 to 2021, provided by YouGov CP Italy. The sample includes 4,985 unique households[2]; each household in the panel records all grocery purchases brought home using a handheld scanner and answers a questionnaire on socio-demographic characteristics administered annually. Panelists receive vouchers for their continued participation.

The dataset contains aggregated weekly purchases for all food and drink product categories, as well as selected non-food items (i.e., the total weekly amount purchased by

[2]Although the overall sample is larger (around 9,000 households), variable-weight purchases such as fresh fruit and meat are not recorded for all households. We restrict the sample to those households for which variable-weight purchases are included and retain only households that remain in the panel for the entire three-year study period, i.e., we use a balanced panel.

each household for each category). Each row in the dataset contains information on the amount (in kg or liters), expenditure in euros, and the number of items purchased. Based on a review of the literature, we define emotional foods as those high in fat, sugar, and salt (HFSS), while also exploring alcohol purchases. Specifically, we focus on the following aggregate groups: (1) alcoholic drinks (including beer, wine, and spirits); (2) cakes and biscuits; (3) processed red meat; (4) sugary drinks; and (5) sweets and chocolate (including sweet snacks, ice creams, jams, and chocolate spreads).

For each household, we have socio-demographic information such as household size, the number of children in different age groups, the region of residence, and the age group of the main shopper. Descriptive statistics for the sample are displayed in Table 2.

Table 2: Sample descriptive statistics

Characteristic	Value
Age	
≤ 34	8.43%
$35-44$	29.79%
$45-54$	28.20%
$55-64$	19.00%
≥ 65	14.58%
Area of residence	
North-west	19.00%
North-east	16.25%
Centre and Sardinia	28.45%
South and Sicily	36.31%
Residence in urban areas	
$< 10k$ *inhab.*	24.47%
10k-50k inhab.	26.72%
$> 50k$ *inhab.*	21.06%
Metropolitan area	27.74%
Household members	2.88 (1.14)
Presence of children under 18 years old	36.61%
Presence of children under 5 years old	11.76%
2019-2021	
Food expenditure (? /week)	37.92 (23.40)
Cleaning product expenditure (? /week)	1.58 (1.65)
Cooking ingredient expenditure (? /week)	2.27 (1.73)
First lockdown	
Food expenditure (? /week)	44.38 (32.33)
Cleaning product expenditure (? /week)	1.77 (2.38)
Cooking ingredient expenditure (? /week)	2.99 (2.68)
Number of households	4,985

Standard deviations are in parentheses. Balanced panel 2019-2021.
Expenditures are average values per household.

4 Empirical Models

The empirical strategy employed in this study is based on distinct periods of the year, corresponding to the varying levels of restrictions in effect at each time. Table 3 displays the six periods used in the analysis, along with the corresponding reference weeks for each year.

Table 3: Periods considered in the models

Period	2019	2020	2021
T_1 Baseline	7 Jan – 17 Feb	6 Jan – 16 Feb	4 Jan – 14 Feb
T_2 Lockdown	11 Mar – 19 May	9 Mar – 17 May	8 Mar – 16 May
T_3 Post-lockdown	3 Jun – 1 Sep	1 Jun – 30 Aug	31 May – 29 Aug
T_4 Autumn	2 Sep – 3 Nov	31 Aug – 1 Nov	30 Aug – 30 Oct
T_5 Regional zones	4 Nov – 5 Jan 20	2 Nov – 3 Jan 21	31 Oct – 2 Jan
T_6 Other	Any other date not included above		

