Those Whose Calorie Consumption Varies Most Eat Most

Anya Skatova[1,2], Neil Stewart[2,3], Edward Flavahan[3,4], James Goulding[5]

[1]School of Psychological Science, University of Bristol, 12a Priory Road, Bristol, BS8 1TU, UK

[2]Alan Turing Institute, London, British Library, 96 Euston Rd, London NW1 2DB

[3]Warwick Business School, University of Warwick, Coventry, CV4 7AL, UK

[4]Behavioural Insights Team, 4 Matthew Parker St, Westminster, London SW1H 9NP, UK

[5]Nottingham University Business School, University of Nottingham, Jubilee Campus, Nottingham, NG8 1BB, UK

Corresponding author: Anya Skatova, School of Psychological Science, University of Bristol, 12a, Priory Road, Bristol BS8 1TU, UK, +44 (0) 117 331 6757, anya.skatova@gmail.com

The current version is updated on 18th of July 2019

Abstract

Unhealthy eating habits are associated with higher mortality rates and various negative health outcomes, including diabetes, heart disease, Alzheimer's disease and various types of cancer. We used 2,831,403 machine recorded 'meal deal' transactions from 205,781 individuals over the course of one year from one of the UK's largest suppliers of lunch time foods to investigate whether there is a relationship between patterns of choice and higher calorie consumption. Controlling for gender, general index of variety in the choice of lunch food items, income and education, we found that individuals who vary in their calorie consumption most across the time of day, day of the week, and month of the year are the individuals who consume the greatest number of calories overall. These time sensitivity effects are large, together explaining a substantial amount of variance in calorie consumption. Time sensitivity effects are strongly correlated across all three time scales suggesting they measure a stable underlying trait.

Keywords: Obesity, consumer behaviour, decision making, public health

Significance

Individuals vary calorific composition of their lunch over time of the day, day of the week and month of the year by 100 calories per meal between highest and lowest in sensitivity which is about 9% of the recommended by Public Health England amount of lunchtime calories. Those whose consumption varies the most with time consume the most calories, independently of income and gender. The variation in calories at all three time scales demonstrates the properties of an individual disposition. These findings can be used to understand why and when people make unhealthy food choices.

Introduction

Despite the level of attention that healthy and unhealthy eating received from academic research, policymakers and the wider public, objective data on food consumption is limited. This is because studies of individual eating patterns using food diaries are subject to underreporting (1), particularly by people who are overweight (2, 3). For example, the UK population is estimated to consume between 30% to 50% more calories than they report in surveys (5). New data sources such as office canteen ordering systems and individual records of supermarket transactions recorded through supermarket loyalty or bonus cards offer larger and potentially more robust data on real world individual eating behaviours (6-8). However, it can be difficult to say for certain *which individuals* in a household consume which foods, and *when* the foods are consumed. It is therefore useful to examine datasets of food purchases which are likely to be eaten by the purchaser within a short time of the purchase. Here we use bundles of lunchtime foods sold at a fixed price and targeted at lunchtime purchasers; namely 'meal deals'.

A meal deal comprises three items; a main (e.g., a sandwich or a salad), a snack (e.g., crisps, fruit or a chocolate bar) and a drink (e.g., a smoothie or a bottle of water). The meal deals usually have a fixed price and in case of our datasets it was £3.29 or ~$4.23 USD, (£3.79 in London and airports, or ~$4.87 USD). Our dataset comprised 2,831,403 machine recorded lunch time meal deal only transactions (43.18% out of all transactions containing meal deal where purchased items included additional items, food and often non-foods, that were not part of the meal deal) for 205,781 individuals over one year. The exact calorific content of each meal deal was available for the analyses. In contrast to diary studies or aggregate transactional data from supermarkets, our dataset had three distinct properties which made it suited to studying individual food choices and consumption. First, a lunch (meal deal) purchase is highly likely to be made by an individual for their own consumption soon afterwards. Second, we were able to link food choices to each individual across time through the retailer's loyalty (bonus) card scheme. Third, within the meal deal set price, one can choose items of varying calorific content, as well as items which are more or less healthy, meaning choices are not affected by cost or pricing. For example, for the same price within the three items in the meal deal (main lunch item, snack and drink) one can purchase a low-calorie salad, a bag of fruit and a bottle of water; alternatively, one can purchase more calorific and less healthy options such as a triple bacon, lettuce and tomato (BLT) sandwich, crisps and a sugary fizzy drink. This can allow us to study the patterns of healthy and unhealthy food choices in a real world context.

The choices of unhealthy food are often linked to obesogenic environment (the abundance of easily available, cheap, calorie dense food). The increase in the availability of calorie dense, cheap food, is one of the major factors in raising levels of obesity (9). Whilst the obesogenic environment is linked to obesity, it is not clear exactly what in this environment prompts some people to make food choices that lead to unhealthy weight gain.

Socioeconomic status may explain why some individuals are more affected than others by the obesogenic environment. People of lower socioeconomic status have, on average, poorer diets, consume less fruit and vegetables, and purchase more unhealthy food, such as ready meals (10-12). These effects have been linked to lower education levels (12, 13) and lack of knowledge about adverse health consequences of calorie dense food. In addition, healthier foods are often more expensive, and people of lower socioeconomic status cannot afford to buy enough healthy food to feed their families (14). For policy making, it is important to understand the relationship and effects between education and income levels and unhealthy diets. If education is a factor driving choices, then we might reasonably hope that educational interventions could help improve the diets of people from lower socioeconomic groups. However, if income is a more important factor then it may be possible to improve people's diets with financial support or financial incentives for healthy food choices. In our main analysis we controlled for the price of the meal deal by selecting a sample of the most frequently priced meals only, costing £3.29, which allowed us to rule out the cost of the lunch as a factor influencing the healthiness of lunchtime food choices. We further studied the effects of education and income level on lunch food choices on a smaller sample, as well as controlled for the price of the meal deal basket when additional food items that could have bought as extra snacks were included.

