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Vincenzo Carrieri
"Magna Graecia" University, RWI and IZA

Francesco Principe
Erasmus School of Economics and HEDG, University of York

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

WHO and for How Long? An Empirical Analysis of the Consumers’ Response to Red Meat Warning*

Do health warnings change consumer behaviour? And for how long? We address these questions by studying the effects of the 2015 WHO’s warning about the carcinogenic effect of red meat consumption. We use high-frequency data and implement a difference-in-difference-in-differences model which exploits the seasonality in red meat consumption and the heterogeneity in household’s internet access due to historical infrastructure as a measure of intensity of exposure to the warning. We find generally short-lived effects and more pronounced in less processed meats contrary to the contents of the warning. Households with higher levels of education correctly reduced red meat consumption and over a longer period. Our findings suggest that the design of health warnings should account for such heterogeneity in the consumers’ response.

JEL Classification: D12, I18, Q18

Keywords: health warnings, WHO, consumers’ response, carcinogenic red meat

Corresponding author:
Vincenzo Carrieri
Department of Law, Economics and Sociology
”Magna Graecia” University
Viale Europa 100
88100 Catanzaro
Italy
E-mail: vincenzo.carrieri@unicz.it

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1. Introduction

The increasing incidence of non-communicable diseases, of which unhealthy diet is one of the key risk factors, represents one of the main health challenges nowadays. According to the WHO (2018), these diseases kill 41 million people each year, equivalent to 71% of all deaths globally. The poor eating behaviour of the individuals is associated with a vast array of health issues such as obesity, diabetes and cancer, resulting in detrimental effects on individual well-being and leading to poor economic outcomes (Cawley 2015).

In response to this sort of epidemic, the public authorities have increased the volume of information provided about the consequences of unhealthy diets. As documented by the Food and Agriculture Organisation of the United Nations (FAO), there have been increased efforts by international organisations, governments, civil society and the private sector to promote healthy diets in the last twenty years, in both developed and developing countries (Hawkes 2013). The main actions have included media campaigns, nutritional labelling and food safety warnings. However, as with other kinds of information policy, these initiatives are welfare-improving insofar as they produce a persistent shift in behaviours which is able to generate significant and long-lasting improvements in individual outcomes. As Weiss and Tschirhart (1994) correctly point out, "looking at the effectiveness of public information campaigns directs attention toward the capacity of campaigns to capture the attention of the right audience, to present a clear message, to influence the beliefs or understanding of the audience, and to create the contexts for desired social outcomes". Moreover, insofar as promoting equity is also a twin objective of information activities, it is also important that these activities should be designed in a way of granting accessibility and interpretation also for less-educated groups (Shapiro, 2005).

Despite the great relevance of these issues for social welfare, the evidence on the effects of health warnings on consumer behaviour is mixed and mostly refers to health warnings targeting specific groups. But, do general health warnings change consumer behaviour? And for how long? This paper addresses these questions by investigating the effects of one important health warning released by the International Agency for Research on Cancer (IARC) of the WHO in October 2015. This was based on a relevant publication appeared on an issue of *The Lancet Oncology* reporting evidence about the carcinogenicity of the consumption of red meat and processed meat. In particular, the WHO warning classified some kind of red meat as *Group 2A*, i.e. probably carcinogenic to humans, and processed red meat as *Group 1*, i.e. carcinogenic to humans. The warning is particularly significant as it concerns highly consumed foods which are included in many daily meals around the world. In fact, the news was rapidly circulated by national health authorities, magazines and mass media, and also the demand for information around the topic was rapidly increasing in the period following the warning. Both factors made "red meat" one of the trending topics on the web in October 2015 around the World (see Section 2 for more details).

We investigate this issue in the geographical context of Italy using data from the Household Budget survey (HBS) which collects expenditures of a large and representative sample of Italian Households. Italy represents an ideal setting to test these effects for a number of reasons. First, given the high attention that Italians paid to the warning. This is witnessed, for instance, by a huge amount of related Google searches in the period following the warning; an amount significantly larger than the one observed in almost equally sized countries, such as the UK (see Section 2 for further details). Secondly, available data from Italy includes accurate information on all kinds of expenditure made by a family collected on a diary-form from the 2014 to 2016. Diary based survey is usually taken to be the most reliable way to gather information expenditures and are considered to be of high quality (Browning *et al.* 2003; Browning and Leth-Petersen 2003). Importantly, our data are recorded on a monthly basis. This is a rare feature of expenditure data which are often available only on a quarterly basis. Monthly data allow us to compare households' expenditure variation in a narrow window across the delivery of the WHO warning and thus to allay concerns on long-term trends in consumption.

To assess the effect of the warning on household behaviour we follow two routes. First, we exploit the strong seasonality in red meat consumption observed in Italy. Indeed, as shown elsewhere (Cozzi and Ragno 2003) and also found in our data (see Section 2 for more details), red meat consumption in Italy follows a long-lasting seasonal trend with higher consumption concentrated in specific periods of the year, i.e. December and March/April for catholic celebrations, and a steady pattern in the other months of the year. We exploit this in an intention to treat difference-in-differences (DiD) framework that compares variations in household consumption before and after the October 2015 warning to the same variation occurred in the previous year. As a second and sharper test, we exploit information on household's internet access at home as a measure of intensity of exposure to the warning. Indeed, due to the long-lasting "digital divide", there exists a large heterogeneity in internet access across Italy with more than 30% of the country that was without a broadband coverage in 2016 (Eurostat 2017). As this mostly depends on the local historical infrastructural system which- in turn- is dependent on the historical condition of the telephone line network (Infratel 2011; Campante et al., 2018), it represents a useful source of heterogeneity in the intensity of exposure to the warning, which was largely conveyed through the web. Discontinuities in internet coverage have been widely used to estimate the effect of the internet and media exposure on other relevant outcomes (see e.g. Falck *et al.*, 2014; Gavazza *et al.*, 2018; Carrieri *et al.* 2019). Thus, we combine this information in a difference-in-difference-in-differences (DiDiD) specification that compares red meat consumptions before and after the warning to the same variations in the year before across households differently exposed to the warning, i.e. with/without the access to internet connection at home.

We analyse both the short and the long-run effects of the WHO warning and their variations across households differing with respect to average educational level. Indeed, when a new piece of health information becomes available, people might respond differently according to their diverse stock of information and/or ability of processing it as well as to their awareness about the health consequences of certain behaviours (Shapiro, 2005). Moreover, households may need some time to absorb the new pieces of information and to adapt their behaviour and this may lead to very different responses in the short *versus* long run.

This analysis makes a number of contributions to different strands of literature. Firstly, there is a large volume of literature exploring the effects of health authorities' announcements on the households' consumption patterns. Seminal papers (Hamilton 1972; Warner 1989) mostly focused on the smoking hazard campaigns, while more recent papers also focused on the impact of graphic/pictorial cigarette package warnings on tobacco consumption (White *et al.* 2008; Fong *et al.* 2009). More directly relevant to our study, a number of papers investigate the effect of food safety advisories on both health and economic outcomes. Smith *et al.* (1988) analyse the impact of media coverage of milk contamination in Hawaii and find that negative news had a greater impact than positive news on consumers' behaviour. Rousu *et al.* (2007) use an experimental design to examine the impact of information about genetically modified food on consumers' willingness to pay. Schlenker and Villas-Boas (2009) found that health warnings about mad cow disease significantly reduced beef sales. Yadavalli and Jones (2014) examine the news media portrayal of lean finely textured beef (LFTB) and show only temporary effects on consumer demand for aggregate meats and disaggregate beef. Other studies (Oken *et al.* 2003; Shimshack *et al.* 2007; Shimshack and Ward, 2010) document strong evidence of the effects of the 2001 FDA advisory about mercury–related risks in fish consumption. However, the evidence about the effectiveness of public advisories to improve welfare is mixed. On one hand, evidence shows that consumers may under-respond or distrust the advisory (Burger and May, 1996). On the other hand, several studies (e.g. Viscusi 1997; Fox *et al.* 2002) document an alarmist over-reaction to negative information and that consumers tend to place greater weight on more pessimistic sources of risk information. While these studies advance current knowledge on the reactions of consumer to health warnings, they mainly focus on a short-run effect and do not analyse the heterogeneity in the consumer response.

Secondly, our analysis is linked to the literature exploring the nexus between health policies and preventative behaviour. This literature generally suggests that, consistently with the predictions of rational economic actions (Viscusi *et al.* 1986), the provision of health risk information induces individuals to adopt precautionary behavioural changes. However, with few exceptions (Viscusi *et al.* 1986; Carrieri and Wuebker 2016; Capacci *et al.* 2018), this literature relies essentially on observational data and studies the effects of specific warnings aimed to a specific target population (i.e. invitation letters for mammography to women over 40). We instead analyse the effect of a public warning without a specific targeting.

Lastly, there is a large body of literature documenting the heterogeneous effects generated by new technology introduction or information availability as a main source of socio-economic status (SES) related health inequalities. In fact, as shown by Contoyannis and Forster (1999), responsiveness to these innovations may vary across socio-economic groups - i.e. a higher take-up rate among the richer or more educated- resulting in a trade-off between efficiency and equity: average population health and inequalities in health may both increase. As suggested by Deaton (2002) and verified by several empirical papers (Cutler and Lleras-Muney 2006 for a survey, Goesling 2007, Conti *et al.* 2010, Clark and Roayer 2013, Lundborg 2013, Brunello *et al.* 2016, Böckerman *et al.* 2017), education seems to be the key element to disentangle the relationship between socioeconomic status, health outcomes and health innovation uptake. In line with this literature, our paper confirms the beneficial effect of education on responsiveness to health warnings. However, it also finds that more educated groups exhibited a stable, more accurate- and not just higher- consumption shift in response to the warning. This may contribute to a better understanding of the role of education on SES-related inequalities.

The remainder of the paper is organised as follows. The following section provides more insights into the WHO warning and its media resonance. Section 3 presents the data. In section 4, we discuss our identification strategy. Section 5 presents and discusses the results. Section 6 reports some robustness checks. The last sections summarise and conclude.

2. Institutional setting: the WHO warning

In October 2015, the International Agency for Research on Cancer (IARC) of the WHO published an issue of *The Lancet Oncology* reporting evidence about carcinogenicity of the consumption of red meat and processed meat. In particular, red meat was classified as *Group 2A*, i.e. probably carcinogenic to humans, which refers to evidence from epidemiological studies about the association between meat consumption and developing colorectal cancer. On the other hand, processed meet was classified as *Group 1*, i.e. carcinogenic to humans, which refers to sufficient causal evidence linking red meat consumption and cancer in humans. Red meat refers to all mammalian muscle meat, including beef, veal, pork, lamb, mutton, horse, and goat. Processed meat includes meat that has been transformed through salting, curing, fermentation, smoking, or other processes to enhance flavour or improve preservation (e.g., hot dogs, ham, sausages, corned beef and canned meat). According to the IARC, eating 50 grams of processed meat per day increases the risk of colorectal cancer by about 18%, while red meat consumption is associated with an increased risk of developing colorectal, pancreatic, and prostate cancer. These estimates suggest that about 34,000 cancer deaths per year worldwide are attributable to diets high in processed meat; a number that would increase by 50,000 if the relationship with Group 2A red meat was proven to be causal (Global Burden of Disease Project 2016).