4.1 Excess Sales of Psycholeptic Drugs

We first estimate a model to assess the impact of pandemic restrictions, their lifting, and their reintroduction through the regional zoning system on the sales of psycholeptic drugs. This model also tracks the evolution of these effects throughout 2021. Using our dataset, which provides regional monthly per capita drug sales from 2016 to 2021, we employ the following panel specification:

$$
\begin{aligned}
D_{rtz} =& \alpha_r + \sum_{i=2}^{12} \beta_i M_{it} + \sum_{i=2}^{12} \gamma_i M_{it} z + \sum_{y=2019}^{2022} \sum_{i=1}^{12} \delta_{iy} Y_{yt} M_{it} \\
&+ \sum_{y=2019}^{2022} \sum_{i=1}^{12} \mu_{iy} Y_{yt} M_{it} z + \rho_0 t + \rho_1 t z + \epsilon_{rtz},
\end{aligned} \tag{1}
$$

where D_{rtz} is the natural logarithm of per capita sales of drug z in region r at month t, from January 2016 to December 2021. The variable z is binary, with $z = 1$ for psycholeptic drugs and $z = 0$ for bone disease drugs. The variable M_{it} equals 1 if month t matches month i, and 0 otherwise; Y_{yt} equals 1 if month t belongs to year y, and 0 otherwise. In this specification α_r are regional fixed effects, β_i and γ_i are ifferential seasonal (monthly) patterns for bone disease and psycholeptic drugs, respectively, ρ_0 and ρ_1 are differential linear trends between the two drug classes, and δ_{iy} are departures from monthly seasonal patterns after January 2019. The coefficients of interest are μ_{iy}, and estimate differential monthly effects relative to the baseline period (2016?2018). Hence, the time pattern of μ_{iy} reflects the evolution of psycholeptic drug sales from January 2019, relative to the baseline and the pattern of bone drugs.

As a robustness check, the model can also be estimated without including placebo drug sales. In this case, the coefficients reflect the average monthly change in per capita sales relative to 2016?2018, while accounting for within-year monthly seasonality and a linear trend. For our objective of exploring associations, the model is estimated separately for each region, which allows region-specific excess sales to be linked to regional prevalence of excess household purchases of emotional foods.

4.2 Excess Household Purchases of Food Groups

The YouGov CP home scan data enable us to estimate the effects of pandemic restrictions and their lifting on purchases of specific food groups, using a strategy similar to that applied to drug sales. To this end, we specify a fixed-effects panel model to estimate how the average volumes of each aggregated food group purchased by Italian households evolved during 2020 and 2021.

During lockdown periods – and even after restrictions were lifted, while risk perceptions remained high – any increase in consumption of the selected food and drink groups could be attributed to both the increase in time spent at home (due to movement restrictions, remote work, and health concerns) and the perceived stress-relieving function of these foods. To isolate the first component, we control for purchases less likely to have an emotional component, such as household cleaning goods and laundry products, along with basic cooking ingredients (e.g., yeast, salt, spices, tomato sauce, etc.).

Hence, the dependent variable in our model is the purchased volume by the n-th household in week t, with $t = 1, \ldots, 156$. To ensure comparable estimates across different goods, purchase volumes are scaled to the sample mean from the 2019 baseline period (i.e., January 7 to February 17, 2019). For instance, a value of 1.2 indicates that purchases are 20% higher than the baseline sample mean.

We estimate the equation below, separately for each food category (the food group subscript g is not shown for ease of understanding):

$$V_{nt} = \alpha_n + \beta P_{rt} + \sum_{i=2}^{6} \gamma_{1i} T_{it} + \sum_{i=1}^{6} \gamma_{2i} T_{it} Y_{t\in 2020} + \sum_{i=1}^{6} \gamma_{3i} T_{it} Y_{t\in 2021} + \delta_1 C_{nt} + \delta_2 K_{nt} + \varepsilon_{nt} \quad (2)$$

where P_{rt} is the average regional weekly price of the relevant good, in region r and week t; T_{it} is a binary variable that equals 1 if the observed week t falls in period i, where $i = 1, \ldots, 6$ are the periods defined in Table 3; $Y_{t\in 2020}$ and $Y_{t\in 2021}$ are binary variables that equal 1 if the observed week belongs to the respective year; C_{nt} and K_{nt} are the (scaled) volumes purchased of cleaning and cooking goods, respectively.

