# Health's Kitchen: TV, *Edutainment* and Nutrition

Francesco Principe[*] and Vincenzo Carrieri[†]

November 10, 2020

Latest version here

**Abstract**

Does media exposure affect health behaviours? And how? We exploit the idiosyncratic switchover to digital television across Italian regions which exogenously increased the number of free view national channels and we link this to high-frequency data on the supply of food-related contents on the TV. We find that increased exposure to these contents improved the size and the composition of households' food baskets and, in particular, caused a reduction of expenditure on food high in fats and carbohydrates and an increase on food high in protein. Consistently with such a change in food basket composition, we also document a significant reduction in BMI among individuals more exposed to food-related TV contents which is not explained by any change in physical activity. Finally, we find support for the imitation and learning-by-watching mechanism as driving our results, by documenting a significant increase in the volume of Google and YouTube searches for recipes and video-recipes. Our findings question the health-related negative stereotypes often associated with TV exposure and highlight its potential as a brand-new health policy lever.

**JEL Codes**: D12; I12; L82

**Keywords**: Food shows; dietary patterns; digital switchover; home cooking.

[*]Erasmus School of Economics, Rotterdam, The Netherlands; HEDG, University of York, United Kingdom. E-mail: principe@ese.eur.nl

[†]Department of Law, Economics and Sociology, Magna Graecia University, Catanzaro, Italy; IZA;RWI-Research Network. E-mail: vincenzo.carrieri@unicz.it

We are grateful to Anne Burton, Andrew Jones, Jan C. Van Ours, participants at the Risky Health Behaviors Workshop 2019 (Hamburg), NHESG 2019 Conference (Iceland), the Italian Association for Health Economics (AIES, Pisa 2019), alongside seminar participants at the Erasmus School of Economics, University of York, for helpful comments on previous drafts of the paper.

# 1 Introduction

People spend a significant amount of their time watching TV. In the US, this is an average of 2.7 hours per day. In Italy, TV is the main leisure activity: 92% of people watch TV, 87% watch every day and for an average of 2.8 hours per day. A recent body of literature has documented that exposure to TV contents has a powerful impact on virtually all aspects of people's lives, such as consumption, education, political behaviour, crime perception and divorce, among others [1]. But, does media exposure also affect health behaviours? And, if so, how? Despite the great relevance of health for people's lives, these questions have remained substantially unanswered so far. In a recent review of the literature on the economic and social impact of the media, DellaVigna and La Ferrara (2015) explicitly argued that *"... surprisingly given the interest in health economics, the evidence is limited and mostly comes from outside economics, such as health and communication studies"*. The aim of this paper is to fill this gap.

This article combines three empirical analyses based on four distinct sources of data. We explore the effect of media exposure on dietary patterns and individual health and we investigate the role of imitation and learning-by-watching as key mechanisms linking media exposure to dietary patterns and, therefore, to health. This focus on the effects of media on diets is not incidental. On one hand, eating behaviours are extremely important for health. Non-communicable diseases, of which poor diet is a key risk factor, caused 68% of the deaths globally in 2012 (World Health Organization, 2014) and poor eating behaviours are associated with a vast array of health issues such as obesity, diabetes and cancer, resulting in detrimental effects on individual well-being and economic outcomes (Cawley, 2015). On the other hand, the supply of media contents hasincreasingly tended to focus on food TV shows in recent times (i.e. *Hell's Kitchen*; *Masterchef*, etc.). The momentum of these shows was accompanied by a sharp increase in public approval and viewing. For instance, only looking at the food show *Masterchef*, the average minute audience sharply rose from around 500,000 viewers in the first season to almost 2 million in the following seasons (Auditel). More generally, the number of hours of programming for all these types of TV shows boomed from nearly 50 in 2007 to around 500 in 2013 in Italy; an increase of around 900% in six years (see Figure 2 and Section 2 for more details).

We exploit a natural experiment that occurred in Italy between 2008 and 2012, in-

[1] See DellaVigna and La Ferrara (2015) for a review.

duced by the idiosyncratic switchover to digital television, which exogenously increased the number of free view national channels. One key advantage of digital technology is that it allows broadcasting on more channels, due to the less room occupied in terms of frequencies and generating the so-called digital revenues. Thus, the digital switchover largely increased the possibility for new TV channels to enter the market, resulting in a massive shock of the contents' supply. In Italy, the switchover from analogue to digital TV was implemented region by region between October 2008 and July 2012, and the calendar of the switchover dates was set according to the state of the post-WW2 infrastructure, alternating regions from the South with regions from the North. The geographical heterogeneity in the timing of the digital switchover represents a good as random variation in the media exposure, which we exploit in a staggered Difference-in-Differences (DiD) framework.

To evaluate the influence of media exposure on dietary patterns, we merge two sources of data. We collected data from the Italian TV programming available on the magazine *TV Sorrisi e Canzoni*, and selected the entire programming of all food shows scheduled on Italian TV, including the dates of the episodes and the minutes of programming for each show. We link this unique dataset to a representative sample of around 150 thousand Italian households' monthly-expenditure diaries, available in the Italian Household Budget Survey. The detail of the registered consumption is so accurate that it allows the recording of expenditures on macronutrients, such ascarbohydrates, proteins and fats according to the FAO's classification. The quasi-experimental setting, combined with the availability of data on the minutes of exposure to the food shows and the absence of any change in the intensive or extensive margin of TV watching (see Section 2 for more details), allows us to rule out one of the key limitations in the analysis of the effects of the media: the possibility of selection into television use and into a particular media (DellaVigna and La Ferrara, 2015).

As a second analysis, we assess whether induced changes in food basket composition produced concrete beneficial effects on health. Thus, we study the effect of TV exposure on individual Body Mass Index. To this end, we merge data on the supply of the food TV shows described above to the annual data from the Italian Multipurpose Survey, which includes information about a large number of socio-economic variables and individual BMI on a representative sample of the Italian population. We are thus able to test for the effect of the region-specific digital switchover on the BMI of individuals, while accounting for the intensity of exposure in terms of both contents' supply and time since the treatment occurred. To identify a clean effect, we take advantage of the fact that the survey takes place always in the same month. In addition, by exploiting data on Italian TV programming described above, we can account also for the time variation in the supply of food shows contents and, thus, we are able to document the effect on BMI produced by exposure to specific food show contents.

This paper speaks to the growing literature analyzing the effects of media, and in particular television, on a variety of outcomes such as adult and teenage fertility (Chong and Ferrara, 2009; Kearney and Levine, 2015), consumption (Bursztyn and Cantoni (2016)), education (Gentzkow and Shapiro, 2008; Kearney and Levine, 2019; Hernæs et al., 2019), voting behaviour (DellaVigna and Kaplan, 2007; Enikolopov et al., 2011; Gerber et al., 2009) and crime (Dahl and DellaVigna, 2009).

With respect to the Italian case, Mastrorocco and Minale (2018) also use the transition to digital TV to explore the effect of media coverage of crime episodes on crime perception and find that the digital switchover led to a decrease in crime concerns. Durante et al. (2019) find that individuals with early access to Berlusconi's all-entertainment TV channels (Mediaset) were more likely to vote for his party in 1994. On the other hand, Barone et al. (2015) show that after a supply shock of TV contents, due to access to new digital channels, there was a drop in Berlusconi's vote share in the following elections. We contribute to this literature by exploring the influence of media in a domain that has received very little attention so far, but that represents a key dimension of people's lives: their health.