Following the evaluation from IARC, the WHO gave health recommendations to prevent the risk of cancer associated with the consumption of meat, inviting individuals to moderate their consumption of meat, particularly processed meat, to reduce the risk of developing cancer. Since the publication of the WHO report in October 2015, the news of the WHO warning had a huge echo across the mass media and was rapidly spread through social networks. To give an idea of this resonance, Figure 1 shows the Google trends for both the search engine hits (as a proxy of the *demand* of information) and the volume of news (the *supply* of information) related to red meat in Italy from 2004 to 2017.

[Figure 1 around here]

As can be seen, both lines representing the relative frequencies, reach their peak in correspondence of October 2015, which is by far the month with the highest volume since 2004 (the first year in which data are available). In Italy, the news had even more echo if compared to countries with a similar population size. For instance, according to the volume data provided by Google AdWords, the term "carne rossa", in Italy, has been searched around 49500 times in October 2015, while its English corresponding "red meat" has been searched only 9600 times in the United Kingdom (a country with an even slightly larger population) in the same period. Interestingly, Figure 1 also shows the presence of other peaks for what concerns the news supply, starting approximately around the middle of 2011. This is attributable to the diffusion of the research outcomes of the first studies exploring the link between the consumption of red meat and some types of cancer, i.e. especially colorectal and prostate cancer (Punnen *et al.* 2011; Takachi *et al.* 2011). However, if in the other cases there was only a consequent negligible increase in the number of search hits by the consumers, the 2015's official warning by the WHO generated by far the highest frequency for both the supply and the consequent demand of information around the health effects of red meat consumption.

3. Data and Variables

Our data come from the Italian Household Budget Survey, which is a cross-sectional survey carried out once a year by the Italian National Institute of Statistics (ISTAT). In agreement with EUROSTAT, the survey is based on the harmonised international classification of expenditure voices (Classification of Individual Consumption by Purpose - COICOP) to ensure international comparability and it is included in the National Statistical Program. This involves two important features. First, the survey is used to collect official national statistics such as the relative and absolute poverty thresholds. Since the purpose of the survey is also that of monitoring the evolution of these official statistics over time, there is large comparability across waves[1]. Second, it includes the "obligation of response" which includes a fine for households who refuse to respond to the survey and this highly limits the cases of non-responses. The survey involves more than 32,000 households who are randomly selected each year from the Italian official census and provides detailed information about the monthly expenditure of the household for goods and services destined for consumption, alongside a number of demographic and socioeconomic information. Data are collected using a dual system: a pre-survey face-to-face interview in which socio-economic information about households are collected, followed by a diary survey. In fact, every sampled household receives a diary every month where they are asked to record the daily expenditure sustained by all the household's components, the consumption of goods produced by the household and the place of purchase of goods and services. Data are finally made public every year with expenditures listed on a monthly basis. As stressed in the introduction, this is a rare feature of household survey and it will be particularly useful to carefully identify our effects of interest.

In this paper, we use data from 2014 to 2016. Our sample thus consists of about 17,000 households per wave. Data before 2014 were collected in a different fashion and thus they are not directly comparable to the last two waves. However, main aggregates of expenditure are still comparable and we will use them for placebo regressions and to illustrate the validity of the common trend hypothesis (see Section 6 for more details)[2].

Our outcomes, following the IARC's report, refer to the expenditures for the different kind of meats grouped according to their risk classification. Thus, the variable *Group 2A* includes expenditure for beef, pork, lamb and goat; *Group 1* includes cured meat, sausages and canned meat and the variable *Red Meat* includes meats from both groups. Expenditures are expressed in Euros and VAT included.

In the baseline specification, we include the total amount of food expenditure as a control variable. This is in line with the literature about household expenditure (Deaton, 1997) and it is useful to take into account variations over time and between households in the general level of household consumption. As robustness, we also consider a larger set of variables including household demographic and socioeconomic variables: household size, the age range of the household reference person (available in three categories: 18-34, 35-64, 65+), a dummy to indicate whether the household includes migrants and a dummy indicating whether there is at least one graduate in the household. Information about the presence of migrant is useful for taking into account cultural-related food preferences and fasting periods related to religion while the presence of a graduate in the household is useful to take into account both the availability and the ability to process information, which may influence the dietary choices of the entire household. Finally, in order to take into account heterogeneity in regional consumption due to the prominent local food tradition in Italy, we also control for the region of household residency.

[1] We investigate this issue in Table A1. We show that the main households variables employed in our empirical analyses are very-well balanced across waves.

[2] Since the 2014, the ISTAT have changed the purpose of the survey, collecting data about expenditures instead of consumption. Moreover, many demographic and socio-economic variables are collected in a very different fashion. As a result, data collected in the waves before 2014 are not directly linkable to the last two waves as explicitly indicated in the data-release documentation.

Furthermore, we also use pre-survey information from the inquiry which precedes the month of the expenditure survey. First, we gather data on internet availability by exploiting a question in which household are asked if they have any potential access to internet connections, including those not requiring any payment (i.e., free wi-fi networks or local libraries).

Second, in order to also analyse heterogeneous effects of the warning, we distinguish households with a different level of education i.e. households composed by at least one graduate *vs* households with no graduates. Importantly, both variables are pre-determined since they are collected in the pre-survey period and this allows us to exclude any simultaneity issue. A complete description of all these variables along with some descriptive statistics is provided in the next Section.

3. 1 Descriptive statistics

Table 1 shows descriptive statistics of all variables employed in our empirical analysis. Concerning our outcomes, we find that an Italian household spends on average about 78 Euros per month on red meat, while the monthly expenditure for meat included in Group 1 and Group 2A amounts to 34 and 44 Euros, respectively. These expenditures represent 17%, 7%, and 10% of the total expenditure for food, respectively. This confirms the relevance of these items for the Italian household budgets.

[Table 1 around here]

However, average data masks two important features of the expenditure for these items in Italy. These are instead highlighted in Figure 2, which reports the non-parametric distribution of these expenditures. First, we find that the distributions are highly right-skewed. This indicates the presence of very few households consuming high quantities of red meat per month. Second, we find that there is a non-negligible share of households which did not report any expenditure for red meat (about 12% for Group 1 and 18% for Group 2A). Both features are generally common to all households' expenditure data through a log transformation of the dependent variable. An alternative estimation based on Tobit model is presented in Section 6.

[Figure 2 around here]

Regarding the other variables used in our analysis, Table 1 shows that households spend on average 456 Euros per month on food and this represents about the 20% of the total monthly expenditure. In about 20% of the households in our sample there is at least one university graduate and 4% of the households consist of migrants. Finally, it is important to note that about 38% of the households did not have any potential access to internet connections, including those free of charge.

Table 2 shows other features of the expenditure on red meat in Italy. First, it highlights the presence of a high regional heterogeneity in the expenditure. Regions in central Italy show higher monthly expenditure in red meat, exceeding by approximately 10 Euros red meat expenditure of Northern and Southern regions. In particular, due to the culinary traditions, Northern regions show higher monthly expenditure in Group 1 meat, while Group 2A meat is more highly consumed in the Southern regions. This heterogeneity confirms the need to control for regional fixed effects in our estimates.

[Table 2 around here]

Figure 3 shows a last interesting feature of the red meat expenditure in Italy, i.e. a strong seasonality. This is a long-lasting pattern for Italy also documented elsewhere (e.g., Cozzi and Ragno, 2003). In particular, it emerges that higher expenditure is coincident with the two important Catholic holidays such as Easter (March/April) and Christmas (December). In these periods, Italian households cook traditional meals based on red meat, in particular lamb and cured meat, and this explains the peak in consumption during these periods. On the other side, lower consumption during the summer time is likely to be due to the hot temperatures, which make fresh meals based on fruits and vegetables more desirable.

[Figure 3 around here]

4. Identification strategy

The identification of the effect of the warning on red meat consumption in our setting requires us to address two main challenges. The first challenge is the possible presence of a long-term trend in red meat consumption. Such a trend -especially if negative- would lead to an overestimate of the impact of the warning in a simple before-after framework, as it would confound the effect of the warning with the "natural" trend in red meat consumption. Our data released on a monthly basis allow us to control for this issue since we compare expenditure variations over a rather narrow window around the time of the release of the warning (i.e. up to one year before and after the warning) and this should reduce long-term trend effects.[3] However, a potential threat to this strategy might be represented by the existence of a specific shift in red meat consumption after October 2015 - other than the one caused by the warning - which may bias our effect of interest.

To address these issues, we follow two routes. First, we exploit the strong seasonality in red meat consumption in Italy as documented in Section 3. Thus, we consider a generalized differences-in-differences (DiD) framework in which variations in red meat expenditure over a narrow window around the release of the WHO warning (October 2015) are compared with the variations in the same period of the previous year which actually acts as a "control group".

More formally, we estimate the following empirical model:

$$Ln(\text{Meat})_{imy} = \alpha + \beta T_{im} + \gamma S_{iy} + \delta(T_{im} \times S_{iy}) + X'_i\theta + \lambda_m + \mu_{ir} + \varepsilon_{imy} \quad (1)$$

Where the dependent variable is the log of expenditure of household i on red meat, Group 1 or Group 2A meat in the month m of the year y, respectively. T_{im} is a dummy that takes the value 1 for all the households interviewed after October and its related coefficient β captures variations in expenditure between the period before and after October, independently of the year. This represents a pure seasonal effect. S_{iy} is a dummy which takes value one if the household is observed in 2015. The coefficient γ captures the effect of general changes in red meat expenditures across years, i.e. due to macroeconomic conditions. Coefficient δ is the DiD parameter as it measures the effect of the warning on households expenditures on red meat before and after October net of the variations occurred in the same period in the year before. λ_m accounts for month fixed effects, while μ_{ir} accounts for region fixed effects and

[3] It is important to note that both the price of red meat and the general price index did not change in a significant way in our observational period, as shown in Figure A1. This should rule-out concerns on price effects in our estimates.

ε_{imy} is the residual term. X_{iy} is a set of control variables. In the baseline specification, we include only the logarithm of total amount of monthly food expenditure at time m among controls. This allows to interpret variation in red meat expenditure as a share of total food expenditure in equation (1). Additional specifications include a larger set of controls that are pre-determined with respect to the treatment since they are measured during the pre-survey interview. These include household's size, the age category of the head of the household, the presence of at least a university graduate in the household , whether the household previously migrated to Italy from another country and the region of residency. Moreover, in the Section 6, we experimented with several specifications including additional control variables (i.e. non-food expenditure at time m and car and house ownership) that lead to similar results.