In our specification, α_n represents fixed household effects; β captures the effect of a unitary change in price on scaled volume purchases; the coefficient γ_{1i} captures the seasonal variation across the six time periods T_i in 2019. Our coefficients of interest are γ_{2i} and γ_{3i}, which estimate the change in average purchased volumes relative to the same period in 2019, after controlling for household fixed effects, price effects, and purchases of cleaning and cooking goods, which serve as proxies for increased time spent at home (either due to restrictions or individual choices to stay at home).

Given the extended period covered by the dataset and the disaggregation of weekly purchase data, model (2) can be estimated for individual households (156 observations for each household). This approach allows us to obtain a separate set of γ_{2i} and γ_{3i} coefficients for each household, enabling exploration and monitoring of the distribution of excess purchases. Furthermore, the model can be specified using the same monthly dummies M_{it} as in (1). This step is required to derive a regional distribution of monthly excess purchases for specific food groups, which can then be linked to the excess sales of psycholeptic drugs as estimated in (1).

4.3 Prevalence of excess purchases of emotional foods over time

Our assumption is that an increase in the prevalence of excess purchases of emotional foods serves as an early indicator of stress and anxiety within the population. Our definition of prevalence is based on the excess consumption estimate from model (2) for January 2020, before the onset of the Covid pandemic in Italy. Hence, we consider the distribution of the household-level estimates of γ_{21}, and we define excess purchases as those exceeding the 90th percentile of that distribution. Under this operational definition, 10% is the baseline quota of households that exceed in consumption, for each food. In the subsequent months we estimate the prevalence using the same percentile as a reference value, and we expect such prevalence to increase in times of stress and anxiety, i.e. more than 10% of households exceed the January 2020 reference value, and to decrease below 10% in times with less collective psychological concerns relative to January 2020.

Our final objective is to explore the strength of the association between this prevalence of purchases of emotional foods and the excess sales of psycholeptic drugs, as estimated at regional level through model (1). Beyond simple pairwise correlations on regional and monthly estimates for 2020 and 2021, we specify a panel model to control for seasonal patterns and regional fixed effects, for each food category:

$$H_{rt} = \alpha_r + \beta F_{rt} + \sum_{i=2}^{12} \gamma_i M_{it} + \eta_{rt} \tag{3}$$

where H_{rt} are excess regional monthly per capita sales of psycholeptic drugs (in natural logarithms) as estimated at the regional level by the coefficients μ_{iy} in equation (1), with $t = 1, ...24$ for the 2020 and 2021 months; F_{rt} is the regional prevalence of excess purchases of the emotional food in each time period; M_{it} is the usual set of monthly dummies. The coefficients α_r are regional fixed effects, and the coefficient β represents the elasticity, which can be interpreted as the percentage change in per capita sales of psycholeptic drugs corresponding to a 1% increase in the prevalence of excess (emotional) food purchases.

5 Results

We present here a selection of the results from our study, focusing on the food groups that emerged as the most relevant in terms of sustained consumption changes and the strength of their association with sales of psycholeptic drugs.

Figure 2 reports the results of estimates from model (1), estimated as a panel with regional monthly data. The graph shows the evolution of the average national monthly excess sales, as captured by the μ_{iy} coefficients, between 2019 and 2021. We used 2016?2018 as the baseline period and modeled the explicit effect in 2019 as a placebo test. Our estimates show a sharp impact on psycholeptic drug sales in March 2020, with sales remaining significantly higher in April 2020 before returning to baseline levels in May. After the end of the lockdown, we observe rising volumes again, and excess sales become significantly higher than 0 in November 2020, when regional lockdowns were implemented.