Lastly, an additional key contribution of our analysis is to explore possible mechanisms linking media exposure to dietary patterns. In particular, we investigate on the role of imitation and learning-by-watching mechanism which are salient features of edutainment (education and entertainment) in the context of cooking shows. Indeed, imitation and learning-by-watching from media can arise for two reasons. On the one hand, the cultivation theory (Gerbner et al., 1980) suggests that the accumulated exposure to TV contents can shift people's beliefs towards representation that is consistent with the social reality portrayed on the screen. In this respect, TV leads viewers to believe that some jobs or activities – i.e., the chef - are more attractive than they are in reality. On the other hand, wishful identification theory (Feilitzen and Linné, 1975) explains viewers' desires to become or to behave in the same way as a certain TV character seen as a role-model and this acts as a link between media exposure and emulating behaviours. These features are inherent to cooking shows that may be best labelled as edutainment, as they have evolved from being predominantly about educating viewers to a mix of education and entertainment (De Backer and Hudders, 2016). The educational element is mainly characterized by the information provision on both the nutritional values of food and the methods to process raw ingredients into cooked meals. The entertainment element is often offered by embedded competitions organized in the spirit of sports competitions, where participants get eliminated at every subsequent round and, finally, a winner is elected in the concluding episode for the season according to the votes of a jury of experts. Additionally, some elements are common to both education and entertainment, such as the preparation of meals under real-life situations: time constraints, limited ingredients or budget availability.

Some relevant empirical literature has shown that exposure to a particular behavior on television changes behavior in the audience. For instance, La Ferrara et al. (2012) estimate the long-term imitation effects on fertility rates in Brazil of exposure to telenovelas, taking advantage of the staggered introduction of *Globo*, the network that broadcasted telenovelas in Brazil. Similarly, Kearney and Levine (2015) estimate, among other outcomes, the impact of the US show *16 and Pregnant* on Google searches for keywords related to fertility choices. A number of papers has also found that imitation channel is extremely important for explaining the effect of media exposure on crime (Dahl and DellaVigna, 2009; DellaVigna and La Ferrara, 2015). However, there is scant evidence on the imitation channel in the context of healthy/unhealthy behaviours. An exception is represented by some studies on suicides. In a seminal paper, Bollen and Phillips (1982) combine U.S. daily suicide statistics and the Vanderbilt data set of television news stories on ABC, CBS, and NBC to code all stories under the heading 'suicide' broadcast between 1972 and 1976 and find evidence of a significant increase in suicides occurring on the first two days and on days 6-7. Baron and Reiss (1985) show that the evidence in Bollen and Phillips (1982) and in other related papers is not reliable and this is due to a lack of a clean identification strategy (DellaVigna and La Ferrara, 2015).

Our paper contributes to this literature by investigating the presence of an imitation channel concerning home cooking. Indeed, the key elements of food-TV shows are the charismatic chef's image and the attention to high-quality foods in terms of both ingredients and cooking methods. For instance, looking at the recipes provided by main cookery TV shows, a higher attention towards the use of healthier ingredients such as fish and white meat over more fatty ones (i.e., cured meat, butter, etc.) clearly emerge (as documented in Section 2 of the paper). We thus investigate whether exposure to these media contents influences the propensity for home cooking by increasing the researches on

Google and YouTube about recipes and video-recipes proposed by TV shows. To the best of our knowledge, no previous papers have used data on video contents, which instead are proven to be very useful in order to get insights into the imitation channel as the main mechanism through which the media influence behaviours.

Our analysis leads to a number of original results. First, we find that the increased exposure to cooking show that the contents improved the size and the composition of households' food baskets. In particular, we document a reduction of monthly expenditures on foods high in fats and carbohydrates, and an increase in the expenditure on those high in protein. Consistently with such a change in consumption, we also document that the exposure caused a significant reduction in individual BMI. The effect is found especially among individuals watching more TV (i.e. low-educated, younger and older individuals) and it is not driven by any change in physical activity behaviours. Event study specification shows that the significant decline in BMI starts to occur after the first 12 months of exposure and persists in decreasing in subsequent years. Moreover, it does not reveal any systematic pre-trends in the four years before the region-specific switch-over. Finally, we find that the learning-by-watching channel plays a key role. We document a significant increase in home cooking and in the demand for recipes on the web. These results have relevant policy implications and highlight the potential of role models on the TV to convey health-related information and promote healthier lifestyles.

The remainder of the paper is structured as follows: in Section 2, we provide further details on the institutional setting. In Section 3, a description of the dataset and main variables is provided. Identification strategy is presented in Section 4. In Section 5, we present the main results. Section 6 provides some sensitivity analyses and robustness checks, while Section 7 summarizes and concludes the paper.

# 2 Institutional Setting

The digital switchover, i.e. the transition from analogue to digital TV broadcasting, was defined as part of the Action Plan *eEurope* 2005, approved by the Seville European Council in June 2002, and aimed at translating connectivity to increase economic productivity and improving the quality and accessibility of services for all European countries. One key advantage of digital technology is that it allows the broadcasting of more channels, due to the lesser room occupied in terms of frequencies and generating the so-called digital revenues. Thus, the digital switchover largely increased the possibility for new TV channels to enter the market, resulting in a massive shock of the contents' supply.

The switchover from analogue to digital TV was implemented in Italy region by region between October 2008 and July 2012, as shown in Figure 1. Italian territory was divided into 16 areas, mostly corresponding to one or more regions, and the calendar of the switchover dates was set according to the state of the post-WW2 infrastructure, by alternating regions from the North with regions from the South in order to avoid geographical disparities. At the date of the switchover, the analogue signal was switched off and households had no further access to the old analogue broadcasting on their TVs. In order to receive the new digital TV, a decoder at the cost of about 50 Euros was required; this was entirely subsidised by the government through vouchers.

[Figure 1 here]

As a result, there was a massive entrance of new channels into the market. The seven traditional free-view national channels (three from the public television Rai, three from the Berlusconi's Mediaset and the independent La7) were complemented by more than 50 new channels. Interestingly, these new TV channels - to attract their share of viewers - had to differentiate themselves in terms of contents, centring their offer on lifestyle-related contents, such as reality shows of various kind and in particular food TV shows, such as *Masterchef* and *Hell's Kitcken*, among others. The massive growth in the supply of cooking shows is documented in Figure 2, which displays an increasing intensity in the exposure to food-related contents on the TV. Overall, from 2007 to 2013 the number of hours of programming for these shows on the TV changed from 50 to around 500 -a massive increase of around 900%. This was almost entirely caused by the entry of the new digital channels, which covered around the 80% of the overall supply of food-related contents on TV in 2013. On the other hand, the supply of food-related shows in the traditional channels remained fairly flat and even showed a deflection after the digital transition was completed in all the Italian regions.

[Figure 2 here]

Concerning the content of the cooking shows, some key elements emerge. First, they propose a new image of the chef, represented as a "cool" and charismatic person with both cooking and managerial skills[2]. Second, the recipes proposed are generally very healthy, favouring the use of ingredients low in fat and wholesome cooking methods. For example, through a text analysis performed on the universe of recipes proposed in cookery shows on Italian TV (summarized in Figure A2), we find that about 50% of the TV recipes include fish or white meat as the main ingredient, while just 2% include cured meat that is considered to be less healthy. The recipe is the main focus of these shows and it is always available to the public; for example, on the show's website, the chefs explain to viewers how to prepare a meal by manipulating unprocessed foods (De Backer and Hudders, 2016). Last, they generated what the sociological literature has defined as *foodporn*: mass-media overexposure to food. According to a recent survey, 30% of Italians post pictures of food they cook or have at the restaurant on social media (Coldiretti/Ixe' 2016). On Instagram, the most popular photo sharing social networking service, the hashtag #foodporn counts about 250 million posts to sum up with thousands of other associated hashtags that make food the most shared topic on the platform. All in all, cooking TV shows convey both elements of entertainment and viewers education, so that they can be labelled as edutainment.

It is important to highlight some aspects of this transaction process that represent key elements of our analysis. First, since the state of post WW2 infrastructure was the criterion for implementing the switchover calendar, there was no possibility for local authorities or TV networks' ownerships to lobby towards an early and more favourable transition for their areas of interest. This feature of the Italian digital transition is highlighted in Figure 1, which shows the absence of any geographical pattern and the homogeneity between North, Centre and South in the timing of the digital switchover. Importantly, this technological change is clearly unrelated to our outcomes of interest (i.e., expenditure on food) and this allows us to treat the staggered time of the digital switchover as good as random, in our paper.