As discussed in the introduction, we also aim to distinguish short *vs* long run effects of the warning. Thus, T_{im} is accordingly adapted in different specifications to consider from 1, 2, 5 months and up to one year after October 2015, respectively. We estimate equation (1) using OLS estimator. An alternative estimation using Tobit model is reported in Section 6.

A similar identification strategy - but using a larger window around the event - has already been employed in other policy-evaluation frameworks dealing with seasonal effects (i.e. Del Bono and Vuri 2017). An appealing feature of this approach is the possibility of inspecting both graphically and with placebo regressions the credibility of the common trend assumption. In our case, this would require a parallel variation in red meat consumption in the months just before and after October over the pre-treatment years. In order to assess the credibility of this assumption, in Figure 4 we compare variations in expenditure in November (one month after the warning) with average expenditures in the period January-October in pre-treatment years (2013 and 2014) and in the year of the warning (2015). Figure 4 shows that these variations are effectively "parallel" , i.e. very similar in 2014 and 2013 and this is found for both kinds of red meat (Group 1 and Group 2A) and also when expenditure for all kinds of red meat is jointly considered. By contrast, significant deviations to this pattern are found in 2015 -the treatment year- as a result of the warning release. This anticipates the existence of a negative and significant consumer response to the WHO warning.

[Figure 4 around here]

DiD coefficient δ in equation (1) can be given an intention to treat interpretation as it reflects the impact of the general exposure to the warning on red meat expenditure. As a second sharper test, we exploit information on the possibility of having an internet connection at home even free of charge as a measure of intensity of exposure to the treatment. This includes public hot-spots and local internet facilities, for instance. As shown in Figure 1, the warning largely spread on the web, through social networks, online newspapers and institutional web-sites (i.e. Istituto Superiore di Sanità). The possibility of having internet connection at home represents a useful source of variation in the intensity of exposure to the warning concerning red meat consumption. Indeed, internet coverage in Italy depends essentially on the local historical infrastructural system, which has undergone several structural changes in the last periods to bridge the long-lasting "Digital Divide". This was essentially due to the "Digital Italy" plan launched by the Italian Government in 2008 to reach the ambitious goals of "Europe 2020". Basically, all territorial areas were supposed to reach these goals and, with different intensities and timings, were exposed to broadband deployment and upgrade. In practice, the local availability of broadband coverage was dependent on the historical condition of the telephone line network. This is because the broadband network exploits the regular copper phone lines once adapted with xDSL technologies (Infratel, 2011)[4]. Further, the complex orography of the territory makes the adaptation of the phone lines even more difficult in some areas and this represents a further source of heterogeneity in broadband coverage across the Italian territory. As a matter of fact, more than 30% of the country was without a broadband internet coverage in 2016 (Eurostat 2017) and this is in line with what we observe in our sample, as shown in Section 3.1. Given these features, the possibility of having internet connection at home represents a useful source of variation in the exposure to the news which is plausibly unrelated to the demand for red meat. Similar identification strategies using heterogeneity in broadband coverage have been widely used to estimate the effect of the Internet and media exposure on other relevant outcomes (see e.g. Carrieri et al., 2019; Falck et al., 2014; Gavazza et al., 2018; Campante et al. (2018)). Notably, in our case, the narrow window considered around the release of the warning allows to rule-out long term trends in red meat consumption and to allay concerns around other shocks potentially affecting its consumption. Moreover, in order to reduce residual concerns we also take into account a set of factors that might be potentially linked to the demand for internet - and thus indirectly also linked to red meat consumption- such as education, age, some measures of living standards (expenditure on food) and region fixed effects.

Our identification strategy is supported by Figure 5, which shows parallel trends in the average red meat expenditure, in a period of 12 months before the WHO's warning, for households with and without internet access. Interestingly, Figure 5 also shows that after the warning, the trend in red meat consumption between these households diverges, with the households with internet accessibility decreasing their consumption. This is consistent with the effect of the warning and supports the internet channel as a measure of exposure intensity. In order to further check the validity our identification strategy, we also perform several placebo regressions using fake warning periods of different length, we implement randomization tests based on simulated placebo warnings for non-parametric inference and we run placebo regressions using spending on goods and services unrelated to food consumption. Results are reported in Section 6.

[Figure 5 around here]

Formally, we adopt a difference-in-difference-in-differences (DiDiD) specification which compares variations in expenditures before and after the warning to the same variations in the year before across households differently exposed to the warning, i.e. with/without the access to internet connection at home. The estimated model is the following:

$$Ln(\text{Meat})_{imy} = \alpha + \beta T_{im} + \gamma S_{iy} + \sigma Internet_{im-1y} + \delta(T_{im} \times S_{iy} \times Internet_{im-1y}) + \\ + \rho_1(T_{im} \times S_{iy}) + \rho_2(S_{iy} \times Internet_{im-1y}) + \rho_3(T_{im} \times Internet_{im-1y}) + X'_i\theta + \\ \lambda_m + \mu_{ir} + \varepsilon_{imy} \qquad (2)$$

Where $Internet_{m-1y}$ indicates the possibility of an internet connection at home even free of charge as reported by the household in the pre-survey interview $(m-1)$ and thus predetermined with respect to

[4] A thorough description of the aspects of the diffusion of ADSL technology in Italy are included in Campante et al. (2018).

the outcome. All the remaining variables, including the set of controls, are the same discussed in equation (1). The model also includes all the double-interaction terms.

5. Results

5.1 Short-term effects

Table 3 reports the results of the estimates of the generalized DiD model described in Equation (1) for Red meat, Group 1 and Group 2A meat, respectively. All estimates refer to the short-term effect of the WHO's warning, i.e. one month after the warning took place. In columns 1-3 we report the estimates of the treatment effect without controls, while in columns 4-6 we report the estimates of the treatment effect with control variables. For all the outcomes of interest, we report estimates that include standard errors clustered at month level that are robust to correlated monthly shocks in red meat expenditure. However, in Section 6 we demonstrate that our results are robust also to different approaches to statistical inference (block-bootstrap, clustered standard errors at month and year level and randomisation tests based on simulated placebo warnings).

[Table 3 around here]

A comparison between columns 1-3 and 4-6 demonstrates that the estimates of the average treatment effect are substantially unchanged when covariates are included. This gives further confidence to the validity of our quasi-experimental design. Table 3 shows that the WHO's warning had a strongly significant impact on consumers' behaviour in the short-term. In fact, in the first month after the treatment, consumers responded to the warning by reducing expenditure on red meat by about 4%. Interestingly, the reduction for probably carcinogenic meat (Group 2A) was higher than the one observed for carcinogenic meat (Group 1), amounting on average to 6.2% and 2.4%, respectively. This pattern is likely due to the fact that the news was mainly conveyed through mass-media as a generic "red meat danger" and this induced consumers to reduce especially the consumption of the most known red meats such as beef, pork, lamb and goat. However, as will be shown in the next sub-section, this pattern is highly heterogeneous across households as more educated families interpreted the warning more correctly, especially in the long-run.

With respect to the control variables, we find that larger households are associated with higher expenditure on red meat. While, households with at least one university-graduated member spend on average about 11%, 9% and 14% less than less educated households on red, Group 1 and Group 2A meat, respectively. This might be due to a preliminary knowledge around the dangers caused by an excess of red meat consumption which is strengthened by the first research outcomes reporting a correlation between red meat consumption and some kinds of cancer available since 2011 (see the discussion in Section 2). Concerning age, we find that households with an older head of the household spend more on red meat, in particular for what concerns Group 2A meat, for which they spend on average about 9% more than their counterparts. This might be indicative of some cohort effects in red meat consumption. Lastly, as expected, we find that households with migrants are associated with a lower expenditure on red meat and this is likely due to different dietary habits and possibly also related to religious beliefs for some sub-groups of migrants, e.g. Muslims.

The results reported in Table 3 have an intention to treat interpretation. Thus, Table 4 presents a shaper test on the effect of WHO's warning on households' expenditures, given by a DiDiD specification in equation (2).

[Table 4 around here]

Interestingly, the results shown in Table 4 are similar to our baseline specifications. In the first month after the warning, consumers reduced their expenditure on red meat, Group 1 and Group 2A by about 5%, 2.3% and 7.2%, respectively. These confirm that the WHO's warning had a strongly significant impact on consumers' behaviour in the short-term. In terms of magnitude, we find that the estimated treatment effects are somewhat higher in the DiDiD than in the DiD specification. This suggests that the web played a significant albeit not a large role in the spreading of the news. This can be explained by the fact that the news was conveyed also through other channels, such as official health bodies, TV, media and newspapers.[5] Additionally, Table 4 shows that education, age and cultural differences (i.e. migrant status) are significant determinants of red meat expenditure. Interestingly, coefficients of the control variables both with respect to the sing and the magnitude are substantially in line with those presented in Table 3.

5.2 Long-term and heterogeneous effects

In Table 5, we report the estimates of the long-term effect of the warning on households' red meat expenditure. Estimates are based on the same equation described in equation (1) and include the same set of controls but employs a longer post-warning observational period including estimates at two months, five months and one year after the WHO warning, respectively.

[Table 5 around here]

Remarkably, we find that the treatment effect coefficients are negative but never statistically significant at conventional levels in the following months after the release of the warning. This result is consistent across all our outcomes. It is important to observe that testing for the effect up to one year after the warning and accounting for seasonality allows us to reduce any concern about the fact that this result might be influenced by festivity bias and new year's resolutions which might play a role in the adoption of any kind of health behaviour, as already shown by other papers (e.g. Del Bono and Vuri 2017 for smoking; Cherchye *et al.* 2017 for food purchases). Moreover, for sake of brevity, we report in Table 4 only results for two, five months and one year after the warning but additional analyses exclude the presence of any significant treatment effect from two months and up to one year after the release of the warning (results available upon request). Overall, this indicates the presence of a negative effect of the warning limited to one month after its release while levels of expenditure in red meat came back to before-warning average levels just two months after its release.

However, these results apply only for the average household and they are indeed extremely heterogeneous across different sub-groups of households, as shown in Tables 6. In Table 6, we report both the short and long term estimates of the treatment effects of the WHO's warning for households with at least one university-graduated component *versus* households with no graduate member, respectively. As a short-

[5] We also find suggestive evidence on the significant role of the "offline" channel by estimating a DiDiD specification as in equation (2) but using the pre-determined subscriptions to newspapers in place of internet as a measure of intensity of exposure to the news. These results are merely descriptive as we cannot rely on any shock on the newspaper market to carefully identify the effect and are available upon request.

hand we refer to these groups as High-educated *versus* Low-educated households. For the sake of brevity, we report in Tables 6 only the coefficient measuring the treatment effect. Estimates are based on the same specification discussed so far and includes the same set of controls with the obvious exception of the variable used for sample stratification (i.e. education in the case of comparison between high *vs* low educated households).