Those with poor self-control have also been found to be more affected by the obesogenic environment (15-17). Self-control is a behavioural mechanism which can express itself both dispositionally and situationally. An individual with a lower self- control disposition will be more likely to act impulsively in any environment, but specifically in an environment which promotes unhealthy choices: low individual self-control has been linked to higher Body Mass Index and poorer dietary choices (18-20). Individuals can also find themselves in a situation when their ability to control impulses is diminished (e.g., being tired at the end of the day). This could be another route through which self-control problems lead to poorer dietary choices.

Situational self-control can play role in explaining the "fresh start" effect that can cause variation in calories consumer over certain time periods: more situational self-control is needed to stick to normal calorie consumption when we feel very hungry, tired or run down (e.g., before holidays such as Christmas, towards the end of the work day or before weekends). People buy higher calorie, unhealthier foods when they are hungry (21, 22).

Ordering lunch further in advance of consumption, when you are less likely to be hungry, leads to healthier choices (7) and induced cognitive load leads to less healthy choices (23). In this situational self-control account, these occasional lapses in self-control can explain the "fresh start" effect and its flipside, higher consumption when under stress or tired at the end of the day, or year.

Further, previous research has linked variations in the time of food purchases with the calorific value of the food basket: the more people's purchasing habits vary over time, the less healthy food they buy (5). The most relevant study on food purchase patterns to date (5) used information on entire shopping baskets of single-person UK households and the UK Living Cost and Food Survey to show consistent within-person variations of food consumption and purchasing over the months of the year, with low in unhealthy/high in healthy food consumption in a "fresh-start" January, increased intake of unhealthy food towards Easter time, decreased intake of unhealthy food in the summer months and an increased intake of unhealthy food in the approach to Christmas (see also 24, 25). The "fresh-start" effect may not only be relevant to the new year, but also to other time scales, like the start of a new week or even just a new day. Consider a situation when you worked beyond your normal lunch hours, became very hungry, rushed to the shop and ended up buying crisps and chocolate as snacks instead of fruit. Similarly, it is easy to imagine needing a "pick me up" at the end of the week, for example in the form of an extra snack, when you are tired.

Time variation in month-of-year consumption has been also associated with dispositional self-control (5), suggesting that higher variation in calorific consumption over other time scales, namely day-of-week and time-of-day, could also be reflective of the lower dispositional self-control, which in turn would make those individuals more susceptible to the obesogenic environment.

Finally, a combination of socio-economic status, self-control and sensitivity to variation over time could interact, contributing to unhealthier food choices and higher susceptibility to the obesogenic environment. Cherchye et al (5) showed that people from lower income bands and who self-reported lower self-control show a stronger seasonal variation effect in healthiness of their shopping baskets after controlling for variation in prices, advertising and the weather.

The work presented in this paper examines why some people are more likely to buy unhealthy food in the obesogenic environment. We study the effect of the time the purchase was made on the calories in the lunch basket, and whether higher calorific consumption is associated with factors such as socio-economic status and trait like patterns in behaviour previously related to self-control. Unlike previous research where food shopping purchases might not have been indicative of what a person ate in a particular week (e.g., 5), our datasets enabled us to study not just purchasing, but individual consumption behaviour with month by month, day by day and hour by hour precision because the meal deal purchases in our dataset were time stamped and were likely to be bought for individual lunch consumption shortly after.

Using these meal deal transactions, we derived three time-sensitivity parameters for each individual, reflecting individual variation in calorie intake over the time-of-day, day-of-week and month-of-year. If the 'fresh start' effect is related to seasonal changes (i.e., month-of-year) in ability to control impulse (e.g., when one is tired), situational changes related to time-of-day and day-of-week might also explain the variability in people's choices over shorter timescales, as they tire towards the end of the week or are too busy to get lunch on time, making them consume more calories. This will suggest that those most influenced by changes due to different timescales are also those who eat the most calories. If the three time variation effects correlate across time scales, then susceptibility to situational effects introduced by the time-of-day, day-of-week and month-of-year could represent data driven measure of an individual propensity or a dispositional trait related to self-control. The variation in calorie consumption over the three time parameters could be explained by all or some individuals making choices to buy calorie dense food in certain time of the day, day of the week and month of the year which may or may not be due to variation in the amount offered with a discount in particular time of the day (e.g., post regular lunch hours), day of the week (e.g., in the end of the week or on the day before the shop restocks), or month of the year (e.g., Christmas offers in December). Because of that, in the additional analyses we tested whether the three time effects can be explained by discounts and food on offers by controlling for the price of the average meal deal basket which included a meal deal plus up to two extra items. Moreover, based on Cherchye et al (5) we expected that those who have lower socio-economic status will buy lunches higher in calories, and in an additional sample, for whom we had education and income, we studied whether time sensitivity effects predict calories in lunches over income and education, in addition to gender.

Results

We studied the relationships between time sensitivity parameters (i.e., sensitivity to time-of-day, day-of-week and month-of-year) and calorific intake in a sample of 2,831,403 meal deals of 205,781 individuals (Sample 1) drawn from the loyalty card holders of a large UK retailer. See Methods for the details about Sample 1. On average, the individuals consumed 675.86 calories per person per meal with standard deviation of 153.35 calories (Female: M = 640.14; SD = 140.41; Male: M= 757.37, SD = 154.34), see Figure 1 for the density distribution of calorie intake broken by gender. Lunch food calories bought by females were slightly higher than the 600 calories recommended per lunch both for men and women (26), whilst males typically bought food that was much higher than the recommended 600 calories for lunch.

For each individual, in addition to their average calorie consumption per meal, we calculated four different parameters. First, we calculated three time sensitivity parameters measuring the extent to which calorie consumption varies by time-of-day, day-of-the-week and month-of-the-year (see details below).

Second, to control for the variability of purchased items we used normalised purchase entropy (also called efficiency; see, e.g., 27). Normalised purchase entropy captures the variety in individual food choices controlling for the frequency of purchasing: people with more variable food choices will have a higher normalised entropy parameter. Entropy was calculated over the item names in each participant’s purchase history and normalised against the number of different item names, and subsequently standardised. Mean unstandardised normalised entropy was 1.21 bits (SD = 0.11 bits).