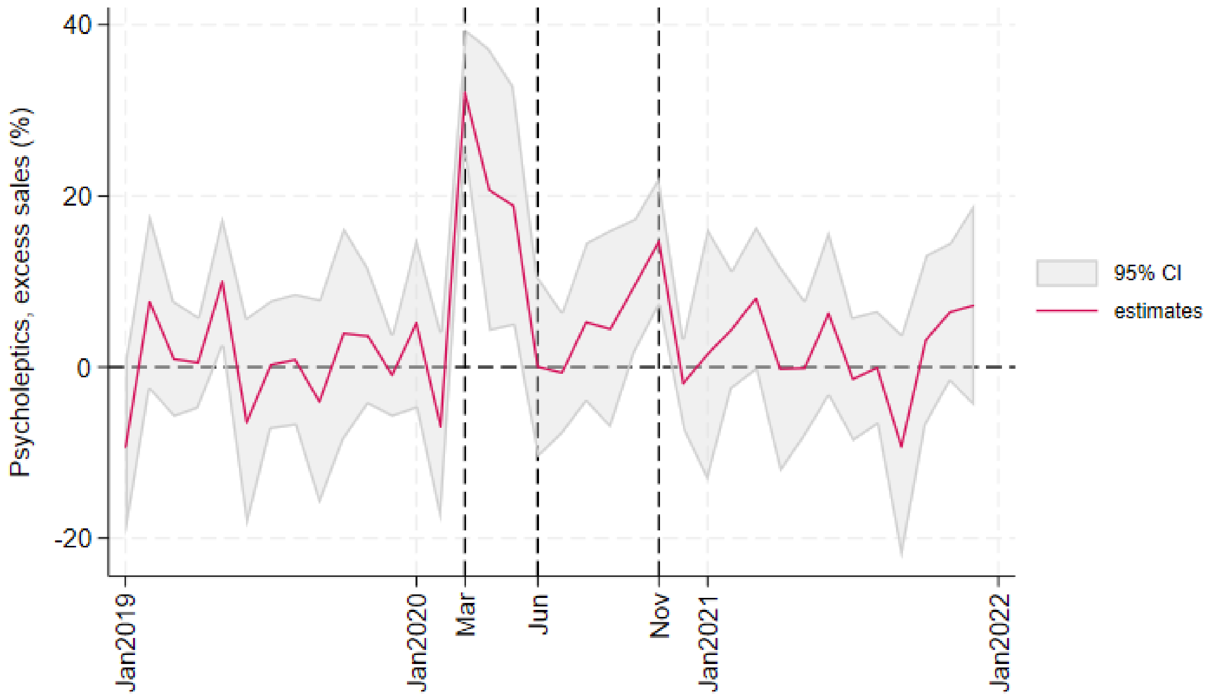

Figure 2: Excess per capita sales of psycholeptic drugs, 2019-2021, relative to the 2016-2018 baseline and to the placebo.

This increase is short-lived, and sales are relatively stable afterward, with no clear trend.

Estimates for periods two (lockdown) to five (regional zones) are represented in Figure 3 for different food groups. After controlling for sales of cooking and cleaning goods, we still find significantly positive excess consumption during the lockdown period for alcohol, processed meats, sweets, and chocolate, whereas savory snacks remain at baseline levels. On average, the post-lockdown period is associated with a relative decrease in purchases for all foods. For chocolate and sweets, as well as alcohol, the reduction is significant. During the early autumn period in 2020 (roughly September?October), none of the average effects are significant, but the resurgence of the pandemic in November and the new regional lockdowns result in increased consumption across all food groups. However, the average impact exceeds the 2019 baseline only for processed meat and, to a lesser extent, alcohol. In 2021, all values are either below the baseline or not significantly different from it.