[Table 6 around here]

We find that high-educated households had a stronger and more stable response to the warning. Our estimates suggest that these households reduced the expenditure on red meat by about 12% in the first month after the warning, as indicated in the first row of Table 6. This reduction is found to be fairly stable over time being equal to around the 8% in a span that covers up to one year later the release of the warning. This pattern suggests a sort of permanent shift in red meat consumption for these households. Furthermore, a comparison of results reported in Table 6 suggests that while in the first month after the warning the reduction was higher and significant for Group 2A meat- in line with the "average household" (as discussed in Section 5.1)- the pattern changes quite substantially when considering long-term effects. Indeed, consumption shifts points towards a higher and stable reduction of carcinogenic Group 1 meat (about 6% in a span that covers up to one year later) and non-significant variations for group 2A meat expenditure. We may speculate that high-educated families took time to go deeper into the warning and were able to process the information more accurately. This has led to a stable reduction in the more dangerous meat especially in the long run in a way which is consistent with the contents of the WHO warning. This result is not found for low-educated families who instead reduced the generic red meat consumption only in the first month and returned to before-warning expenditure levels just two months after the release of the warning, as shown in the second panel of Table 5.

6. Robustness checks, sensitivity analyses and additional results

In this section, we perform a number of checks to test the validity of our identification strategy, and a set of sensitivity analyses based on alternative model specifications. Moreover, we analyse some general equilibrium effects of the WHO warning.

As a first robustness check, we focus on the plausibility of the common trend assumption of the DiD model. In Figure 4 discussed in Section 4 we have shown that expenditure variations between November and previous months of the year are effectively parallel across time. The graphical analysis leads us to be confident about the credibility of common trend assumption in our setting. However, as a further test, we also replicate the estimates of our DiD regression based on the specification introduced in equation (1) but with "fake warning" periods. In Table 7 we report placebo DiD estimates assuming a fake warning occurred in October 2014, i.e. exactly one year before the real warning, and using the same post observational period employed for short and long term treatment effects reported in Section 5. We thus basically compare the red meat expenditure in the months before the fake warning with periods of up to one year later than the fake warning while accounting for seasonality in red meat expenditure. As expected, the DiD estimates in Table 7 show that treatment variable are never statistically significant alongside all our outcomes and, interestingly, for all post observational period considered (one, two, five months and up to one year later). The coefficients of the control variables are instead very comparable to the ones found in the main regressions reported in Section 5.

[Table 7 around here]

We also repeated the same exercise dating the fake warning to two years before, i.e. October 2013, and using a post-observational period of the same length, i.e. up to one year later than the fake warning. Also in this case we do not detect any statistically significant treatment effect. Moreover, we do not detect any significant effect also when performing placebo DiD estimates on the subgroup of households considered for heterogeneous treatment effect estimates as in Section 5.2 (results are available upon request).

As a second check, we explore the robustness of our results to assumptions about the structure of the error distribution. Indeed, inference in DiD setting might be problematic especially in the presence of a small number of clusters (Bertrand et al., 2004; Donald and Lang, 2007). In our analysis, given the seasonality of the red meat expenditure, the month seems to be the most appropriate level at which to cluster the standard errors. This is the strategy we effectively adopted for the regressions shown in Section 5. Technically, these standard errors are consistent provided that there is a sufficiently large number of clusters. Albeit the literature does not offer conclusive evidence around the sufficient number of cluster do draw credible inference, 12 clusters might be effectively "at the boundary". In Table A2 we show that our results are statistically significant at conventional levels also when based on bootstrapped standard errors clustered at the monthly level (with 200 replications). Moreover, we also find similar results when using a two-way clustering (survey wave* month) to take into account that data stem from three different samples[6]. However, in both cases, inference in based on a small number of clusters. Thus, to rule out any possible concern, we follow Bertrand et al. (2004) and we implemented a randomization test based on placebo warnings. Essentially, we randomly select a set of different periods (month x year) for simulating the treatment effect of "fake warnings" and estimate our generalised DiD by using the placebo fake warnings in place of the real one. This process is repeated 2000 times and the estimated coefficients from permutation tests based on Monte Carlo simulations are stored in order to plot the non-parametric distribution of placebo warnings. The main assumption behind this test is that, on average, the fake warning should not generate any effect on the households' red meat expenditure, since the months of treatment effects are randomly chosen.

Figure 6 shows the kernel density distributions of the coefficients generated by the simulation process explained above for our outcomes of interest: red meat, Group 1 and Group 2A meat. As it is possible to observe, the means of the distributions are virtually zero, which implies that estimator of placebo effect is unbiased. More importantly, average treatment effects we estimate for the real WHO's warning (around 4% for red meat, 2.4% for Group 1 and 6.2% for Group 2A as shown in Section 5) fall in the very extreme tails of the distribution of placebo effects. This check provides further confidence that the effect we estimated was not observed by chance and therefore reduces any concern about the fact that our results might be incorrect due to invalid assumption on the standard errors distribution.

[Figure 6 around here]

As a third check, we perform another kind of placebo regression using spending on goods and services unrelated to food consumption as outcomes, i.e. expenditures on transports and furniture. The WHO

[6] These results are available upon request.

warning is clearly unrelated to these kind of expenditures and thus we should expect that the treatment effect should be not significant in these estimates. Results of this check based on the main specification in equation (1) are reported in Table 8. We do not find any significant treatment effect and point estimates very close to zero for both outcomes. This further reinforce our identification strategy.

[Table 8 around here]

We also perform a number of sensitivity analyses by using alternative specifications. As a first analysis, we explore the robustness of our results to a closer control for income and wealth effects. We thus re-estimate the main models using two additional control variables: household's total expenditure (measured as the sum of food+ non-food expenditure) and household's house ownership and car ownership. Results of this analysis are included in Table A3. We find that -while these variables significantly affect the red meat consumption- our treatment effect is not significantly affected and our findings are all confirmed, also in magnitude.

As a second analysis, we employ a Tobit estimator to verify the consistency of our results with respect to the excess of zeros problem, a common alternative in the empirical literature on the analysis of expenditure data (e.g. Donkers et al. 2017, for charity expenditure; Tansel and Bircan 2006, for education expenditure; and Cai 1998, for food expenditure). Estimates are reported in Table A4 and are qualitatively unchanged when compared to our main estimates both in the short (one month after) and long run (i.e. 2-5 and up to year post warning). Notably, these specifications confirm that the warning produced only short-lived effects, on average.

The coefficients of the Tobit model encompass both changes in the probability of having positive expenditure on red meat and changes in red meat expenditure for those with a positive expenditure in red meat. Thus, we apply the decomposition method suggested by McDonald and Moffitt (1980) which allows us to assess the relative weight of these two effects. We find that 73% of the total change in expenditure on red meat is on the intensive margin (i.e. changes in the value of positive expenditures) whereas 27% was generated on the extensive margin (i.e. changes in the probability of spending anything at all for red meat)[7]. This is consistent with the contents of the WHO warning which was that of reducing rather than eliminating red meat consumption. However, we find that effects are 65% and 35% for Group 1 and 60% and 40% for Group 2A, respectively. Interestingly, this indicates that warning seems to have worked more on the extensive margin for the less dangerous red meat (Group 2A) than carcinogenic meat (Group 1). This supports the common misinterpretation of the generic "red meat danger" previously discussed.

Lastly, we investigate some general equilibrium effects of the WHO warning. First, we look at the effect of the WHO warning on the expenditures on some substitute meats such as "white" meats, i.e. chicken and rabbit meat. Second, we look at the impact on some foods which are either complements or substitutes in terms of protein intake. These includes cheese, potatoes, legumes and vegetables. Estimates

[7] Mc Donald and Moffit (1980) decompose the total effect of a determinant X_i in a tobit model as: $\delta Ey/\delta X_i = F(z)(\delta Ey^*/\delta X_i) + Ey^*(\delta F(z)/\delta X_i)$, where $F(z)$ is the share of observations with non-zero expenditures, $\delta Ey^*/\delta X_i$ is the impact of the determinant on the expenditure above zero, Ey^* is the average positive expenditure and $\delta F(z)/\delta X_i$ is the impact of the determinant on the probability of any expenditure. In the case of red meat, the decomposition is $5.24 = (0.93 * 3.9) + (80.9 * 0.02)$. Thus, the first term (0.93*3.9)/5.24) accounts for 73% of the final coefficient, while the remaining 27% is explained by the second term (80.9*0.02/5.24). Same procedure was applied for the other outcomes.

of the DiD coefficient are reported graphically in Figure 7 for the full sample as well as for the subsamples of low and high educated households.

[Figure 7 around here]

Interestingly, we find that households compensate the reduction in red meat consumption by substituting it with white meat. This substitution effect is larger for high educated households. On the other hand, less educated households seem to substitute more with legumes and potatoes. The positive effect on cheese is consistent with its possible substitution with cured meat in the Italian cuisine, mostly regarding entry and side dishes. Finally, we find no statistically significant effect on vegetables.

7. Conclusions

This paper studies the effects of the 2015 World Health Organization's warning about the carcinogenic effect of red meat consumption on household behaviour. We investigate this topic in Italy due to the great resonance that the news had and for the availability of high-quality data collecting expenditures for a large and representative sample of Italian Households on monthly basis and with rich information on household characteristics. Monthly data allow us to compare households' expenditure variation in a narrow window across the delivery of the WHO warning and thus to rule-out on long-term trends in consumption. Moreover, we exploit a unique feature of red meat consumption in Italy which is the presence of a strong seasonality in consumption. We combine both features in a DiD framework that allows to retrieve the causal effect of the warning on red meat expenditure under the assumption of a common trend in expenditure over the same period of the year, which seems to be largely supported in our case. Moreover, we use a DiDiD specification that exploits internet access at home due to historical local infrastructure as a measure of intensity of exposure to the warning. The availability of data up until one year after the warning and detailed information around household's characteristics and expenditures allows us also to analyse both the short and the long-run effect of the WHO warning and their variation across different consumers' subgroups.