[2]Indeed, the popularity of the chefs dramatically increased on the media. For example, as showed in Figure A1 in the Appendix, in Italy the Google searches for the chef Gordon Ramsay, after the digital transition was completed, reached the same levels of David Beckham, the most famous British footballer and public figure worldwide.

# 3 Data and variables

The data used in this paper are drawn from four main sources. First, data about households' expenditure come from seven waves of the Italian Household Budget Survey, from 2007 to 2013. This 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 Programme. 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. 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 several 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 available every year with expenditures listed on a monthly basis. As stressed in the introduction, the disposal of high frequency data is a key element to precisely identify our effects of interest.

With respect to the outcomes, we group the items in the households' food basket according to their macronutrients composition as provided by FAO (Food and Agriculture Organization of the United Nations). The macronutrients - i.e. carbohydrates, proteins and fats - generate satiety signals of varying strengths. The evidence suggests that fats have the lowest satiating power, carbohydrates have an intermediate effect and protein are found to be the most satiating (Stubbs et al. 1996). Thus, following the Percent Daily Value (DV) as defined by the Food and Drug Administration (FDA), our outcomes of interest consist of expenditure on foods high (i.e. the modal nutrient) in fats, carbohydrates and protein, respectively.

Second, data about all the food TV shows broadcasted in Italy are extracted from *TV Sorrisi e Canzoni*, the most famous Italian magazine publishing weekly TV schedules. In particular, we collected figures about all the TV shows included in the category "cuisine" and then compared those with the information present on the website of the network that broadcasts the show in order to retrieve data about the content, the length and the number of episodes. Hence, we built our treatment variable, which refers to the average monthly minutes of (new) food-related TV contents. To ease the interpretation of the results, we rescale our main explanatory variable, *Exposure*, by dividing the original exposure length by its standard deviation/45-minute episodes.

Third, data on the indexed values of searches on Google and YouTube come from Google Trends, the tool that provides information about the frequency of the researches for keywords or terms on the internet. Importantly, Google Trends allows selecting the geographical area of interest, the period of time, the language and the category of reference. We collected longitudinal information, at regional level, about the monthly queries for some terms as "how to cook [x]", "recipe [x]", "recipes TV" and "video-recipe", for the period from 2007 through to 2013. Our sample consists of about 1600 region-month observations.

Finally, we use data from the Multipurpose Survey carried out every year (in March) by the Italian National Institute of Statistics. This is a repeated cross-sectional survey, representative of the entire Italian population, aimed at collecting information about individuals' characteristics and their lifestyles. This allows us to retrieve anthropometric information in order to estimate individual BMI. Moreover, it contains several socio-demographic variables such as age, gender, family type and education, which we use as control variables in our analysis.

The full list of variables included in our dataset is presented in Table 1, along with mean values and standard deviations. Concerning our outcomes, we find that an Italian household spends on average about 103, 115 and 150 Euros per month on food high in fats, proteins and carbohydrates, respectively, while the overall expenditure on food amounts to about 490 Euros per month, which represents about the 20% of the total monthly expenditure.

[Table 1 here]

For what concerns the other variables of interest, Italian households consist of 2.5

members on average and there is at least one university graduate in about 20% of the households in our sample. With respect to the cooking shows, in the analysed period, the Italian TV channels broadcasted about 45 new shows, consisting on average of 17.8 episodes per season with a duration of 52 minutes each. This amounts to a massive supply of about 500 hours of new food-related content in 2013 and denotes an increase of 900% compared to the pre switchover year (2007).

# 4 Empirical Stategy

In order to identify the effect of media exposure on dietary choices, we exploit as a natural experiment the timing of the regional switchover to digital television and implement a staggered difference-in-differences study design. More formally, we estimate the following equation:

$$Y_{irt} = \alpha + \beta DSO_{rt} + \delta X_{irt} + \gamma_r + \mu_t + \gamma_{irt} \tag{1}$$

where Y is the outcome of interest such as the expenditure in macro-nutrients and BMI of individual i, living in region r at time t. DSO is an indicator that takes value 1 if the region r had digital switchover at time t, $X_{irt}$ denotes a set of household characteristics,$\gamma_r$ and $\mu_t$ are region and time (month and year) fixed effects, respectively. The coefficient represents the effect of media exposure on the outcome and can be given an intention-to-treat interpretation as it reflects the impact of the general availability of new TV contents (including food-related ones) on dietary choices. Standard errors are clustered at regional level.

Additionally, we exploit information about the average monthly minutes of (new) food-related TV contents to investigate the effects of the intensity of the exposure to such contents on households' dietary choices. Thus, we estimate the following equation:

$$Y_{irt} = \alpha + \beta DSO_{rt}\ x\ Exposure_{rt} + \delta X_{irt} + \gamma_r + \mu_t + \gamma_{irt} \tag{2}$$

where the interaction term ($DSO_{rt}$ x $Exposure_{rt}$) captures the direct effect of the exposure to food-related contents, given by the average monthly minutes of food show broadcasted. All the other terms are the same as discussed in Equation (1). This specification relies on an additional source of exogenous variation (other than the staggered regional switchover) which is the monthly variation in the supply of food related contents on TV.

The main identifying assumption to interpret the estimates of the effect of media exposure on our outcomes as causal relies on the existence of a common trend in the outcomes, alongside different regions, in the pre-switchover periods. In our context, this equates to assuming that in the absence of the switchover and despite its timing, individuals in different regions would have reported the same trends in expenditure on foods high in fats, carbohydrates and proteins and BMI. In order to check the validity of this identification assumption, we perform visual inspections of common trends, falsification tests based on placebo digital switchovers, additional specifications including several trend functional forms and region-specific trends in our model. Lastly, we perform event study analysis to rule-out systematic pre-trends affecting the results and to explore the dynamic effect of the exposure to cooking shows. Results are reported in Section 6 and provide strong support for our identification strategy.

# 5 Results

This section presents the main results of our empirical analysis. We first estimate the effect of media exposure on the dietary choice of Italian households with different exposures. Second, we evaluate the consequences of these behaviours in terms of individual health. Finally, we investigate the mechanisms driving these results exploiting longitudinal data about the frequency of the queries about food preparation on the internet.

## 5.1 Does media exposure affect dietary choices?

Difference-in-Differences estimates of the model in Equation (1) are reported in Table 2. On average, we find that the availability of new TV contents, generated by the digital switchover, leads to a 2.2 Euros increase in the expenditure on food high in protein (column 2), and a reduction in expenditure on fats and carbohydrates by 0.9 and 1.3 Euros, respectively (Columns 1 and 3), while no significant change in the total food expenditure is observed (Column 4). Interestingly, results are similar also in terms of magnitude when controls for average education and household size are included (Columns 5-8).

[Table 2 here]

As already stated in the previous section, these estimates have an "intention to treat" interpretation, since the DiD coefficient, identified by the staggered timing of the digital switchover has the limitation of capturing all the new contents supplied through the new digital TV channels and not just the food-related ones. Therefore, in order to narrow the focus of our analysis, Table 3 presents estimates of the DiD model which captures the actual exposure to the treatment as defined in Equation (2), thus interacting the exogenous timing of the digital switchover with the intensity of the exposure to food-related contents. Interestingly, we find that an increase in the average monthly minutes of exposure has a statistically significant effect on the expenditure on all macronutrients. The coefficients are scaled up to account for an exposure to an episode of 45 minutes. Thus, the monthly expenditure on food high in protein increases by about 1.9 Euros for each episode, on average, while expenditure on food high in both fats and carbohydrates is reduced by about 1.5 and 1.6 Euros, respectively. When compared to the average monthly expenditure on these foods, these amount approximately to 1.6%, 1.48% and 1.09% of the average expenditure. Finally, column (4) shows a positive effect of the exposure on the overall food expenditure, i.e. around 1.8% of the monthly food expenditure.

[Table 3 here]

Overall, according to our estimates, the exposure to cooking TV shows improve both the size and the quality of the households' baskets. In fact, treated households increased their expenditure on food while favouring a healthier composition of their food baskets by consuming more proteins and less fats and carbohydrates. This suggests an overall improvement in their dietary choices.