We estimate the same model using the 156 weekly observations for each household. Figure 4 summarizes the distribution of the impact across households in the sample for the three most relevant periods in 2020 (lockdown, post-lockdown, and the introduction of the regional zones in November). The distributions remain fairly symmetric, although

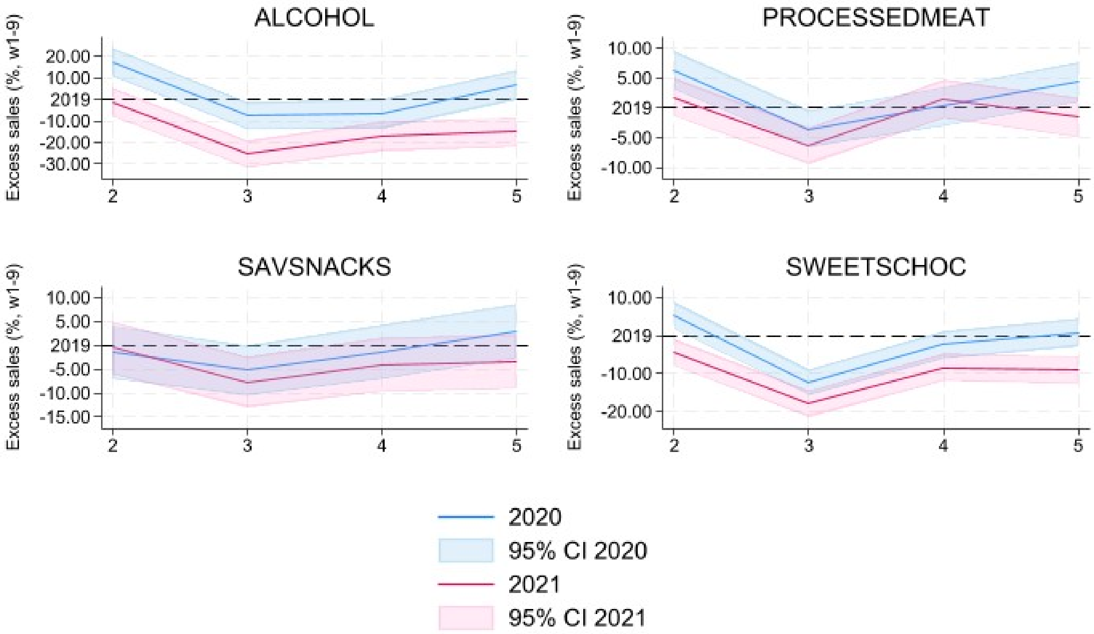

Figure 3: Average effects on household purchases of emotional foods and drinks over different time periods as captured by the μ coefficients in equation (2). Time periods are those defined in Table 3, i.e. 2=Lockdown (weeks 10-19); 3=Post-lockdown (weeks 22-34); 4=Autumn (weeks 35-43); 5=Zone restriction (weeks 43-52)

the variability of the effects is larger for savory snacks relative to sweets and chocolate and processed meats.

To obtain estimates related to excess sales of psycholeptic drugs, the same model is also estimated at the individual household level using monthly variables instead of aggregated time periods. For weeks spanning two months, the monthly variable reflects the proportion of weekdays falling in that month. These household-level monthly estimates are then used to monitor the prevalence of excess consumption over time. Figure 5 shows how the prevalence departs from the baseline 10% over time. These estimates add valuable information about the evolution of the distribution. For example, the prevalence of households consuming excess sweets and chocolate is permanently above 10% after March 2020, with peaks during the first two months of the lockdown and again in November 2020 and March 2021. For savory snacks, the initial increase seems short-lived, but excess purchases rise again in October 2020 and remain well above the 10% baseline until May 2021. Processed meat follows a similar pattern, although prevalence returns to baseline levels slightly earlier.

The last step involves quantifying the co-movements between estimates of excess consumption of emotional foods and excess sales of psycholeptic drugs. This requires calculat-