Our analysis leads to a set of findings. Firstly, we find that WHO's warning had a strongly significant impact on consumer's behaviour but only in the very short-term. In fact, we find that in the first month after the warning, consumers reduced their expenditure on red meat by around 4%, 2.3% and 6.3% of the average monthly expenditure in generic red meat, in carcinogenic meat (*Group 1)* and in probably carcinogenic meat (*Group 2A)*, respectively. However, expenditures on red meat returned to pre-warning levels just two months after its release. Secondly, we find that only more educated families (i.e. at least one graduate in the household) changed their eating behaviours in the long run, i.e. over a one year post-warning observational period. On the contrary, poor-educated households reduced their consumption in a less significant manner and only in the very short-term. Thirdly, we also find that these groups differ significantly with respect to the correct interpretation of the warning. More educated households reduced especially the consumption of carcinogenic meat (Group 1) while their counterparts reduced mostly the consumption of relatively less dangerous meat (Group 2A). We may speculate that this is due to the fact that the news was mainly conveyed through mass-media as a generic "red meat danger" and this prompted less educated consumers to reduce particularly their consumption of the most common but relatively less dangerous red meats such as beef, pork, lamb and goat. Fourthly, we find that most of the change in red meat expenditure is on the intensive margin (i.e. changes in the value of positive expenditures) rather than on the extensive margin (i.e. changes in the probability of spending anything at all for red meat). This is somewhat in line with the content of the warning aiming at reducing rather than eliminating red meat consumption. Finally, we find that especially high educated households compensate the reduction in red meat consumption by substituting it with white meat, while less educated households seem to have substituted more with alternative sources of proteins, such as legumes and potatoes.

These results contribute to several strands of the literature and offer potentially relevant implications around the design of health warnings. Firstly, we contribute to a large volume of literature exploring the effects of health authorities' announcement on households' consumption patterns. We add to this literature by showing that the effect of an announcement might be very different in the short *versus* long run and highly heterogeneous across subgroups of consumers. Secondly, we report evidence on the effect of a delivery of a generic, i.e. warning without a specific targeting, on risk-taking decisions. Thirdly, we contribute to the literature exploring the distributive consequences of new technology introduction or information availability. In line with this literature, we confirm that education plays a significant role in the responsiveness to health warnings. Indeed, education is found to be associated with a stable, more accurate -and not just higher- consumption shift in response to the informational shock. This offers a perhaps more pessimistic view on the possibility of contrasting health inequalities through educational campaigns especially when the aim is to change behaviours in a permanent way.

8. Policy Implications

In terms of policy, our paper has a number of implications for design of health warnings. Firstly, the fact that the consumers - on average- only responded in the very short-term suggests that health warnings should pay attention to the flow and not just to the stock of information delivered. The empirical literature on the effects of tobacco control policies providing a constant flow of information (e.g. health warnings and images on packages) is mixed and this suggests that the delivery of a constant flow of information might not be a panacea. However, the evidence provided in our paper suggests that "one-shot" warnings are substantially ineffective among the general population. Secondly, the misinterpretation of the warning by some subgroups may suggest to pay attention also to how the warnings are designed and delivered. Finally, our findings confirm the strategic role played by education for health. Other than to reduce the well-known health gap, our finding indirectly suggests also that education is able to increase the health returns on investments in health campaigns and health educational activities since the latter are misinterpreted by low educated individuals and produce only short-term effects among them. In a general equilibrium perspective, higher investments in education are then likely to bring both equity and efficiency gains to the health production process.

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Tables and Figures

Table 1. Summary statistics

Variable	*Description*	*Mean*	*Std. Dev.*
Dependent variables			
Red Meat	Monthly expenditure on Red meat	78.29	69.98
Group 1	Monthly expenditure on Group 1 meat	34.00	32.73
Group 2A	Monthly expenditure on Group 2A meat	44.29	49.48
Other variables			
Food expenditure	Monthly expenditure on food	456.54	304.48
HH size	Household size	2.35	1.22
High-Educated	At least one graduate in the household (share)	0.21	0.40
Age	Age category of the household's respondent	18-34 (7%)	
		35-64 (55%)	
		>64 (38%)	
Migrant	At least one migrant in the household (share)	0.04	0.20
Internet	Access to an internet connection at home (share)	0.62	0.002

All expenditure values are in Euros

Table 2. Meat expenditure by subgroup: mean values

	Red Meat	Group1	Group 2A
All	78.29	34.00	44.29
North	76.68	35.46	41.22
Centre	85.42	36.11	49.31
South	75.74	30.73	45.00
High Education	82.79	36.37	46.42
Low Education	77.12	33.38	43.73

All expenditure values are in Euros

Table 3. DiD estimates of the effect of the warning on meat expenditure: short-term effects

	(1) Red	(2) Group 1	(3) Group 2A	(4) Red	(5) Group 1	(6) Group 2A
DiD	-0.0390***	-0.0231**	-0.0626***	-0.0391***	-0.0237**	-0.0620***
	0.0053	*0.0079*	*0.0089*	*0.0053*	*0.0077*	*0.0090*
(log)Food Exp.	1.0344***	0.9253***	1.1653***	1.0163***	0.8942***	1.1622***
	0.0063	*0.0052*	*0.0119*	*0.0063*	*0.0066*	*0.0123*
H Size				0.0214***	0.0247***	0.0158***
				0.0021	*0.0030*	*0.0037*
High-Educ.				-0.1107***	-0.0888***	-0.1450***
				0.0085	*0.0099*	*0.0101*
HH Age 35-65				0.0025	-0.0219**	0.0287
				0.0104	*0.0088*	*0.0219*
HH Age>65				0.0085	-0.0748***	0.0838***
				0.0124	*0.0135*	*0.0207*
Migrant				-0.1097***	-0.1839***	-0.0603***
				0.0105	*0.0159*	*0.0153*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30852	30852	30852	30852	30852	30852

OLS estimates of Equation (1). Clustered standard errors at month level in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 4. DiDiD estimates of the effect of the warning on meat expenditure: short-term effects

	(1) Red	(2) Group 1	(3) Group 2A
DiDiD	-0.0501***	-0.0229***	-0.0719***
	0.0013	*0.0017*	*0.0022*
S*T	-0.0069	-0.0087	-0.0155*
	0.0051	*0.0069*	*0.0086*
T*I	0.0029	-0.0061	-0.0032
	0.0040	*0.0056*	*0.0078*
S*I	-0.0097*	0.0146*	-0.0374***
	0.0053	*0.0075*	*0.0092*
Internet	-0.0317***	-0.0161**	-0.0505***
	0.0047	*0.0067*	*0.0093*
Food Exp.	1.0197***	0.8960***	1.1676***
	0.0061	*0.0065*	*0.0121*
HH size	0.0240***	0.0261***	0.0200***
	0.0022	*0.0032*	*0.0038*
High Educ.	-0.1034***	-0.0849***	-0.1331***
	0.0086	*0.0097*	*0.0100*
HH Age 35-65	-0.0004	-0.0235**	0.0240
	0.0105	*0.0089*	*0.0223*
HH Age>65	-0.0061	-0.0825***	0.0605**
	0.0135	*0.0139*	*0.0229*
Migrant	-0.1142***	-0.1862***	-0.0676***
	0.0110	*0.0161*	*0.0160*
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	30852	30852	30852

OLS estimates of Equation (2). Clustered standard errors at month level in *italics*.
***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 5. DiD estimates of the effect of the warning on meat expenditure: long-term effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Red			Group 1			Group 2A	
	2-month	5-month	1-year	2-month	5-month	1-year	2-month	5-month	1-year
DiD	-0.0156	-0.0157	-0.0159	0.0020	0.0020	0.0021	-0.0341	-0.0343	-0.0345
	0.0161	*0.0161*	*0.0158*	*0.0184*	*0.0185*	*0.0179*	*0.0201*	*0.0201*	*0.0201*
(log)Food Exp.	1.0174***	1.0160***	1.0041***	0.8960***	0.8920***	0.8875***	1.1627***	1.1634***	1.1452***
	0.0070	*0.0079*	*0.0074*	*0.0066*	*0.0077*	*0.0080*	*0.0119*	*0.0118*	*0.0110*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	32782	35814	45837	32782	35814	45837	32782	35814	45837

OLS estimates of Equation (1). Clustered standard errors at month level in italics. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 6. DiD estimates of the effect warning on meat expenditure: heterogeneous effects

	(1)	(2)	(3)	(4)	(5)	(6)
	1-month	2-month	3-month	4-month	5-month	1-year
High Educated						
Red meat	-0.1170***	-0.0755**	-0.0757**	-0.0751**	-0.0759**	-0.0768**
	0.0132	*0.0293*	*0.0292*	*0.0291*	*0.0293*	*0.0291*
Group1	-0.0538***	-0.0561***	-0.0562***	-0.0556***	-0.0564***	-0.0570***
	0.0156	*0.0160*	*0.0160*	*0.0159*	*0.0158*	*0.0154*
Group 2A	-0.1696***	-0.0921	-0.0924	-0.0918	-0.0932	-0.0932
	0.0158	*0.0522*	*0.0519*	*0.0519*	*0.0522*	*0.0520*
Low Educated						
Red meat	-0.0186**	0.0010	0.0009	0.0009	0.0009	0.0010
	0.0065	*0.0147*	*0.0147*	*0.0147*	*0.0148*	*0.0146*
Group 1	-0.0154*	0.0193	0.0193	0.0191	0.0191	0.0195
	0.0084	*0.0244*	*0.0244*	*0.0245*	*0.0245*	*0.0240*
Group 2A	-0.0346***	-0.0192	-0.0193	-0.0192	-0.0192	-0.0193
	0.0106	*0.0154*	*0.0153*	*0.0153*	*0.0153*	*0.0155*

DiD coefficients of OLS estimates of equation (1) by High educated *vs* Low educated households. Full set of controls included. Clustered standard errors at month level in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 7. Robustness checks. Placebo tests for fake warning periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Red meat				Group 1				Group 2A			
	1-month	2-month	5-month	1-year	1-month	2-month	5-mont	1-year	1-month	2-month	5-mont	1-year
Treatment	-0.0023	-0.0104	-0.0111	-0.0114	-0.0102	-0.0276	-0.0280	-0.0279	-0.0035	-0.0019	-0.0029	-0.0034
	0.0039	*0.0075*	*0.0074*	*0.0077*	*0.0082*	*0.0159*	*0.0156*	*0.0151*	*0.0075*	*0.0075*	*0.0073*	*0.0073*
(log)Food Exp.	1.0018***	1.0019***	1.0008***	0.9961***	0.8898***	0.8927***	0.8982***	0.9032***	1.1387***	1.1369***	1.1329***	1.1227***
	0.0047	*0.0045*	*0.0047*	*0.0048*	*0.0088*	*0.0097*	*0.0090*	*0.0082*	*0.0080*	*0.0078*	*0.0076*	*0.0075*
H Size	0.0212***	0.0212***	0.0215***	0.0213***	0.0293***	0.0288***	0.0281***	0.0279***	0.0129**	0.0133**	0.0143***	0.0142***
	0.0028	*0.0028*	*0.0026*	*0.0024*	*0.0030*	*0.0030*	*0.0026*	*0.0025*	*0.0052*	*0.0050*	*0.0045*	*0.0039*
High Educ.	-0.0462***	-0.0471***	-0.0521***	-0.0606***	-0.0199**	-0.0176*	-0.0211**	-0.0348***	-0.0711***	-0.0744***	-0.0825***	-0.0888***
	0.0072	*0.0067*	*0.0060*	*0.0055*	*0.0084*	*0.0083*	*0.0076*	*0.0074*	*0.0104*	*0.0096*	*0.0086*	*0.0080*
HH Age 35-64	-0.0027	0.0015	0.0015	0.0035	-0.0162	-0.0139	-0.0147	-0.0125	0.0063	0.0116	0.0129	0.0151
	0.0097	*0.0108*	*0.0097*	*0.0083*	*0.0150*	*0.0155*	*0.0134*	*0.0096*	*0.0154*	*0.0155*	*0.0137*	*0.0159*
HH Age>65	0.0126	0.0167	0.0155	0.0161*	-0.0694***	-0.0656***	-0.0691***	-0.0659***	0.0667***	0.0712***	0.0710***	0.0718***
	0.0102	*0.0109*	*0.0098*	*0.0082*	*0.0144*	*0.0158*	*0.0146*	*0.0117*	*0.0173*	*0.0167*	*0.0148*	*0.0153*
HH Migrant	-0.1224***	-0.1179***	-0.1247***	-0.1119***	-0.2656***	-0.2487***	-0.2518***	-0.2384***	-0.0558***	-0.0566***	-0.0648***	-0.0439**
	0.0129	*0.0126*	*0.0107*	*0.0103*	*0.0202*	*0.0257*	*0.0251*	*0.0180*	*0.0161*	*0.0146*	*0.0134*	*0.0147*
N	36095	37421	41414	50351	36095	37421	41414	50351	36095	37421	41414	50351