## 5.2 What are the effects on health outcomes?

To better understand the health consequences of these changes in behaviours, we now investigate the effects in terms of health outcomes by looking at the BMI of individuals. In this case, we deal with annual data and we take advantage of the fact that the survey takes place always in the same month: March. To adjust our estimating equation to this feature of the data, we follow Mastrorocco and Minale (2018) by estimating our Equation (2) on annual data while taking into account the distance in months between the date of the digital switchover and the date of the interview. Moreover, we control for the standard set of individual and household characteristics that might explain differences in BMI, such as education, gender, age, number of components and so forth. Results are reported in Table 4. Column (1) shows baseline estimates, while columns (2) and (3) show the results of the heterogeneous effects analysis by gender and age groups, respectively.

[Table 4 here]

On average, we find that an increase in exposure has a negative and statistically significant effect on individuals' BMI, by reducing it by about 0.15 points. We also perform heterogeneous analysis on the categories watching more TV[3]. Interestingly, we find higher and significant effects among these categories. Moving on to age groups, for instance, we find statistically significant effects for both the younger and the older individuals, for which the effect is even stronger also in terms of magnitude. This is also consistent with both previous findings about media exposure effects in Italy (i.e., on crime perception and voting behaviours) and the patterns in TV-watching behaviours we previously documented. In fact, individuals in the 65+ group are those who spend the higher amount of time watching television, and thus are more likely to be exposed to these contents. Moreover, we find a large and significant effect among low-educated individuals and weak effects among high-educated. These results are suggestive of an effect driven by an actual exposure to TV contents. In order to understand whether the changes in dietary patterns are the leading mechanisms underlying our effects on BMI, we also look at whether exposure to TV contents may have affected the frequency of engaging in physical activity. Indeed, as is well known, along with food intake and genetic traits, calories burning might also affect BMI accumulation. While genetic traits are time-invariant, physical activity behaviours might, in principle, be affected by external factors such as exposure to TV contents. In Table 5, we show that the exposure to the new contents induced by digital switch-over did not affect any sort of physical activity, including a regular, occasional and sports club memberships.

[Table 5 here]

All in all, these results suggest that the effect of food-contents on BMI accumulation are driven by an actual exposure to TV contents and through a change in dietary patterns. Next, in order to capture the dynamic effect of the exposure to cooking shows

[3] According to ISTAT (2016) these are mainly individuals with lower education and within the age ranges 17-34 and 64-75

following the digital switchover on BMI, we set up an event study specification. Exploiting information about the month of the interview, we include in our estimating equation lags and leads of up to 4 years before and after the region-specific switchover date. One year pre-switchover is the excluded dummy for each dimension and thus, the effects are relative to the year immediately before the digital switchover, which is set equal to zero in the presentation of the results. The full set of controls is included. The coefficients of the event study specification are reported graphically in Figure 5.

[Figure 5 here]

We find that the significant decline in BMI starts to occur after the first 12 months since the digital switchover and persists in decreasing in the subsequent years. Notably, Figure X also suggests no evidence of systematic pre-trends affecting the results as all the pre-switchover coefficients are close to zero and not statistically significant, which supports that the common trend assumption is likely to hold.

### 5.3 How does media exposure affect dietary choices?

The results reported above show that households responded to the increase in TV exposure to food-related contents by changing their dietary choices and improving both the size and the composition of their food baskets. These results are likely to be driven by imitation and learning-by-watching mechanism induced by the role models proposed on the screen. Indeed, as stressed in the introduction, the fact that the role of the chef is portrayed as a charismatic character and the cooking activities represented in an appealing way, may induce people to change their attitudes towards cooking and increase their wish to emulate the media figures. In order to investigate these mechanisms, we exploit data about the search queries on Google and YouTube for terms that are a popular proxy for research of information about food preparation on the internet.

[Table 6 here]

Table 6 displays the estimates of Equation (1), using the search term as the dependent variable. The first three columns show a strong and significant increase in the Google searches for “how to cook x”, “recipe x” and “recipe TV”. In particular, the last of these confirms that exposed individuals were increasing their demand for the recipes proposed by the TV shows. These results are corroborated by the estimates in columns 4 and 5, which show a strongly significant impact also on the demand of video representing cooking procedures on YouTube[4]. Complemented with the changes in shopping basket composition, these results support the idea that it is exactly the exposure to these contents and not to television viewing per se that explain our results. In a similar fashion, for instance, La Ferrara et al. (2012) find that exposure to telenovelas contents lead to an imitation based on children's naming patterns and novela's content. Similarly, our results suggest that individuals try to imitate what they see on the screen and, in this respect, they rely both on written and visual replications.

Taken as a whole, these results go in the same direction as the previous ones and they contribute by providing a more complete picture. In fact, these results show how the changes in the composition of food baskets, induced by the increased supply of food-related contents, have resulted in health benefits for individuals in terms of BMI reduction. These results are corroborated by the fact that a greater reduction is found for more exposed individuals. In addition, these findings challenge the common idea that TV adversely influences people by promoting negative behaviours. Au contraire, they offer supportive evidence for the potential of using TV as a trigger to promote positive behaviours, in one word to "edutain" people.

# 6 Robustness Checks

In order to explore the possible threats to our identification strategy and to validate our results, we perform several robustness checks. First, we start with a visual inspection of common trends. For the sake of simplicity, we split the 20 Italian regions into quartiles, according to the date of their digital switchover. Figure 4 shows the average monthly expenditure on food. Alongside the parallel trends of the different groups of regions, it emerges that a strong seasonality in food consumption exists, which is taken into account in our empirical approach with both month and year fixed effects. These two key facts emerge even stronger in Figure 4, where we plot the trends for the three macronutrients,

[4]Google Trends report data about changes in the number of searches for a term over time, within an area. The trends data range from 0 to 100, where 100 is the point in which the term had the highest search interest in that area. Thus, these data can be given an ordinal, but not cardinal, interpretation. In our case, our estimates identify changes in the number of searches for a term within a location, compared to its counterfactual.

separately. Additionally, this graph also shows how peaks in expenditure on protein and fats are observed on the occasion of the Christmas celebrations, which represent the significant impact of the Italian (culinary) traditions. This is a general feature of food expenditure (see for instance Carrieri and Principe 2018). Importantly, while our empirical analysis only covers a window of one year before and after the digital switchover was completed, these graphs show trends from 2004, in order to reduce any concern about our estimates capturing any pre-trend unobserved factors. This leads us to be confident about the plausibility of common trend assumptions in our setting.

Second, in order to capture any time varying confounding factor that could bias our results, we estimate different specifications of our model by augmenting our estimating equation through the inclusion of a linear time trend, a quadratic trend and region-specific linear trends, separately. The estimates of the DiD coefficients are reported in Table 7 and are qualitatively equivalent to those reported in the main model specification.

[Table 7 here]

Third, we perform a series of placebo tests by falsifying the dates of the digital switchover. In particular, we estimate analogous regressions to our baseline equation but instead of looking at the effect of past media exposure on current outcomes, we look at the effect of future (placebo) switchovers. The main assumption here is that digital switchovers at t+1 should not have any effect on current individual BMI. Analogously, we look for the effect on current BMI of a placebo anticipated treatment by dating the switchover one year earlier than the actual switchover date. The estimated coefficients are reported in Table 8. We find no significant effects of both past and future switchover on BMI at time t and, in addition, the parameters estimated are all very close to zero. These checks validate both the plausibility of the parallel trend assumption in our DiD settings as well as strongly ruling out the possibility that some time-varying confounders might bias our estimates.