How does the calorie consumption vary over time? The time-of-day, day-of-week and month-of-year sensitivity effects for the whole sample are demonstrated on Figure 2 with a dashed horizontal line indicating mean average consumption per person.

Time-of-Day Sensitivity. Figure 2A represents the average calories purchased in the four half hour bins before and after an individual's average lunch purchase time. For example, if an individual's mean purchase time is 12:00, their calorie intake would be broken down into four time bins of the purchase: before 10:31; 10:31–11:00; 11:01–11:30; 11:31–12:00; and four time bins after the purchase: 12:01–12:30; 12:31–13:00; 13:01–13:30; after 13:30. Fewest calories were purchased for the earliest lunches and lunches at the usual time, with more calories purchased for slightly early and later lunches. An individual's time-of-day sensitivity parameter was calculated as the standard deviation of their mean number of calories purchased across the eight time-of-day bins. The unstandardised mean of the time-of-day sensitivity parameter was 79.50 calories (SD = 52.06).

The average range over the time-of-day bins was 20.73 calories. This is on average a 4% of the 600 calorie Public Health England recommendation and variation of this size could be associated with weight problems. For example, previous evidence suggests that a 5% reduction in calorie intake could prevent obesity in most of the population of the USA (28).

Day-of-Week Sensitivity. An individual's day-of-week sensitivity parameter was calculated as the standard deviation of their mean lunch calorie consumption across the five days of the working week. For the day-of-week, the pattern of meal deal purchases shows that more calories were purchased on later week days (Figure 2B). There is a 4.18 calorie range over the days of the week averages, which is equivalent to 1% of the Public Health England recommended calories for lunch. The unstandardized mean day-of-week parameter was 66.34 calories (SD = 47.70).

Month-of-Year Sensitivity. For the month-of-year, the pattern was similar to previous studies (see 5); a "fresh start" in January and increase over February to April, then a decrease between May and July, with a steady increase from August towards December (Figure 2C). There is a 35.42 average calorie range between different months of the year which is equivalent to 6% of the recommended by Public Health England lunch calories. An individual's month-of-year sensitivity parameter is the standard deviation of their mean lunch calorie consumption across the twelve months. Unstandardized mean month-of-year parameter was 96.32 calories (SD = 51.11).

Sensitivity over time is correlated over timescales. Table S1 shows the correlation between the three time sensitivities (see also Table S1 for the correlations with normalised entropy, and the correlations with the average number of calories purchased). The correlations between the three time sensitivities were all large (ranging from r = .55 to r = .62). The correlations between the three time sensitivities and normalised entropy were small to medium (ranging from r = .29 to r = .41). Normalised entropy had a small negative correlation (r = - .13) with average calories. All correlation coefficients were significant at .001 level.

Sensitivity over time predicts calories purchased per lunch. We further investigated the effect of time sensitivity on average calories purchased per lunch while controlling for gender and normalised entropy. Table 1 presents the results of seven Ordinary Least Squares (OLS) regression models with average calories as an outcome variable: Model 1 serves as a baseline model and includes gender only. Gender significantly predicted average calories purchased per lunch, with men purchasing 117 calories more than women, an estimate that is consistent across the subsequent models.

Model 2 adds normalised entropy, the propensity to buy a variety of items. A one standard deviation increase in normalised entropy is associated with an 8.6 calorie consumption reduction, and again the estimate is consistent over subsequent models. Models 3 to 5 demonstrate effects of each of the time effect separately with Model 6 showing combined contribution. Together the three time sensitivity measures explained considerable amount of variance – a 1/3 of that which is explained by gender – indicating that time sensitivity is having a large effect on calorie purchasing behaviour. A one standard deviation increase in time sensitivity, at any of the time scales, is associated with about a 25 calorie increase in average calories. Those who vary more in their calorie consumption over the time-of-day, day-of-week and month-of-year consume more calories overall. This means that the very highest in time sensitivity – top 2.5% - are consuming about 100 calories more at lunch time than those lowest in time sensitivity, bottom 2.5%. 100 calories are a 1/6th of the recommended lunch intake, and approximately equal to the 5% reduction needed to prevent most obesity in Americans.

Table 1. Beta coefficients and 95% Confidence Intervals from time sensitivity effects predicting calorie intake controlling for gender and normalized entropy scores, Sample 1 restricted to £3.29 only meal deal baskets. Coefficients in bold are significant at least at .05 level. Time-of-day, day-of-week and month-of-year effects were standardized prior to entering in regression. When including only baskets with 3 item meal deals for a fixed price of £3.29 we retained 2,831,403 meal deal transactions (43.18%) of 205,781 individuals. Gender is coded -0.5 Male, 0.5 Female.

	Average lunchtime calorie consumption					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**640.1 [639.4; 640.9]**	**644.4 [643.6; 645.2]**	**647.3 [646.5; 648.1]**	**647.5 [646.7; 648.3]**	**647.4 [646.6; 648.2]**	**648.5 [647.6; 649.3]**
Male	**117.2 [115.7; 118.7]**	**113.4 [111.9; 114.9]**	**112.5 [111.0; 114.0]**	**113.2. [111.7; 114.8]**	**112.3 [110.8; 113.8]**	**112.7 [111.2; 114.2]**
Normalised entropy		**-8.6 [-9.3; -7.8]**	**-15.1 [-15.9; -14.4]**	**-16.7 [-17.5; -15.9]**	**-15.9 [-16.7; -15.1]**	**-18.6 [-19.4; -17.8]**
Time-of-day			**24.0 [23.3; 24.6]**			**9.6 [8.7; 10.5]**
Day-of-week				**24.4**		**10.7**

				[23.7; 25.0]		**[9.8; 11.6]**
Month-of-year					**25.6 [24.9; 26.2]**	**13.2 [12.3; 14.2]**
Adjusted R^2	0.105	0.107	0.132	0.132	0.135	0.144
N	205,781	205,781	200,660	201,003	202,123	194,012

We further replicated these effects using a different sample (see Sample 1 Extended or Sample 1E, Table S2, SI Appendix), which encompassed meal deal baskets with up to five items, thus allowing for two extra "snacks" and costing up to £10. The effects for Sample 1E are unsurprisingly larger (see discussion in SI Appendix), but the main findings remained unchanged in all regression models, including when the price variation for the meal deals that included two extra items was added into regression, suggesting that offers and discounts could not explain relationships between variation in calories purchased for lunch over the three time periods and overall calories consumed measured here.