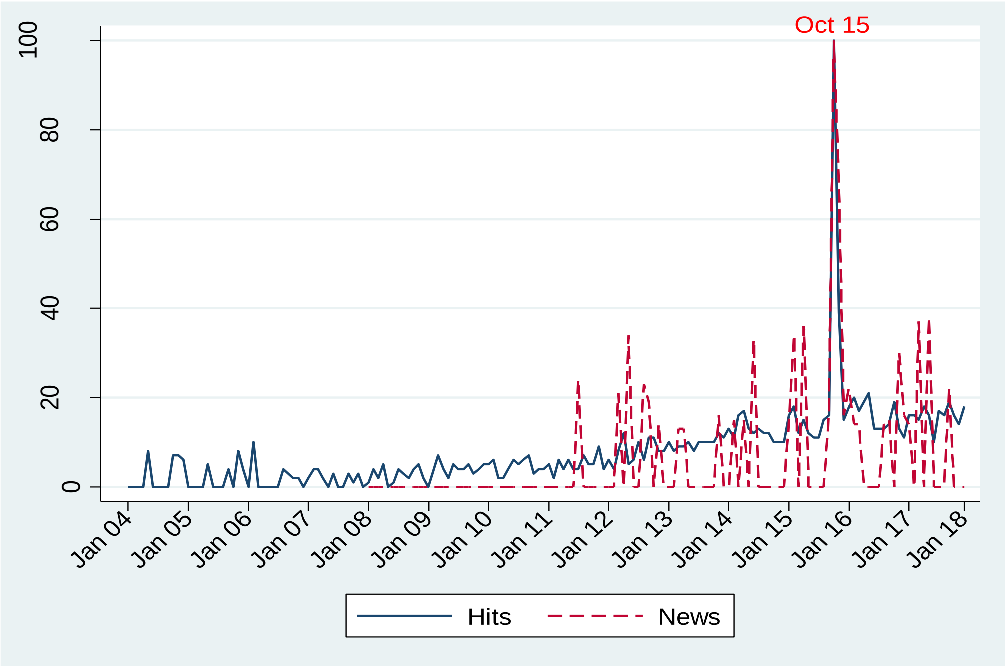
OLS estimates of Equation (1) for fake warning (October 2014). Full set of controls included. Clustered standard errors at month level in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 8. Robustness check: placebo regressions

	(1) Transport	(2) Furniture	(3) Transport	(4) Furniture
DiD	0.0058	-0.0091	0.0025	-0.0095
	0.0099	*0.0164*	*0.0122*	*0.0179*
Controls	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	30852	30852	30852	30852

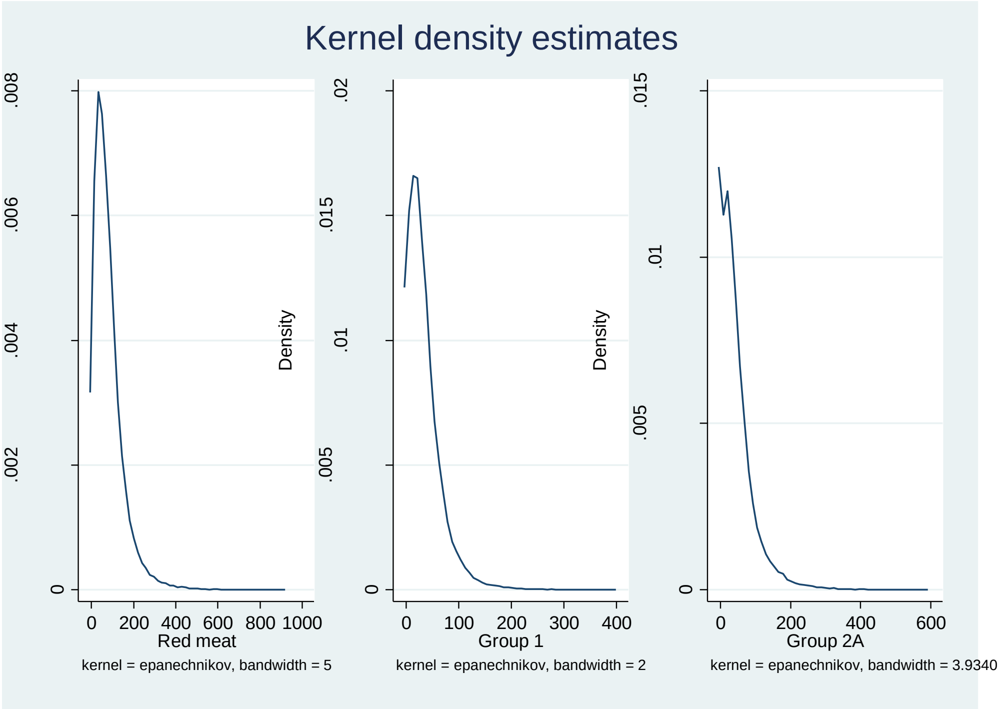
OLS estimates of Equation (1). Clustered standard errors at month level in italics. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Figure 1. Google trends for "carne rossa" (red meat) in Italy, 2004-2018



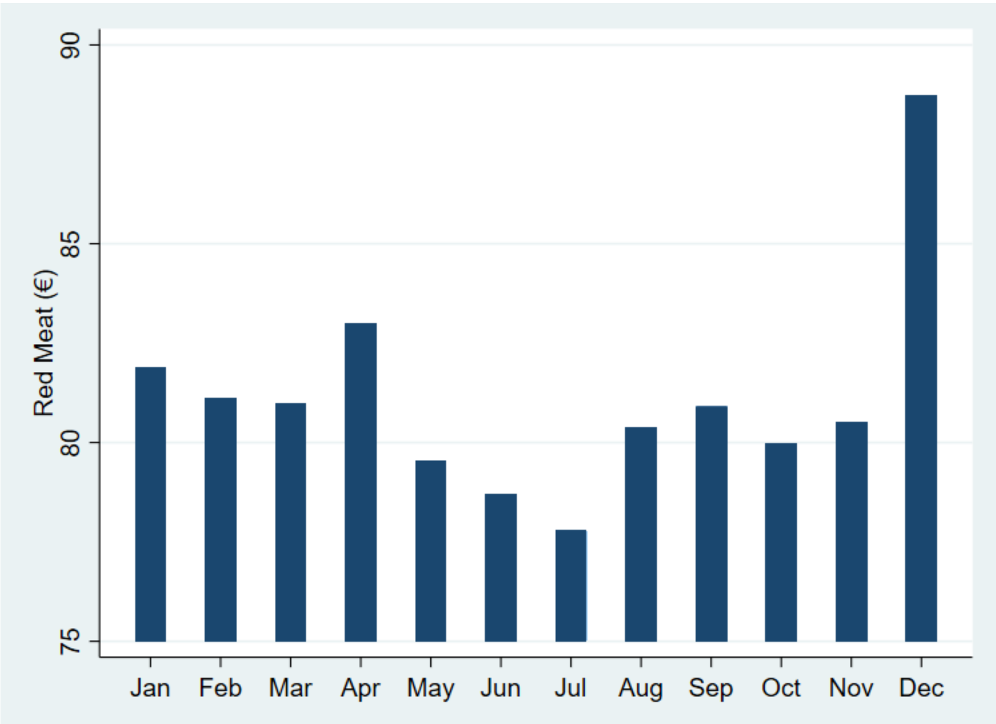
Own elaboration on Google trends data. Google trends data for News are only available from 2008.

Figure 2. Kernel density estimate of monthly expenditure on red meat



Non-parametric distribution of households' expenditures on Red meat, Group 1 and Group 2A.

Figure 3. Seasonality in red meat expenditure in Italy



Expenditures on red meat by month. Pooled sample 2014-2016.