[Table 8 here]

Last, we explore the robustness of our results with respect 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 staggered switchover at regional level, the region 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 clusters to draw credible inference, twenty clusters might be effectively "at the boundary". Thus, as suggested by Cameron and Miller (2015), we also use wild cluster bootstrap standard errors (with 999 replications) and we obtained the same results as with clustered standard errors[5]. However, to rule out any possible concern, we follow Bertrand et al. (2004) and we perform a simulation exercise by means of randomization-based statistical inference for significance tests. We randomly select a set of different time periods and treatment intensities (Month x Year x cooking shows minutes) in order to simulate the effect of a "fake digital switchover" and estimate the average treatment effect in our DiD framework by using the fake switchover in place of the real one. Then, we simulated the model 5,000 times and stored the estimated coefficients in order to plot the non-parametric distribution of placebo estimates. The key assumption of this randomization test based on placebo treatments is that the fake switchovers should not generate any effect on the individual BMI since the timing of the transition is randomly assigned. Thus, on average, the estimated effect should be zero.

[Figure 6 here]

The non-parametric distributions of placebo treatment effect, from the 5,000 iterations, of the media exposure to food-related contents on individual BMI are presented in Figure 6. It shows that the means of the distributions are all virtually zero, meaning that our estimates are unbiased. Indeed, the average treatment effects we estimate, depicted by the vertical red lines in each graph, fall in the very extreme tails of the distributions. As a result, this increases the confidence that the changes in households' expenditures induced by TV exposure were not generated by chance. We also perform the same exercise for the set of results regarding households' expenditure on food high in fats, carbohydrates and proteins, reported in Figure A3.

[5]Results available upon request

# 7 Conclusions

Does media exposure affect health behaviours? And how? While a recent body of literature finds that media exposure has a significant impact on virtually all aspects of people's life, perhaps surprisingly, there is scant evidence on whether and how media exposure affects health behaviours. In this paper, we made use of high-frequency data and a quasi-experimental setting to cover this gap. We used data on both the supply of TV cooking shows and on household expenditures on food and we exploit the staggered switchover from analogue to digital television which occurred in Italy from 2008 to 2013 in order to identify the causal impact of the supply of cooking shows on TV on the dietary choices and BMI of individuals. Moreover, using data extracted from Google Trends and YouTube, we also test whether imitation is the leading mechanism for our results. The use of data on video contents is new in the literature and allows us to assess the role of a more direct measure of imitation.

We find that exposure to cooking shows on TV has a sizable effect on the composition of households' food baskets. In particular, we show a reduction of the monthly expenditure on fats and carbohydrates, and an increase in the expenditure on food high in protein. Consistent with this change in food basket composition, we also document that exposure to food-TV contents caused a significant decline in BMI and, in particular, among more exposed individuals. Such a change is not explained by variations in physical activity, it starts to occur after the first 12 months since the digital switchover and persists in decreasing in the subsequent years. Finally, we also find that the imitation channel largely explains this effect by documenting a significant increase in the demand for recipes and video-recipes on the Internet. These results are robust to several specifications and robustness checks.

Our findings question the health-related negative stereotypes often associated with tv exposure highlighting a significant role of media in shaping dietary choices and health, something that- at least to our knowledge- represents a key element of novelty in our results. This offers a number of policy implications. On one hand, this has relevant implications for what concerns the role of "edutainment" combination (i.e. educational and entertainment) in shaping behaviours. Our results- in line with a growing literature highlighting the potential of edutainment in shaping other important social behaviours such as family outcomes (La Ferrara, 2015)- indicate that "edutainment" has positive effect on dietary choices leading to healthier diets and a higher probability of engaging in home cooking. On the other hand, these results might have relevant health policy implications. Indeed, unhealthy diet represents one of the key risk factors of non-communicable diseases that caused around the 68% of deaths globally in the 2012. This has led to much discussion about whether and how we can improve the quality of dietary intake in the population. Previous literature mainly focused on the role of vouchers, nutritional labelling or general health warnings. For instance, Griffith et al. (2018) found positive effects of nationally-implemented policy – the UK Healthy Start scheme – that introduced vouchers for fruit, vegetables and milk, while Fichera and von Hinke (2020) highlights the effectiveness of nutritional labelling by documenting a significant effect of Front-of-Pack nutrition labels on the nutritional composition of the food basket. Carrieri and Principe (2018) look at the effects of health warning about red meat and found beneficial effects although concentrated only among the highly educated groups.

Our findings contribute to this debate by highlighting the potential of role models on the TV to convey health-related information and to promote healthier diets. Indeed, an increasing number of TV channels are concentrating their offer on lifestyle-related contents, such as reality shows of various kind. While the role model is probably not explicitly designed in these shows but represents only a by-product (DellaVigna and La Ferrara, 2015), our findings still suggest that this may have sizable effects on dietary choices and health and thus might represent a potential brand-new health policy lever. Future research might focus both on the effects of media exposure and role models on a variety of other lifestyles such as physical activity, smoking or alcohol and on the long-term effects of the acquired behaviours. This may contribute to understanding how media affect our lives but also, and perhaps more importantly, how media might contribute to improving them.

# References

Baron, J. N. and Reiss, P. C. (1985). Same time, next year: Aggregate analyses of the mass media and violent behavior. *American Sociological Review*, pages 347–363.

Barone, G., D'Acunto, F., and Narciso, G. (2015). Telecracy: Testing for channels of persuasion. *American Economic Journal: Economic Policy*, 7(2):30–60.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275.

Bollen, K. A. and Phillips, D. P. (1982). Imitative suicides: A national study of the effects of television news stories. *American sociological review*, pages 802–809.

Bursztyn, L. and Cantoni, D. (2016). A tear in the iron curtain: The impact of western television on consumption behavior. *Review of Economics and Statistics*, 98(1):25–41.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, 50(2):317–372.

Carrieri, V. and Principe, F. (2018). Who and for how long? an empirical analysis of the consumers' response to red meat warning. *mimeo*.

Cawley, J. (2015). An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of Health Economics*, 43:244–268.

Chong, A. and Ferrara, E. L. (2009). Television and divorce: Evidence from brazilian novelas. *Journal of the European Economic Association*, 7(2-3):458–468.

Dahl, G. and DellaVigna, S. (2009). Does movie violence increase violent crime? *The Quarterly Journal of Economics*, 124(2):677–734.

De Backer, C. J. and Hudders, L. (2016). Look who's cooking. investigating the relationship between watching educational and edutainment tv cooking shows, eating habits and everyday cooking practices among men and women in belgium. *Appetite*, 96:494–501.

DellaVigna, S. and Kaplan, E. (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3):1187–1234.

DellaVigna, S. and La Ferrara, E. (2015). Economic and social impacts of the media. In *Handbook of media economics*, volume 1, pages 723–768. Elsevier.

Donald, S. G. and Lang, K. (2007). Inference with difference-in-differences and other panel data. *The review of Economics and Statistics*, 89(2):221–233.

Durante, R., Pinotti, P., and Tesei, A. (2019). The political legacy of entertainment tv. *American Economic Review*, 109(7):2497–2530.

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and political persuasion: Evidence from russia. *American Economic Review*, 101(7):3253–85.

Feilitzen, C. and Linné, O. (1975). Identifying with television characters. *Journal of Communication*.

Fichera, E. and von Hinke, S. (2020). The response to nutritional labels: Evidence from a quasi-experiment. *Journal of Health Economics*, page 102326.

Gentzkow, M. and Shapiro, J. M. (2008). Preschool television viewing and adolescent test scores: Historical evidence from the coleman study. *The Quarterly Journal of Economics*, 123(1):279–323.

Gerber, A. S., Karlan, D., and Bergan, D. (2009). Does the media matter? a field experiment measuring the effect of newspapers on voting behavior and political opinions. *American Economic Journal: Applied Economics*, 1(2):35–52.

Gerbner, G., Gross, L., Morgan, M., and Signorielli, N. (1980). The "mainstreaming" of america: violence profile number 11. *Journal of communication*, 30(3):10–29.

Griffith, R., von Hinke, S., and Smith, S. (2018). Getting a healthy start: The effectiveness of targeted benefits for improving dietary choices. *Journal of health economics*, 58:176–187.

Hernæs, Ø., Markussen, S., and Røed, K. (2019). Television, cognitive ability, and high school completion. *Journal of Human Resources*, 54(2):371–400.

ISTAT (2016). *Italia in cifre: 2015*. Istituto Nazionale di Statistica.