Time-of-day sensitivity predicts calorie purchased per lunch independently of socio-economic status. The time effects were replicated on a different sample of individuals (Sample 2, see Methods for details) for whom we had self-reported level of education and income. Income predicted higher calorie intake, with those in lower income bracket consuming more calories than those in higher brackets over gender, entropy and time effects (See Figure 3). Education had no effect on calorie intake for lunch.

We replicated that all three time effects were associated with higher calorie intake, controlling for gender and normalised entropy (see Models 2-4, Table S3), while when all three time sensitivity effects were entered in the model, only time-of-day remained significant (see Model 5, Table S3). When income and education were entered in the regression, time-of-day remained a significant predictor of calories purchased for lunch.

Discussion

We used detailed longitudinal data to look into patterns of lunchtime food consumption. We replicated the distinct pattern of variation in calorific composition over months in the year (e.g., 5). In addition, we showed for the first time that there is a distinct variation in calorific composition over the days of the week and over the time of day. Variation in calories over these three time scales were correlated at the individual level suggesting that there might be an underlying trait explaining variation in time. Further, we show that those who vary in their calorie intake most across these different time scales consume more calories overall.

This effect is robust to controls for gender, purchase variability, amount spent, education, and income. We find that the relationship of variation over time and higher calorie intake was not driven by lower prices, or in other words discounts at specific times of day, days of the week and months of the year. We observe in our sample that something made people more likely to buy higher calorie foods, or calorie dense food in the end of the day, week or towards the end of the year, perhaps due to weakening self-control mechanisms, which drives up calorie consumption. We also find, in a smaller sample for whom we have self-reported income and education, that lower income, but *not* lower education, was associated with higher calorie consumption, and that time-of-day variation was associated with higher calories in meal deals regardless of income.

We show that a combination of situational (e.g., tiredness at the end of the week) and dispositional (i.e., trait-like features of time sensitivity effects) factors on lunch food consumption are observable in our data. While other external factors can explain the relationship between time of purchasing and calories consumed, past research has controlled for some possible explanations. For example, Cherchye et al (5) demonstrated that the month of the year effect did not change if advertising of specific products was taken into account. Further, our results remain the same controlling for the price of the meal deals, ruling out the effects of offers and discounts. Whatever it is that is varying over time in the environment, it is causing those most sensitive to time effects to purchase, and presumably consume, a lot more - with a difference about 100 calories between the most and least sensitive.

Uncovering the reasons why people can change their calorie intake even by 100 calories per lunch on average has powerful implications for public health. Hill et al (28) used data from a large-scale USA nationally representative survey to demonstrate that changing *daily* calorie balance by only 100 calories could prevent weight gain in most of USA population, with similar figures likely to apply to other countries, such as the UK. Given that lunch is supposed to constitute around 30% of daily calorie intake, uncovering and preventing reasons that cause individuals to consumer an extra 100 calories can have three times higher effect that predicted by Hill et al (28) in preventing weight gain in the most of population. Our evidence suggests that lower education is not associated with higher calorie consumption over income. This confirms that people who have less money buy relatively more unhealthy food for lunch, suggesting that educational policy interventions would not be as effective as financial interventions, such as subsidised healthy lunch meals. One caveat is that our datasets do not allow us to observe the behaviour of those who are substituting their regular meal deal purchases at this particular retailer with cheaper (and perhaps in some cases healthier) food during times when their income is constrained which would also explain the effect. Future research using panel data with shopping receipts (e.g., Kantar Worldpanel, similar to 5) can investigate whether individuals switch away from their regular lunch food purchases on specific times of day, day of the week and month of the year, and whether these choices are affected by socioeconomic status or whether the switch is in favour of healthier, regular or unhealthier options.

Our study, for the first time shows patterns in lunch food choices are dependent on the time of day and day of the week, and replicates previous findings regarding month of the year. It lays the foundation for future studies to look into whether time sensitivity effects are also associated with known factors such as personality traits or genetic dispositions, whether the effects replicate on different types of datasets, such as diary studies or other types of digitally collected food consumption data, and whether the effects are applicable to food purchases at different times. Further, interventions that encourage healthy eating in the times of day, days of the week and months of the year where the increases in calorie intake are detected, could help stabilise differences between consumption in different time bins, helping to decrease overall calorie intake in lunch food and beyond.

Materials and Methods

Datasets

We used data from major UK Health and Beauty Retailer, the UK's largest chain of pharmacies, selling medicines, health and beauty products and food and drink, including lunchtime meal deals. The “meal deal” includes a main food item (e.g., a sandwich or a salad), a snack (e.g., fruit, crisps, chocolate bars) and a drink for a fixed price of £3.29 (£3.79 in London and airports). In order to keep the price fixed, for our main analyses we used the most frequent meal deal price of £3.29. In the main analyses, we used two different datasets comprising meal deal transactions from this retailer customers recorded through retailer’s loyalty card.

Sample 1 included individuals with a retailer’s loyalty card who had purchased a meal deal during the weekdays at least 15 times in one calendar year, 2012. A meal deal basket was defined as a purchase containing of no more than 2,000 calories, with 3 items and priced £3.29 exactly. This ensured that the dataset reflects items bought for individual consumption. When we could not obtain calorie data for a particular item, we replaced the item calorie information with a median from a meal deal category: e.g., sandwich, sweet snack. This affected less than 5% of meals. The final sample comprised 2,831,403 meal deal baskets for 278,057 individuals. The sample included 77.15% females.