Figure 4. Common trends in red meat expenditure

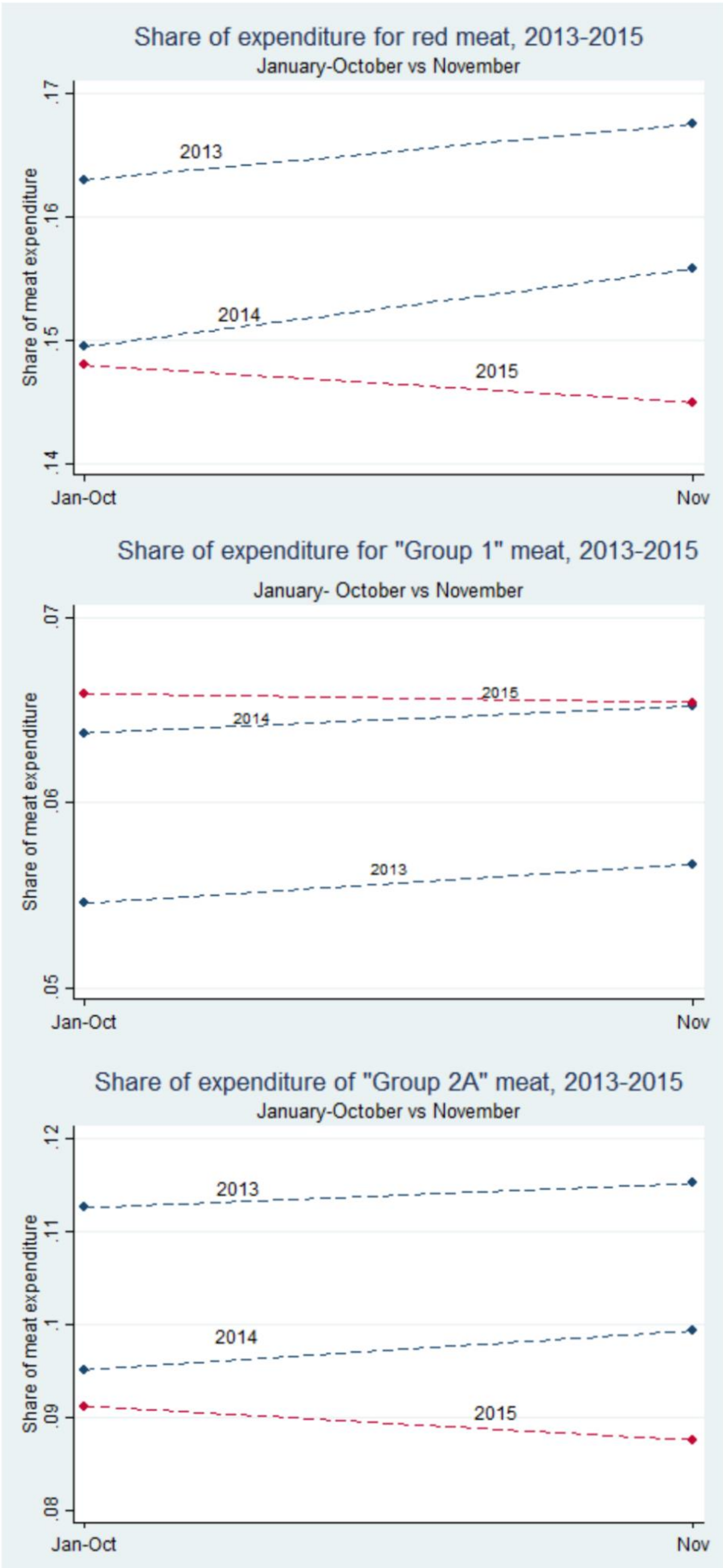
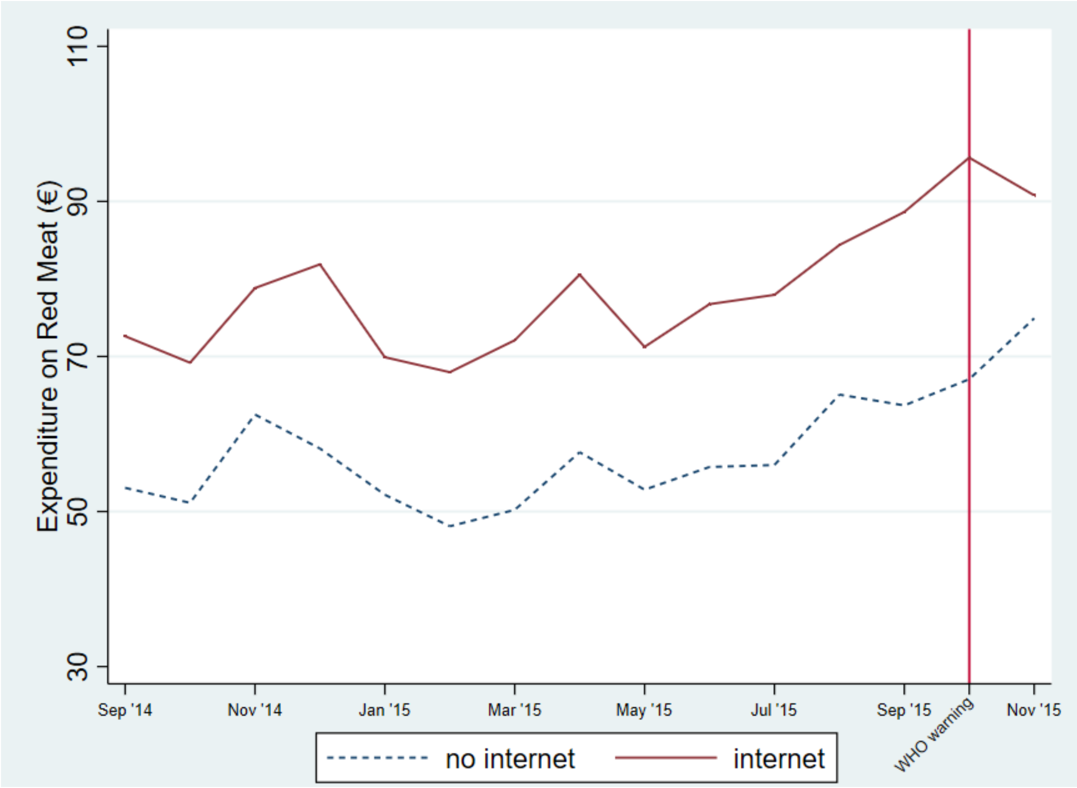
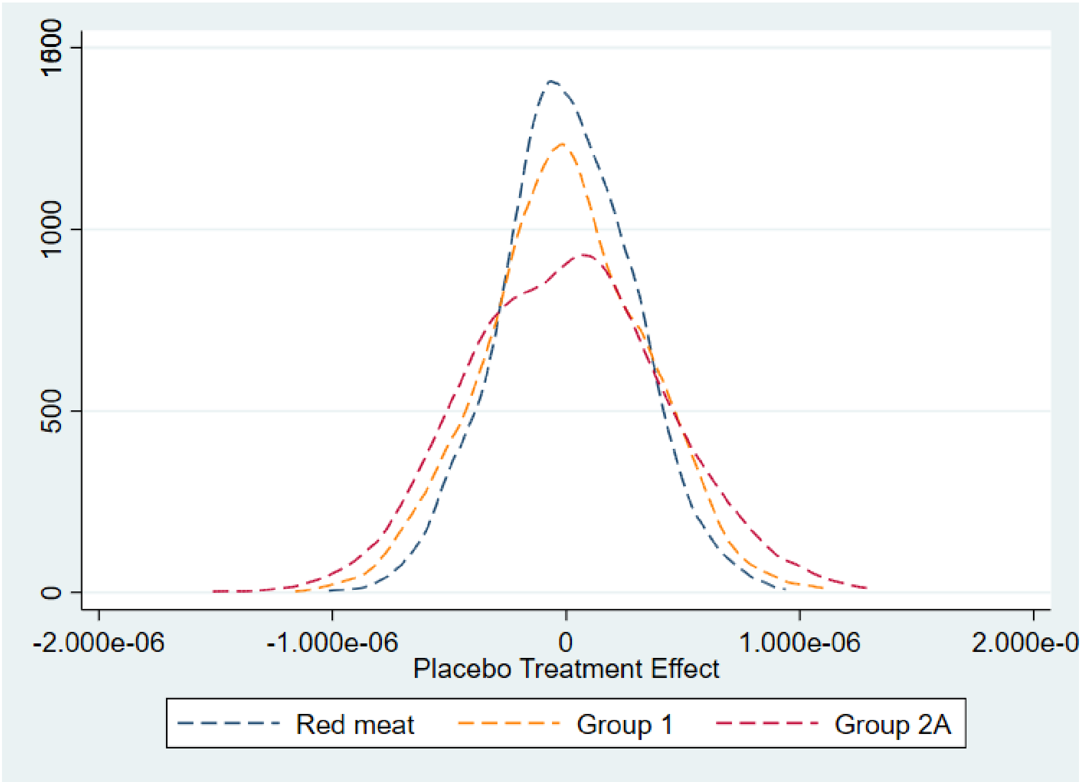


Figure 5. Common trends in red meat expenditures by household's internet access



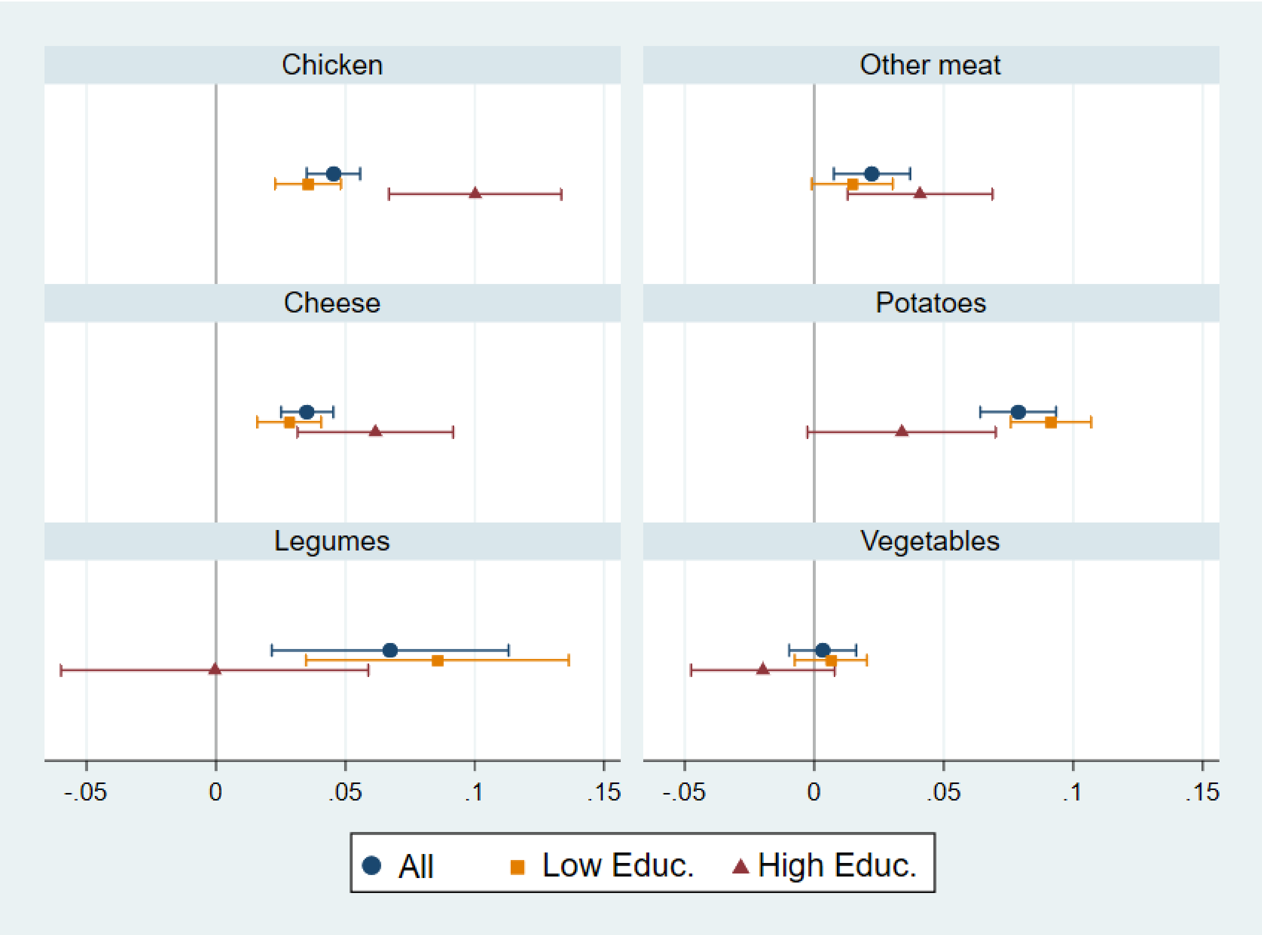
Trend of expenditures on red meat by households with/without internet access.