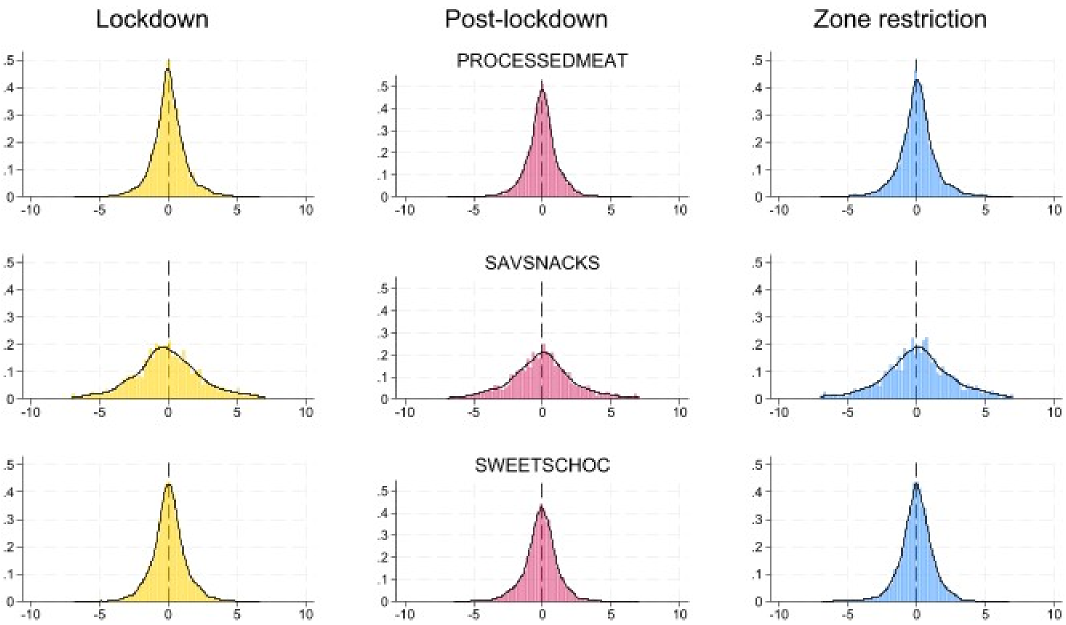

Figure 4: Estimates from individual household models. Distribution of impacts during the lockdown, post-lockdown and regional zone periods in 2020

ing regional monthly prevalence from the individual model. Beyond the three categories discussed here, we also looked at some broader aggregates. Specifically, we created (1) a sugary foods and drinks category, which includes sugary drinks, sweets, chocolate, cakes, and biscuits; (2) a salty foods category, which groups cheese, processed meats, and savory snacks; and (3) a broad ?emotional? category, which includes alcohol, sweets and chocolate, cakes and biscuits, sugary drinks, and savory snacks. Some results are intriguing and are reported in Table 4. We find significant, albeit not very large, correlations for most foods, but not for alcohol. The highest correlation is observed for savory snacks. When considering a one-month lag in the prevalence of excess emotional food consumption, all correlations become non-significant except for savory snacks and the aggregate salty snacks and foods category. The broad aggregate for unhealthy foods does correlate significantly with psycholeptic sales, even when lagged. The estimated elasticities of drug sales to the prevalence of (excess) emotional food purchases control for seasonal effects and fixed regional effects, and some results become more pronounced. Sugary foods are now a major predictor of psycholeptic drug sales, with the latter showing an average increase of 2.28% in response to a 1% increase in the prevalence of excess consumption, even with a one-month lag. Excess consumption of salty snacks and foods also shows a large elasticity (1.79).