Kearney, M. S. and Levine, P. B. (2015). Media influences on social outcomes: The impact of mtv's 16 and pregnant on teen childbearing. *American Economic Review*, 105(12):3597–3632.

Kearney, M. S. and Levine, P. B. (2019). Early childhood education by television: Lessons from sesame street. *American Economic Journal: Applied Economics*, 11(1):318–50.

La Ferrara, E., Chong, A., and Duryea, S. (2012). Soap operas and fertility: Evidence from brazil. *American Economic Journal: Applied Economics*, 4(4):1–31.

Mastrorocco, N. and Minale, L. (2018). News media and crime perceptions: Evidence from a natural experiment. *Journal of Public Economics*, 165:230–255.

Stubbs, R., Van Wyk, M., Johnstone, A., and Harbron, C. (1996). Breakfasts high in protein, fat or carbohydrate: effect on within-day appetite and energy balance. *European journal of clinical nutrition*, 50(7):409.

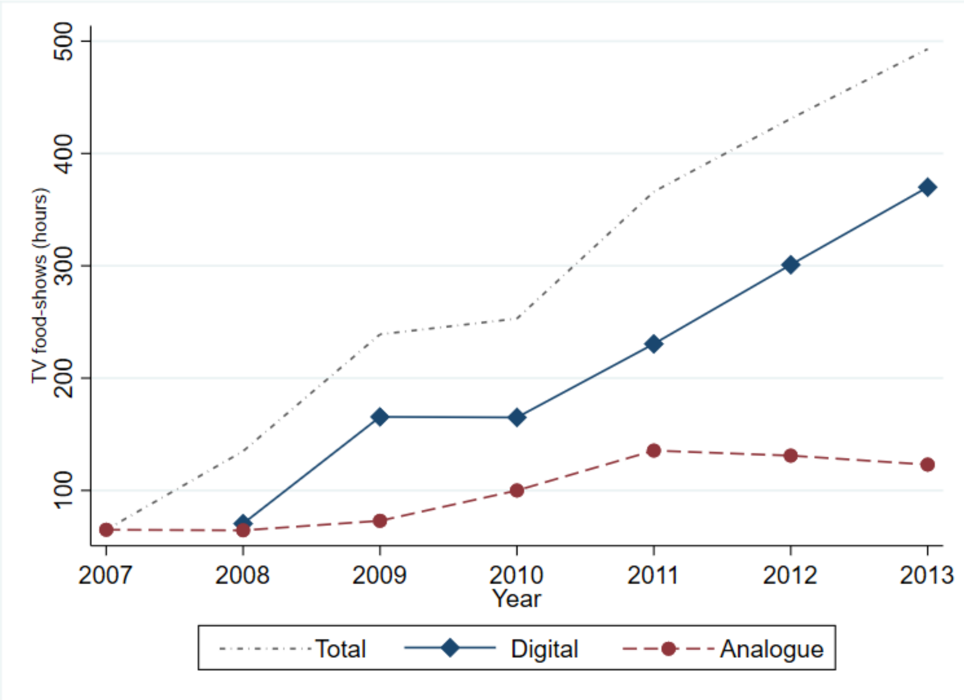
World Health Organization (2014). Global status report on noncommunicable diseases 2014 - "Attaining the nine global noncommunicable diseases targets; a shared responsibility". *WHO Library Cataloguing-in-Publication Data*.

# Figures

Figure 1: Timing of regional digital switchover

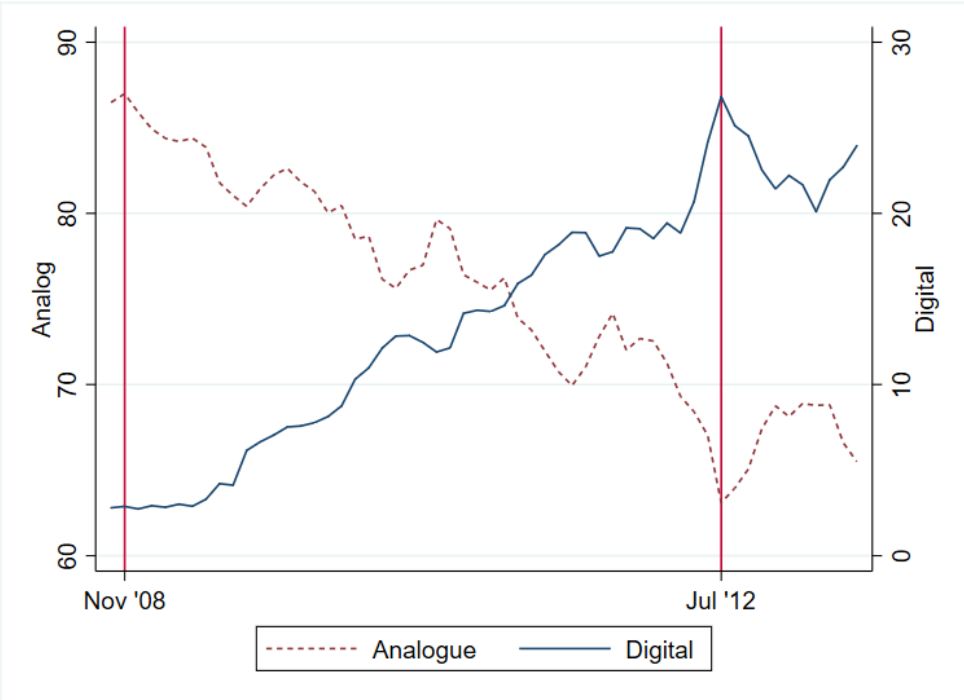

*Notes*: Timings of the regional digital switchover.

Figure 2: Hours of new cooking TV shows broadcasting



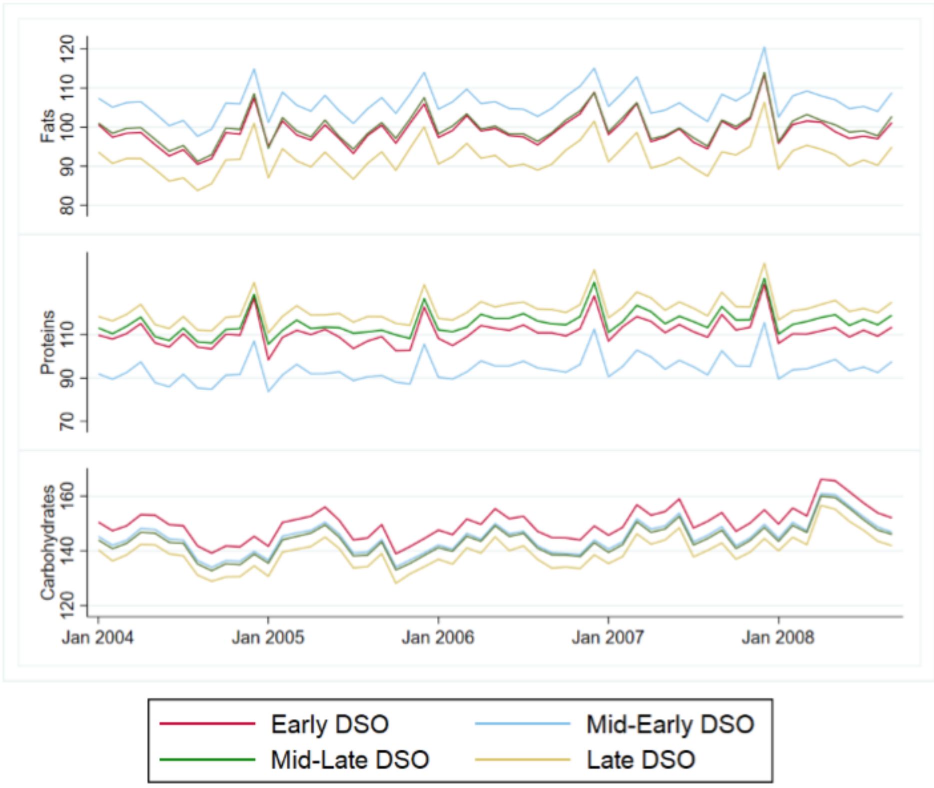

*Notes*: The figure displays the annual minutes of exposure to new food-related contents on the TV for digital and analogue channels, from 2007 to 2013.