Figure 6. Kernel density estimates for placebo warnings



Distributions of the placebo estimates based on 2,000 permutations, for all outcomes.

Figure 7. DiD estimates of the effect of the warning on other foods



DiD coefficients of equation (1) with 90% C.I for the full sample and by subgroups of Low/High Educated households.

Appendix

Table A1. Households characteristics: waves comparison

	2014		2015		2016	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
H size	2.37	1.23	2.37	1.23	2.33	1.21
High-Educ.	0.21	0.40	0.20	0.40	0.21	0.40
HH Age						
18-34	0.07		0.07		0.07	
35-64	0.55		0.55		0.55	
>64	0.38		0.38		0.38	
Migrant	0.04	0.20	0.04	0.20	0.04	0.20

Summary statistics of pre-determined covariates: comparison by survey wave.

Table A2. DiD estimates of the effect of the warning on meat expenditure: short-term effects (Bootstrapped standard errors)

	(1) Red	(2) Group 1	(3) Group 2A	(4) Red	(5) Group 1	(6) Group 2A
DiD	-0.0390***	-0.0231***	-0.0626***	-0.0391***	-0.0237***	-0.0620***
	0.0048	*0.0078*	*0.0080*	*0.0051*	*0.0081*	*0.0087*
(log)Food Exp.	1.0344***	0.9253***	1.1653***	1.0163***	0.8942***	1.1622***
	0.0064	*0.0044*	*0.0117*	*0.0059*	*0.0072*	*0.0110*
H size				0.0214***	0.0247***	0.0158***
				0.0017	*0.0026*	*0.0034*
High Educ.				-0.1107***	-0.0888***	-0.1450***
				0.0064	*0.0097*	*0.0081*
HH Age 35-65				0.0025	-0.0219***	0.0287
				0.0088	*0.0080*	*0.0190*
HH Age>65				0.0085	-0.0748***	0.0838***
				0.0105	*0.0121*	*0.0169*
Migrant				-0.1097***	-0.1839***	-0.0603***
				0.0099	*0.0142*	*0.0133*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30852	30852	30852	30852	30852	30852

OLS estimates coefficients of treatment effect of Equation (1). Full set of controls included. Bootstrapped standard errors clustered at month level based on 200 replications in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table A3. DiD estimates of the effect of the warning on meat expenditure. Additional set of controls

	(1) Red	(2) Group 1	(3) Group 2A	(4) Red	(5) Group 1	(6) Group 2A
DiD	-0.0231**	-0.0626***	-0.0390***	-0.0242***	-0.0624***	-0.0393***
	0.0079	*0.0089*	*0.0053*	*0.0077*	*0.0088*	*0.0053*
Food Exp.	0.9253***	1.1653***	1.0344***	0.9238***	1.2076***	1.0471***
	0.0052	*0.0119*	*0.0063*	*0.0062*	*0.0090*	*0.0049*
H Size				0.0265***	0.0166***	0.0220***
				0.0029	*0.0038*	*0.0020*
High-Educ.				-0.0706***	-0.1174***	-0.0920***
				0.0099	*0.0116*	*0.0089*
HH Age 35-65				-0.0205**	0.0297	0.0034
				0.0091	*0.0214*	*0.0100*
HH Age>65				-0.0785***	0.0812***	0.0068
				0.0140	*0.0195*	*0.0121*
Migrant				-0.2000***	-0.0707***	-0.1179***
				0.0164	*0.0132*	*0.0101*
Other Exp.				-0.0605***	-0.1018***	-0.0686***
				0.0051	*0.0117*	*0.0053*
House				0.0061	0.0229***	0.0139**
				0.0084	*0.0057*	*0.0063*
Car				-0.0253**	-0.0737***	-0.0486***
				0.0103	*0.0097*	*0.0051*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30852	30852	30852	30852	30852	30852

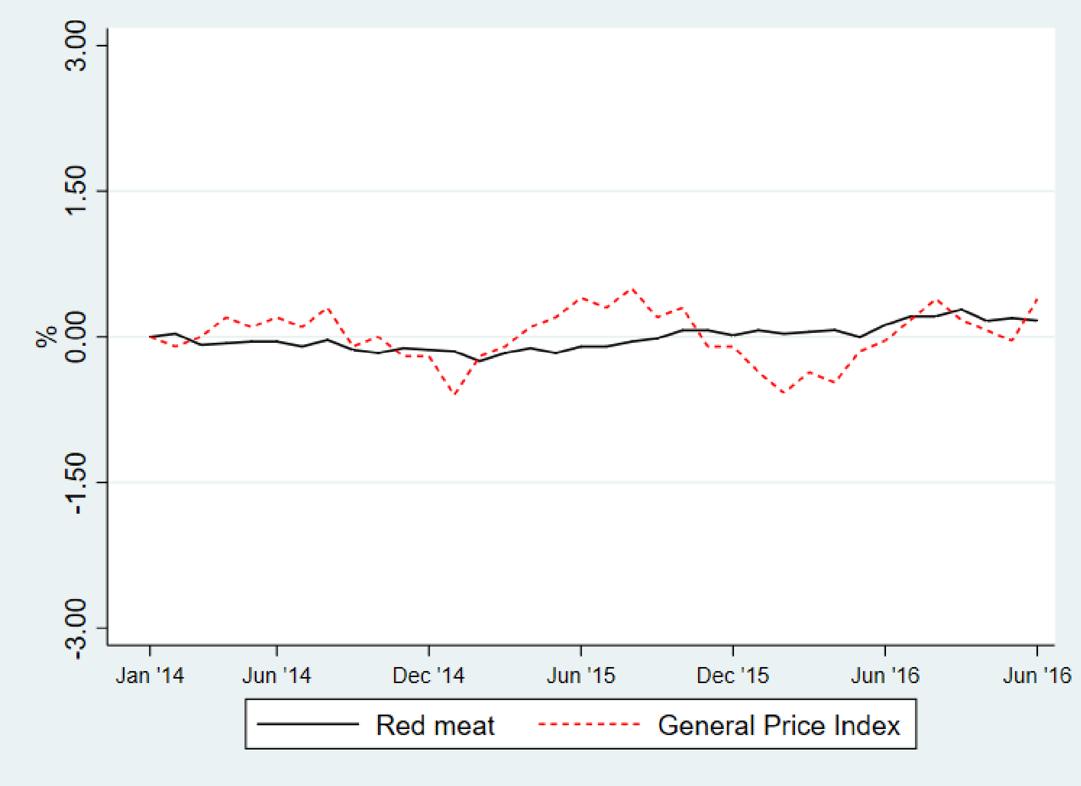
OLS estimates of Equation (1). Specification with an additional set of controls: for non-food expenditure (other expenditure), House ownership and Car ownership. Standard errors clustered at month level in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table A4. Tobit estimates of the effect of the warning on meat expenditure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			Red				Group 1				Group 2A	
	1-month	2-month	5-month	1-year	1-month	2-month	5-month	1-year	1-month	2-month	5-month	1-year
Treatment	-5.2399***	-0.2560	-0.2384	-2.3744	-1.5936***	-2.3264	-2.0380	-0.2208	-4.4777***	-2.4476	-2.4182	-2.2937
	0.6626	*0.9461*	*0.9496*	*1.9082*	*0.3224*	*1.5160*	*1.8172*	*0.9132*	*0.6351*	*1.9368*	*1.9407*	*1.5071*
Food Exp.	0.1866***	0.0730***	0.0724***	0.1802***	0.0736***	0.1257***	0.1255***	0.0714***	0.1257***	0.1861***	0.1851***	0.1217***
	0.0034	*0.0010*	*0.0010*	*0.0023*	*0.0012*	*0.0027*	*0.0025*	*0.0011*	*0.0029*	*0.0030*	*0.0028*	*0.0020*
H size	2.8256***	2.2034***	2.1375***	3.1477***	2.0995***	1.6072***	1.6111***	2.2007***	1.5702***	2.9656***	2.9233***	1.7736***
	0.3935	*0.1737*	*0.1749*	*0.3010*	*0.1896*	*0.3691*	*0.3509*	*0.1699*	*0.3487*	*0.3893*	*0.3958*	*0.2762*
High-Educ.	-11.5601***	-4.8199***	-4.8813***	-11.6018***	-4.5525***	-8.8061***	-9.0256***	-5.0085***	-8.7707***	-11.8136***	-12.0569***	-8.4525***
	1.1091	*0.5319*	*0.5091*	*0.8819*	*0.5947*	*0.6933*	*0.6799*	*0.4744*	*0.7335*	*1.0469*	*0.9947*	*0.6637*
HH Age 34-64	1.4057*	1.8966*	1.8364*	1.9498**	-0.0541	0.0864	-0.0541	0.1844	2.8215**	3.3435**	2.8215**	3.2293***
	0.8123	*1.1086*	*1.0246*	*0.9735*	*0.5713*	*0.5895*	*0.5713*	*0.5447*	*1.1145*	*1.3214*	*1.1145*	*1.2208*
HH Age>65	2.8809**	3.4627**	3.4894***	3.6089***	-1.9694**	-1.8700**	-1.9694**	-1.8834***	7.4073***	8.0750***	7.4073***	8.1415***
	1.1220	*1.4235*	*1.2920*	*1.0858*	*0.7709*	*0.7732*	*0.7709*	*0.7210*	*1.0503*	*1.3456*	*1.0503*	*1.2142*
Migrant	-10.0946***	-9.4579***	-9.0642***	-9.4323***	-9.6441***	-3.0564***	-2.9819***	-8.9267***	-3.5916***	-9.4804***	-9.1176***	-3.6226***
	1.1461	*1.0277*	*0.9969*	*0.7955*	*0.8863*	*0.8538*	*0.7659*	*0.7060*	*0.9479*	*1.3141*	*1.1654*	*0.6937*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30852	32782	35814	45837	30852	32782	35814	45837	30852	32782	35814	45837

Tobit estimates of Equation (1). Clustered standard errors at month level in *italics*. ***, **, * indicate significance at 1%, 5% and 10%, respectively

Figure A1. Price variation



Percentage variations in red meat price and general price indexes. Base: January 2014.