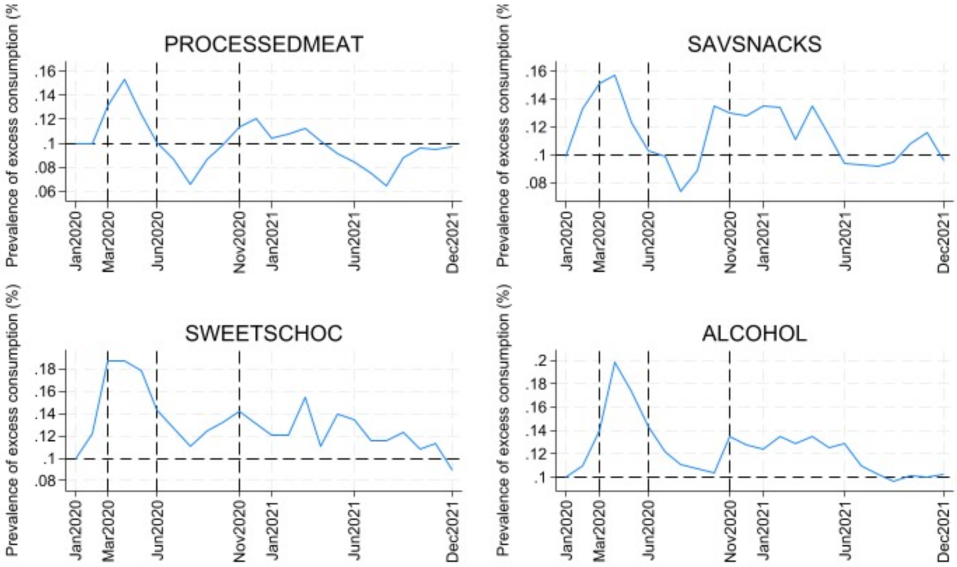

Figure 5: Prevalence of households with excess consumption of selected emotional foods over time. The threshold to define excess consumption is the 90th percentile of the distribution for the $gamma_2 1$ coefficient in equation (2), i.e. the change in consumption relative to the baseline as observed in January 2020

Table 4: Association between prevalence of excess consumption and sales of psycholeptics, correlations and elasticities

	Correlations		Elasticities	
	Contemporaneous	Lagged prevalence	Contemporaneous	Lagged prevalence
Alcohol	0.040	-0.027	0.512	0.372
	(0.460)	(0.628)	(0.315)	(0.326)
Sweets & Chocolate	0.183	0.082	1.097	0.918
	(0.001)	(0.143)	(0.392)	(0.412)
Sugary foods	0.177	0.096	2.281	1.760
	(0.001)	(0.086)	(0.633)	(0.663)
Savoury snacks	0.218	0.262	0.372	0.489
	(0.001)	(0.001)	(0.275)	(0.288)
Processed Meats	0.229	0.072	1.410	-0.133
	(0.001)	(0.195)	(0.459)	(0.480)
Chamomile	0.127	-0.037	0.086	-0.101
	(0.063)	(0.596)	(0.057)	(0.058)
Salty snacks & foods	0.320	0.222	1.793	0.743
	(0.001)	(0.001)	(0.476)	(0.507)
Unhealthy foods	0.212	0.154	0.407	0.357
	(0.001)	(0.006)	(0.122)	(0.129)

Note: Elasticity values reflect the % change in sales of psycholeptics for a 1% increase in the prevalence of excess consumption, as estimated by equation (3). Standard errors in parentheses.

The estimated correlations and elasticities in Table 5 refer to two specific sub-samples. The first sub-sample only considers estimates of excess drug sales and household purchases for regions with higher numbers of COVID-19 cases: Lombardia, Emilia-Romagna, and Tre Venezie (Veneto, Trentino, and Friuli-Venezia Giulia). The second sub-sample considers only households from Northern Italy whose household reference person is aged less than 55. Estimates for the worst-hit regions are much larger than those for the full sample. For this sub-sample, a 1% increase in the prevalence of consumption of sugary foods is associated with a 4.1% increase in psycholeptic drug sales, whereas the elasticity for salty snacks and foods is 3.2. Excess alcohol consumption is also significantly associated with psycholeptic drug sales, whereas the estimated elasticity and correlations are not significant when including other regions. More generally, there are high pairwise correlations between drug sales and excess purchases of aggregate food groups, ranging between 0.57 for foods high in sugar and 0.59 for snacks and foods high in salt and fats.

The second sub-sample considers households with a relatively younger household reference person, aged less than 55. Results are more similar to those for the overall sample, although we find relatively higher elasticities for alcohol and for snacks and foods high in salt and fats. More generally, we explored associations in a variety of sub-samples based on household demographics. Although there were differences in the predictive power of the various sub-samples, there was no clear improvement compared to using the full sample. This is likely due to the nature of our data, as we cannot estimate the excess sales of psycholeptic drugs for the same population sub-samples.