Sample 2 included individuals from the same retailer’s Consumer Panel who were approached with a request to complete a psychometric survey. At the same time, they filled in an informed consent, where they were offered to consent for the research team to link their loyalty cards data to the survey data. The study design was approved by University of Nottingham Computer Science Ethics Committee. Only those consented for data linkage and who completed our psychometric survey and purchased a £3.29 meal deal during the weekdays at least 15 times over four years, from May 2012 to May 2016 were included in Sample 2. A meal deal was defined the same as for Sample 1. Missing calorie information was replaced with medians as for Sample 1. This affected less than 7% of meals. One (0.02%) individual did not disclose their gender and was excluded. The sample included 90.01% females. The final sample comprised 15,870 meal deals for 1,410 individuals.

Acknowledgements
Anya Skatova was supported by ESRC ES/K002201/1, EPSRC EP/N02334X/1 and a VC Fellowship, University of Bristol. Neil Stewart was supported by ESRC grants ES/N018192/1, ES/K002201/1, and ES/P008976/1 and Leverhulme Trust grant RP2012-V-022.

References
1. Y. Park, K.W. Dodd, V. Kipnis, F.E. Thompson, N. Potischman, D.A. Schoeller, D.J. Baer, D. Midthune, R.P. Troiano, H. Bowles, A.F. Subar, Comparison of self-reported dietary intakes from the Automated Self-Administered 24-h recall, 4-d food records, and food-frequency questionnaires against recovery biomarkers. *Am J Clin Nutr* **107** (1): 80–93. (2018)

2. J.T. Winkler, The fundamental flaw in obesity research. *Obes Rev* 6(3):199–202. (2005)

3. L.G. Bandini, D.A. Schoeller, H.N. Cyr, W.H. Dietz, Validity of reported energy intake in obese and nonobese adolescents. *Am J Clin Nutr* **52** (3): 421–425. (1990)

4. H. Harper, M. Hallsworth, Counting Calories. How under-reporting can explain the apparent fall in calorie intake. The Behavioural Insights Team. (2016)

5. L. Cherchye, B. de Rock, R. Griffith, M. O'Connell, K. Smith, F. Vermeulen, A New Year, a New You? Heterogeneity and Self-Control in Food Purchases. Available at: https://papers.ssrn.com/abstract=3089715 [Accessed July 18, 2019]. (2017)

6. K.L. Milkman, T. Rogers, M.H. Bazerman, I'll have the ice cream soon and the vegetables later: A study of online grocery purchases and order lead time. *Marketing Letters* **21** (1): 17–35. (2010)

7. E.M. van Epps, C.A. Roberto, S. Park, C.D. Economos, S.N. Bleich, Restaurant Menu Labeling Policy: Review of Evidence and Controversies. *Curr Obes Rep* **5** (1): 72–80. (2016)

8. N. Darmon, A. Drewnowski, Contribution of food prices and diet cost to socioeconomic disparities in diet quality and health: a systematic review and analysis. *Nutr Rev* **73** (10): 643–660. (2015)

9. K.F. Hulshof, M.R. Löwik, F.J. Kok, M. Wedel, H.A. Brants, R.J. Hermus, Diet and other life-style factors in high and low socio-economic groups (Dutch Nutrition Surveillance System). *Eur J Clin Nutr* **45** (9): 441–450. (1991)

10. K.F. A.M. Hulshof, J.H. Brussaard, A.G. Kruizinga, J. Telman, M.R.H. Löwik, Socio-economic status, dietary intake and 10 y trends: the Dutch National Food Consumption Survey. *European Journal of Clinical Nutrition* **57** (1): 128–137. (2003)

11. A. Drewnowski, Obesity, diets, and social inequalities. *Nutr Rev* **67** Suppl 1: S 36–9. (2009)

12. B. Galobardes, A. Morabia, M.S. Bernstein, Diet and socioeconomic position: does the use of different indicators matter? *Int J Epidemiol* **30** (2): 334–340. (2001)

13. V.L. Cribb, L.R. Jones, I.S. Rogers, A.R. Ness, P.M. Emmett, Is maternal education level associated with diet in 10-year-old children? *Public Health Nutr* **14** (11): 2037–2048. (2011)

14. N. Darmon, A. Briend, A. Drewnowski, Energy-dense diets are associated with lower diet costs: a community study of French adults. *Public Health Nutr* **7** (1): 21–27. (2004)

15. F.M. Stok, E. de Vet, J. Wardle, M.T. Chu, J. de Wit, D.T. de Ridder, Navigating the obesogenic environment: How psychological sensitivity to the food environment and self-regulatory competence are associated with adolescent unhealthy snacking. *Eating Behaviors* **17**: 19–22. (2015)

16. E. Tsukayama, S.L. Toomey, M.S. Faith, A.L. Duckworth, Self-control as a protective factor against overweight status in the transition from childhood to adolescence. *Arch Pediatr Adolesc Med* **164** (7): 631–635. (2010)

17. W. Hofmann, M. Adriaanse, K.D. Vohs, R.F. Baumeister, Dieting and the self-control of eating in everyday environments: an experience sampling study. *Br J Health Psychol* **19** (3): 523–539. (2014)

18. S. Schiff, P. Amodio, G. Testa, M. Nardi, S. Montagnese, L. Caregaro, G. di Pellegrino, M. Sellitto. Impulsivity toward food reward is related to BMI: Evidence from intertemporal choice in obese and normal-weight individuals. *Brain Cogn* **110**: 112–119. (2016)

19. M. Weygandt, K. Mai, E. Dommes, K. Ritter, V. Leupelt, J. Spranger, J.D. Haynes, Impulse control in the dorsolateral prefrontal cortex counteracts post-diet weight regain in obesity. *Neuroimage* **109**: 318–327. (2015)

20. J. Lumley, R.J. Stevenson, M.J. Oaten, M. Mahmut, M.R. Yeomans, Individual differences in impulsivity and their relationship to a Western-style diet. *Pers Individ Dif* **97**: 178–185. (2016)