Figure 3: Monthly viewing shares in analogue vs digital channels



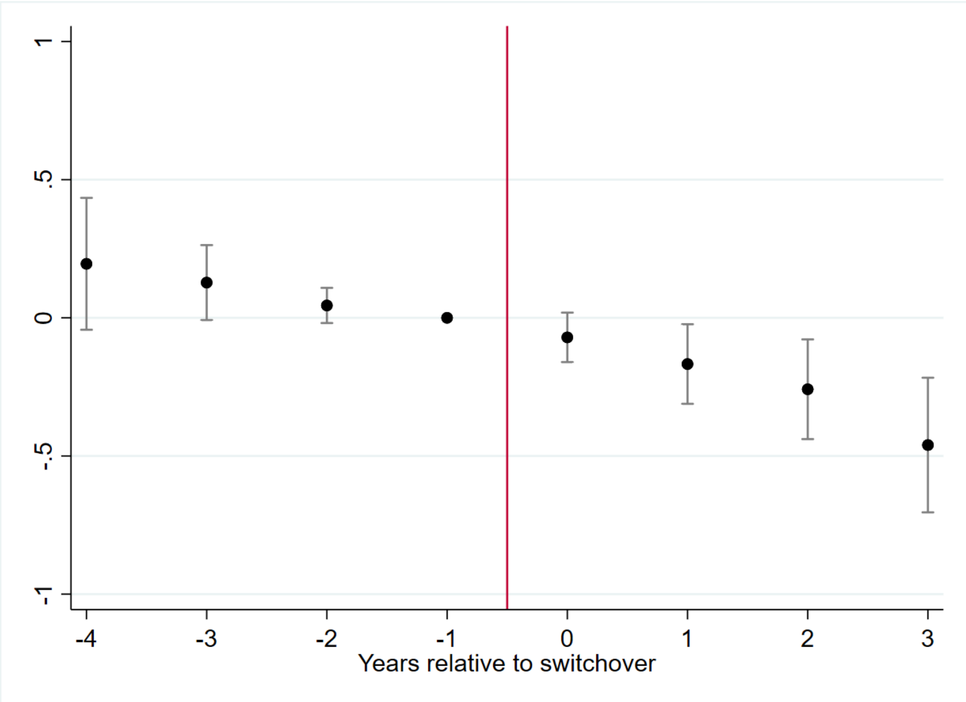

*Notes*: The figure reports monthly TV viewing shares for traditional analogue channels (Rai,Mediaset and La7) vs the new digital channels around the time of the digital switchover implementation, from 2008 to 2013.

Figure 4: Trends in expenditure on macronutrients



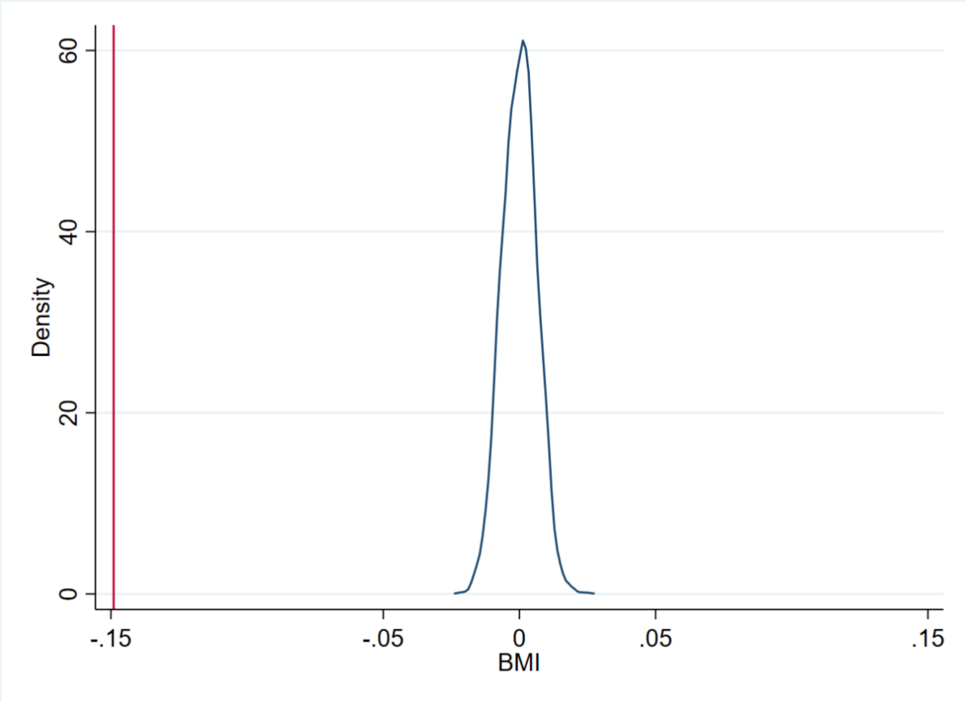

*Notes*: The figure reports trends of average monthly for expenditure on food high in Fats, Protein and Carbohydrates in Italian regions grouped according to the timing of digital switchover.

Figure 5: Event study




*Notes*: The graph plots the coefficients obtained from a regression of the BMI on a set of dummies each for 12 months before and after the digital switchover. Twelve-month pre-treatment is the excluded dummy for each dimension and is set equal to zero. The regression controls for age, gender, education, family size, family type and region and time fixed effects. The Y-axis shows the estimated coefficients and the X-axis shows the timings relative to the digital switchover. Standard errors are clustered at the level of the region. The confidence intervals are at 95%.

Figure 6: Randomization test for placebo switchover




*Notes*: Density distribution of the placebo estimates based on 5,000 permutations

# Tables

Table 1: Summary statistics

| *Variable* | *Description* | *Mean* | *Std. Dev.* |
|---|---|---|---|
| *Outcomes* | | | |
| Food | Monthly expenditure on food | 476.83 | 288.87 |
| Fats | Monthly expenditure on fats | 100.30 | 72.65 |
| Proteins | Monthly expenditure on proteins | 112.76 | 96.88 |
| Carbohydrates | Monthly expenditure on Carbohydrates | 145.74 | 89.42 |
| *Controls* | | | |
| Tot. exp. | Monthly total expenditure | 2492.02 | 1835.73 |
| Educ. | Education of the HH | 3.74 | 1.88 |
| H size | Households size | 2.51 | 1.24 |

*Notes*: The table shows the description, mean and standard deviation of the main variables from Household Budget Survey used in the empirical analysis

Table 2: DiD Estimates: effects of media exposure on macro-nutrients

| | (1) Fats | (2) Proteins | (3) Carbohydrates | (4) Food exp. | (5) Fats | (6) Proteins | (7) Carbohydrates | (8) Food exp. |
|---|---|---|---|---|---|---|---|---|
| DSO | -0.855* | 2.252*** | -1.344*** | 0.257 | -0.866* | 2.171*** | -1.160** | 1.716 |
| | (0.448) | (0.610) | (0.471) | (2.763) | (0.465) | (0.650) | (0.477) | (2.585) |
| Dep. Var. Mean | 103.4 | 115.9 | 149.3 | 490.7 | 103.4 | 115.9 | 149.3 | 490.7 |
| % of Mean | 0.8% | 1.9% | 0.9% | 0% | 0.8% | 1.8% | 0.7% | 0.03% |
| Controls | No | No | No | No | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 145885 | 145885 | 145885 | 145885 | 145885 | 145885 | 145885 | 145885 |

*Notes*: The table shows the estimates of $\beta$ from Equation (1). Control variables include: household size, education of the HH and food or total expenditure. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 3: DiD Estimates: effect of exposure to food TV shows on macronutrients

| | (1) Fats | (2) Proteins | (3) Carbohydrates | (4) Food expenditure |
|---|---|---|---|---|
| DSO x Exposure | -1.492** | 1.894** | -1.601** | 8.639** |
| | (0.665) | (0.936) | (0.669) | (3.753) |
| Dep. Var. Mean | 103.4 | 115.9 | 149.3 | 490.7 |
| % of Mean | -1.4% | 1.6% | -1.1% | 1.8% |
| Controls | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 145885 | 145885 | 145885 | 145885 |