Table 5: Correlations and elasticities in worst-hit regions and households with household reference person aged below 55

	Worst-hit regions		Age HRP<55, North	
	Correlation	Elasticity	Correlation	Elasticity
Alcohol	0.398	1.315	0.084	1.184
	(0.001)	(0.570)	(0.364)	(0.323)
Sweets & Chocolate	0.490	2.648	0.205	1.113
	(0.001)	(0.620)	(0.025)	(0.405)
Sugary foods	0.567	4.131	0.319	2.284
	(0.001)	(0.858)	(0.001)	(0.636)
Savoury snacks	0.471	2.234	0.464	1.163
	(0.001)	(0.704)	(0.001)	(0.307)
Processed Meats	0.435	2.130	0.290	1.261
	(0.001)	(0.858)	(0.001)	(0.436)
Chamomile	-0.099	-0.132	0.140	0.168
	(0.505)	(0.180)	(0.242)	(0.127)
Salty snacks & foods	0.594	3.173	0.522	2.102
	(0.001)	(0.765)	(0.001)	(0.438)
Unhealthy foods	0.584	0.869	0.360	0.532
	(0.001)	(0.177)	(0.001)	(0.110)

Note: Worst-hit regions include Lombardia, Emilia-Romagna, Veneto, Trentino, and Friuli-Venezia Giulia. Standard errors in parentheses.

6 Concluding remarks

This study investigates the relationship between food consumption patterns and mental health, specifically whether changes in the consumption of certain foods could act as early indicators of psychological distress. The research builds on existing literature that has established a connection between overconsumption of certain foods and a heightened risk of depression and declining mental health. It uses the COVID-19 pandemic as a natural experiment, leveraging the heightened stress and anxiety experienced during lockdown periods to explore these patterns. The hypothesis is that emotional eating – characterized by the overconsumption of comfort or "emotional" foods – might be an initial coping mechanism for stress, which in some cases could evolve into diagnosed mental health conditions requiring psychotropic medications.

Our findings reveal a substantial increase in the consumption of unhealthy comfort foods, such as sweets and chocolate, and processed meats, particularly during and following the lockdown periods. Peaks in these consumption patterns were observed during specific stress points, such as the initial months of lockdown and subsequent pandemic waves. Interestingly, while the overconsumption of savory snacks exhibited short-lived increases, sugary foods and processed meat consumption remained elevated over more extended periods.

We also identify a significant association between excess consumption of emotional foods and the sales of psycholeptic drugs. Sugary foods were found to be particularly strong predictors, with a 1% rise in the prevalence of excess consumption correlating to a 2.28% increase in psycholeptic drug sales. The elasticity remains high (1.76) even with a one-month lag in the prevalence predictor. In regions hardest hit by COVID-19, such as Lombardia, Emilia-Romagna, and Tre Venezie, the associations between excess consumption of emotional foods and psycholeptic drug sales were notably stronger. For these regions, a 1% increase in excess consumption of sugary foods corresponded to a 4.1% rise in psycholeptic drug sales, while excess purchases of salty snacks are associated to a 3.2% increase. Unlike the full sample, excess alcohol consumption also showed a significant association with psycholeptic drug sales in these areas. These findings highlight a stronger link between emotional food consumption and stress-related behaviors in regions most affected by the pandemic.

The implications of this research are far-reaching. The ability to use real-time food consumption data as an early warning system for mental health crises presents an innovative avenue for public health monitoring and intervention, especially during societal stress events. By exploiting rapidly available and detailed food purchase data, policymakers could anticipate widespread mental health challenges and implement preventative measures in a timely and targeted manner. This approach could be particularly valuable for identifying at-risk populations or regions.

In conclusion, the study highlights the potential of food consumption behaviors to act as a barometer for mental health issues at the population level. It calls for further exploration into how this data can be integrated into public health frameworks to address mental health concerns effectively.

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