21. D.T. Gilbert, M.J. Gill, T.D. Wilson, The Future Is Now: Temporal Correction in Affective Forecasting. *Organ Behav Hum Decis Process* **88** (1): 430–444. (2002)

22. A. Tal, B. Wansink, Fattening fasting: hungry grocery shoppers buy more calories, not more food. *JAMA Intern Med* **173** (12): 1146–1148. (2013)

23. F.J. Zimmerman, S.V. Shimoga, The effects of food advertising and cognitive load on food choices. *BMC Public Health* **14**: 342. (2014)

24. H. Dai, K.L. Milkman, J. Riis, The Fresh Start Effect: Temporal Landmarks Motivate Aspirational Behavior. *Manage Sci* **60** (10): 2563–2582. (2014)

25. H. Dai, K.L. Milkman, J. Riis, Put Your Imperfections Behind You: Temporal Landmarks Spur Goal Initiation When They Signal New Beginnings. *Psychol Sci* **26** (12): 1927–1936. (2015)

26. Public Health England. Healthier and more sustainable nutrition principles. Nutrition Advice Team, *Public Health England.* Retrieved from: :https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/648744/healthier_and_more_sustainable_nutrition_principles.pdf. (2017)

27. D.V. Budescu, M. Budescu. How to measure diversity when you must. *Psychol Methods* **17** (2): 215. (2012)

28. J.O. Hill, H.R. Wyatt, G.W. Reed, J.C. Peters, Obesity and the environment: where do we go from here? *Science* **299** (5608): 853–855. (2003)

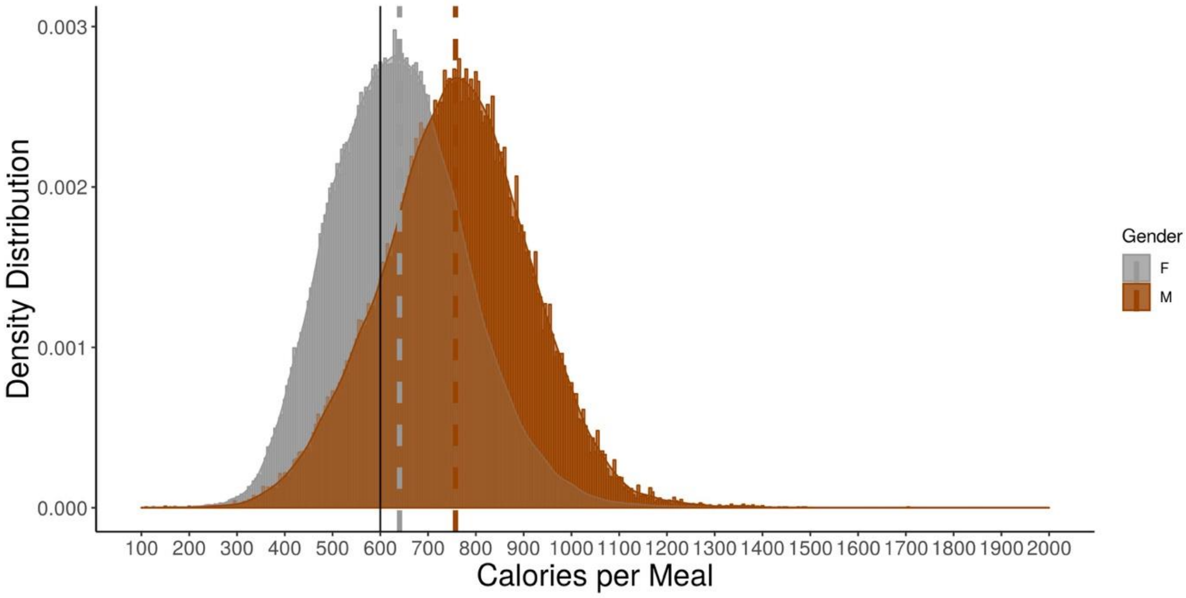

Fig 1. The distribution of calories per meal per person for males and females, Sample 1. Dashed lines represent means for each group and solid line represents the Public Health England 600 calorie recommendation for lunch for men and women.