*Notes*: The table shows the estimates of $\beta$ from Equation (2). Control variables include: household size, education of the HH and food or total expenditure. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 4: DiD Estimates: effect on Body Mass Index

| | (1) BMI | (2) BMI | (3) BMI | (4) BMI |
|---|---|---|---|---|
| DSO*Exposure | -0.150** | | | |
| | (0.055) | | | |
| DSO*Exposure *Male | | -0.157*** | | |
| | | (0.052) | | |
| DSO*Exposure *Female | | -0.143** | | |
| | | (0.059) | | |
| DSO*Exposure *Age 18-34 | | | -0.148** | |
| | | | (0.063) | |
| DSO*Exposure *Age 35-64 | | | -0.007 | |
| | | | (0.055) | |
| DSO*Exposure *Age 65+ | | | -0.371*** | |
| | | | (0.056) | |
| DSO*Exposure *Lower Educ. | | | | -0.167*** |
| | | | | (0.055) |
| DSO*Exposure *Higher Educ. | | | | -0.081 |
| | | | | (0.054) |
| Controls | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 206971 | 206971 | 206971 | 206971 |

*Notes*: The table shows the estimates of $\beta$ from Equation (2). Control variables include: age, gender, education, family size and family type. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 5: DiD Estimates: effect on physical activity

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Physical activity | Regularly | Occasionally | Private | Memberships |
| DSO | 0.004 | 0.008 | 0.008 | 0.005 |
| | (0.346) | (0.005) | (0.429) | (0.657) |
| Controls | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 206202 | 168638 | 55606 | 55353 |

*Notes*: The table shows the estimates of $\beta$ from Equation (1). Control variables include: age, gender, education, family size and family type. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 6: DiD Estimates: effect of media exposure on Google searches

| | Google | | | YouTube | |
|---|---|---|---|---|---|
| | How to cook "x" | Recipe "x" | Recipes TV | Recipe | Videorecipe |
| DSO | 16.660*** | 23.174*** | 6.679*** | 16.377*** | 6.227*** |
| | (1.397) | (1.915) | (2.282) | (3.125) | (1.606) |
| Region FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| N | 1680 | 1680 | 1680 | 1680 | 1680 |

*Notes*: The table shows the estimates of $\beta$ from Equation (1). Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 7: Robustness checks: augmented model specifications

| | (1) Fats | (2) Proteins | (3) Carbohydrates | (4) Food expenditure |
|---|---|---|---|---|
| Linear TT | -1.492** | 1.894** | -1.601** | 8.639** |
| | (0.693) | (0.912) | (0.677) | (3.772) |
| Quadratic TT | -1.590** | 2.012** | -1.594** | 9.633** |
| | (0.672) | (0.958) | (0.688) | (3.928) |
| Region-specific TT | -2.226*** | 2.556*** | -1.508** | 5.689 |
| | (0.638) | (0.953) | (0.696) | (3.814) |
| N | 145885 | 145885 | 145885 | 145885 |

*Notes*: The table shows the estimates of $\beta$ from Equation (2). The equation is augmented with the inclusion of linear, quadratic and region-specific time trends (row 1-3). Control variables include: household size, education of the HH and food or total expenditure. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Table 8: Robustness checks: placebo regressions

| | (1) BMI | (2) BMI | (3) BMI | (4) BMI |
|---|---|---|---|---|
| DSO Placebo (t+1) | 0.022 | 0.029 | | |
| | (0.043) | (0.041) | | |
| DSO Placebo (t-1) | | | -0.009 | -0.0002 |
| | | | (0.036) | (0.031) |
| Controls | No | Yes | No | Yes |
| Region FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| N | 206971 | 206971 | 206971 | 206971 |

*Notes*: The table shows the estimates from placebo regression where DSO is set one year after (columns 1-2) and before (columns 3-4) the actual DSO. Control variables include: age, gender, education, family size and family type. Clustered standard errors at the level of the region in parentheses. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

# Appendix

Figure A.1: Google Trends: Ramsay vs Beckham

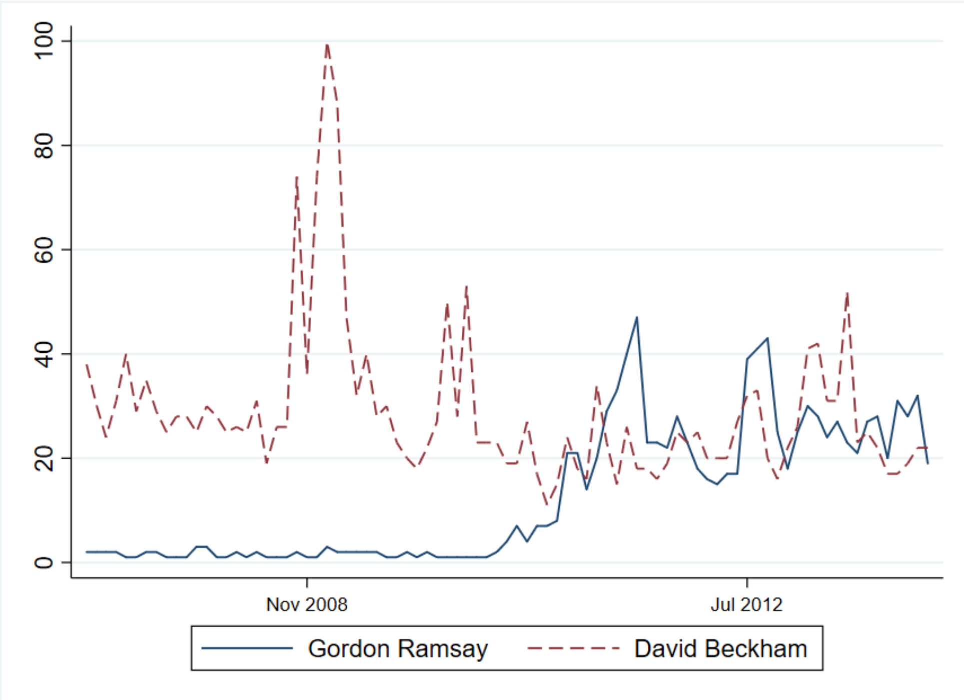


Figure A.2: Main ingredient of TV recipes

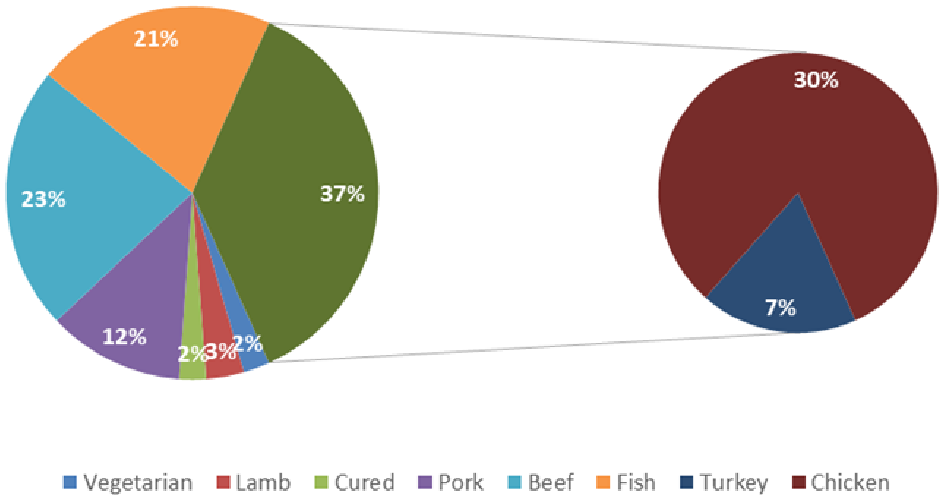


Figure A.3: Randomization test