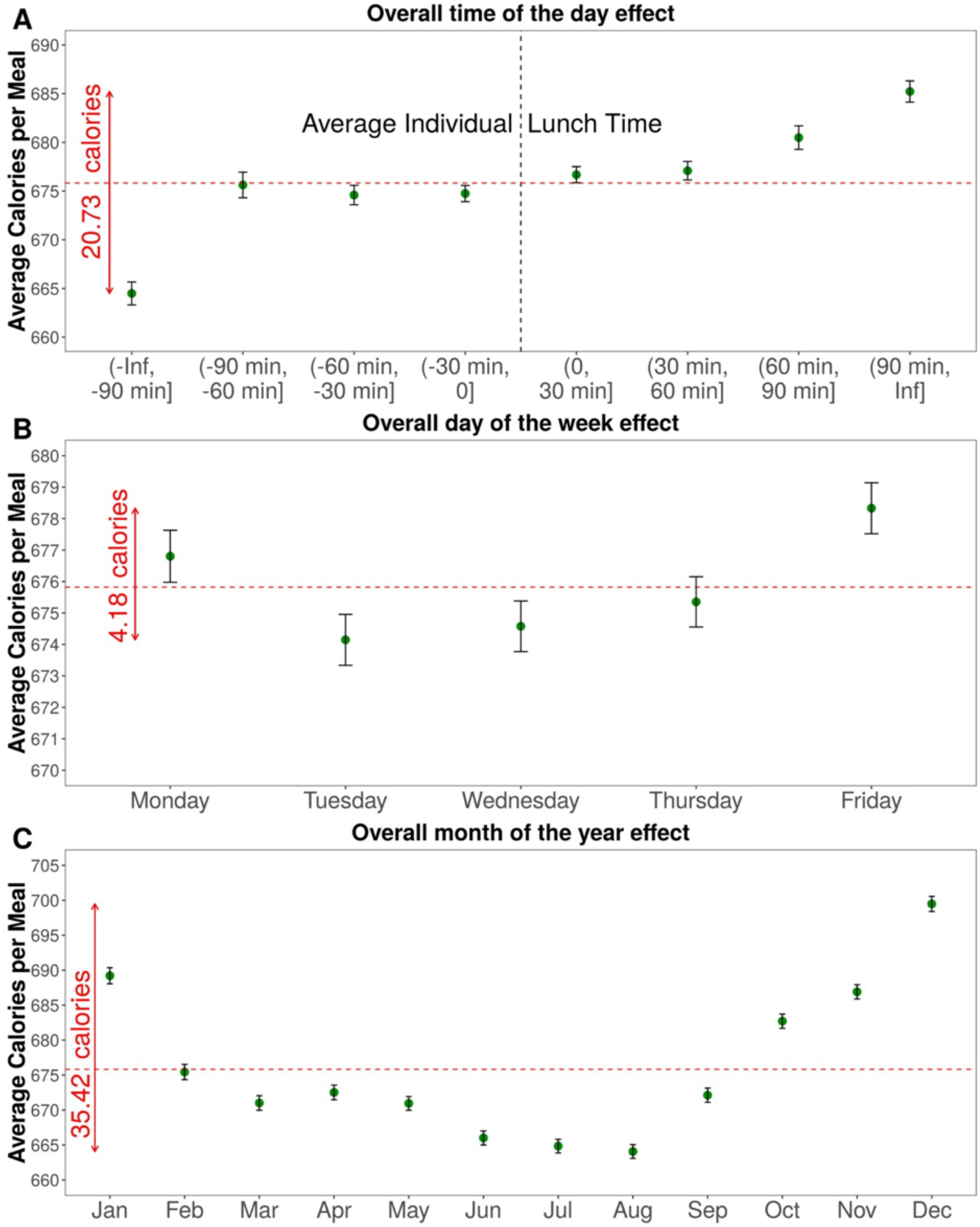

Fig 2. Mean calories over (A) the time-of-day, (B) the day-of-week, (C) the month-of-year, Sample 1. Error bars represent 95% CIs. Horizonal dashed lines indicate the overall mean. Solid arrows demonstrate the difference between maximum and minimum average calories over the time bins. Vertical dashed line for Panel A indicates mean time an individual buys lunch.

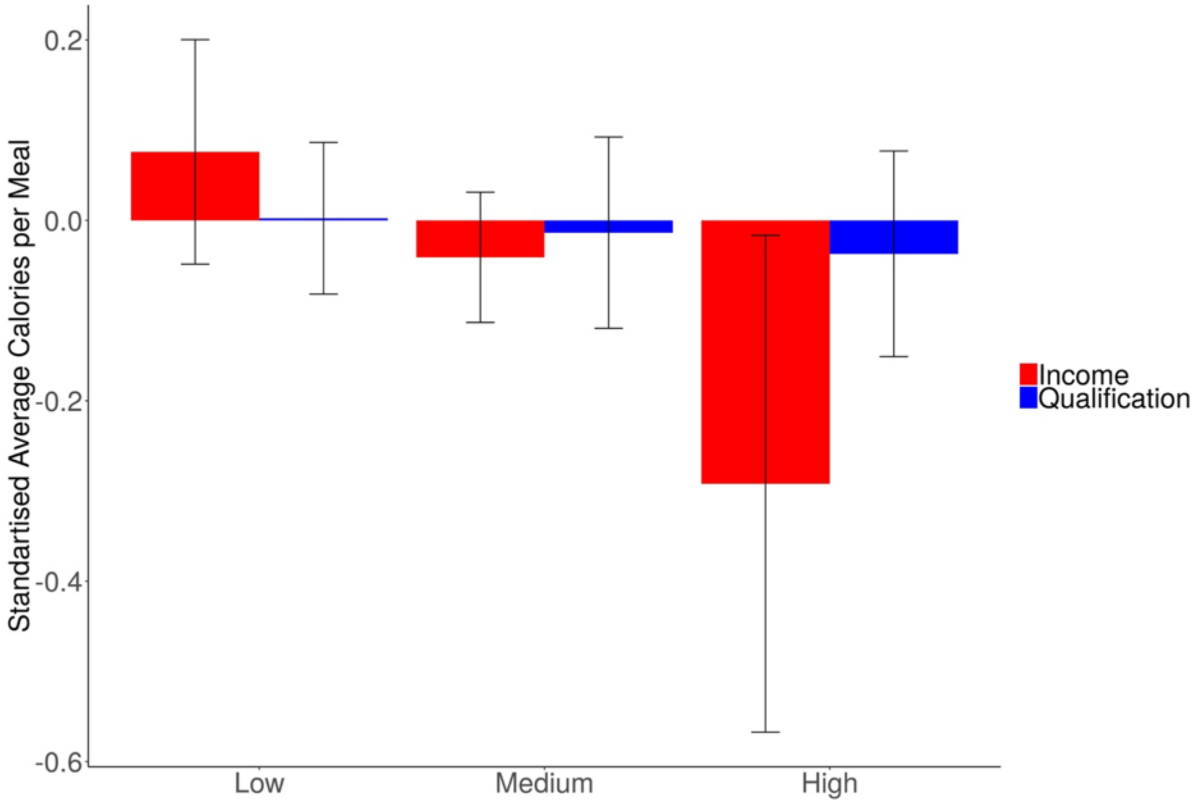

Fig 3. Average calories per meal plotted against sample mean by income (Low = under £25,000, Medium = between £25,000 and £100,000, High = over £100,000 per household per year) and qualification level (Low = School+, Medium = Degree, High = Degree+), Sample 2. Error bars represent 95% confidence intervals.

Supplementary Information Appendix

Sample 1

Table S1. Pearson correlations between normalised entropy, average meal deal basket price, time sensitivity effects, average calories, along with corresponding 95% Confidence Intervals, Sample 1. All coefficients are significant at .001 level.

	Average calories	Normalised entropy	Time-of-day	Day-of-week
Normalised entropy	-0.13 [-0.14; -0.13]			
Time-of-day	.11 [.11; .11]	.29 [.29; .29]		
Day-of-week	.08 [.08; .08]	.41 [.41; .41]	.55 [.55; .55]	
Month-of-year	.12 [.12; .19]	.32 [.32; .32]	.62 [.62; .62]	.61 [.61; .61]

Sample 1E: replication of the time sensitivity effects on calories controlling by price of the meal deal. For additional analyses we relaxed our sampling criteria and selected individuals with a loyalty card who had purchased a meal deal and up to two more items during the weekdays at least 15 times in 2012. This allowed to include extra snacks or/and drinks individuals could have bought with their meal deal. We included meal deals that cost more or less than £3.29, specifically more than £0 and less than £10 to allow price variation to be able to assess whether offers and discount had effect on average calories consumed. This was to ensure that the dataset reflects items bought for individual consumption and excludes the items that were returned. When we could not obtain calorie data for a particular item, we replaced the item calorie information with a median from a meal deal category: e.g., sandwich, sweet snack. This affected less than 5% of meal deal baskets. The final sample comprised 6,592,754 meal baskets for 278,057 individuals. The sample included 75.28% females. Finally, because our meal deal baskets allowed up to two extra items, we were able to control for the price of the basket, which included a meal deal plus up to two extra items. Mean price for the average meal deal basket was £3.48 (SD = 0.4). On average, the individuals in this sample consumed 731.05 calories per person per meal with standard deviation of 164 calories (Female: M = 703.31; SD = 153.02; Male: M= 815.52, SD = 167.36).

We further investigated the effect of time sensitivity on average calories purchased per lunch while controlling for gender, normalised entropy, and price of the meal deal basket. Table S2 presents the results of seven OLS regression models with average calories as an outcome variable which replicate regression in Table 1 with an addition of the price for the meal deal basket

Normalized entropy – or the propensity to buy a variety of items - negatively predicted average calories over gender. Gender significantly predicted average calories purchased per lunch, with men purchasing just over 100 calories more than women, similar to the main analysis. In Sample 1E, together the three time sensitivity measures explain more of the variance in calories bought for lunch, than gender, indicating that time sensitivity is having a large effect. Those who vary more in their calorie consumption over the time-of-day, day-of-week and month-of-year consume more calories overall.

Finally, we replicated that the effect of the price of the average meal deal plus two extra items (see Model 7, Table S2) explained marginal amount of variance on average calories over gender, normalised entropy and the time effects, suggesting that availability of cheaper food does not make a large effect on people’s choice of calorific composition of their lunches. If a particular person buys a lot of calories only if there were discounts, then average spending should have either correlated negatively with overall calories consumed or not correlate at all. When predicting average calories, we found a positive relationship between average spending on a meal deal basket and average calories consumed, suggesting that the more money people spend, the more calories they proportionately purchase, allowing us to reject explanation of increase in calorie consumption by offers and discounts.

Table S2. Gender, normalised entropy, time-of-day, day-of-week, month-of-year and average price of meal deal basket predicting average calories regression models, Sample 2. Numbers are beta coefficients and 95% confidence intervals. The average price of a meal deal basket, time-of-day, day-of-week and month-of-year effects were standardized prior to entering the regression. Gender is coded as -0.5 (Male) and 0.5 (Female).

Average lunchtime calorie consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	**703.3 [702.6; 703.0]**	**704.1 [703.6; 704.8]**	**703.6 [703.0; 704.3]**	**703.2 [702.6; 703.9]**	**703.0 [702.4; 703.7]**	**702.8 [702.1; 703.4]**	**703.7 [703.1; 704.3]**
Male	**112.2 [110.9; 113.6]**	**108.9 [107.5; 110.3]**	**110.6 [109.3; 111.9]**	**112.2 [110.8; 113.5]**	**112.7 [111.4; 114.0]**	**113.4 [112.1; 114.7]**	**109.3 [108.0; 110.6]**
Normalised entropy		**-6.5 [-7.1; -5.9]**	**-16.8 [-17.4; -16.3]**	**-20.6 [-21.2; -19.9]**	**-19.3 [-19.9; -18.7]**	**-24.6 [-25.2; -23.0]**	**-24.3 [-24.9; -23.7]**
Time-of-day sensitivity			**45.2 [44.7; 45.8]**			**20.6 [19.9; 21.3]**	**19.8 [19.1; 20.5]**
Day-of-week sensitivity				**44.6 [44.0; 45.2]**		**19.1 [18.4; 19.8]**	**17.8 [17.1; 18.5]**
Month-of-year sensitivity					**49.9 [49.3; 50.4]**	**28.6 [27.9; 29.3]**	**26.6 [25.8; 27.3]**
Average price of a meal deal basket							**19.5 [19.0; 20.1]**
Adjusted R^2	0.087	0.089	0.161	0.155	0.175	0.2	0.213
N	278,057	278,057	277,370	276,636	277,323	275,424	275,424

Sample 2: controlling for effects of income

Table S3. Predicting average calories regression models. Beta coefficients and 95% Confidence Intervals for education, income and time sensitivity controlling for gender and normalized entropy scores, Sample 2. Reference category for education was School+; reference for income was high income or above £100,000 per household. Values highlighted in bold are significant at least .05 level.

Average lunchtime calorie consumption						
	(1)	(2)	(3)	(4)	(5)	(6)

Intercept	**625.7 [616.9; 634.5]**	**627.8 [618.9; 636.8]**	**627.7 [618.7; 636.7]**	**624.01 [615.2; 632.8]**	**628.7 [619.3; 638.1]**	**571.8 [519.2; 624.4]**
Male	**107.3 [78.7; 135.97]**	**112.2 [82.7; 141.6]**	**114.5 [85.9; 143.1]**	**113.8 [85.1; 142.4]**	**118.7 [88.5; 148.9]**	**126.1 [90.7; 161.4]**
Normalised entropy	6.4 [-2.2; 14.96]	0.8 [-8.2; 9.8]	2.06 [-7.09; 11.2]	1.4 [-7.4; 10.2]	1.7 [-8.02; 11.4]	3.6 [-7.8; 15.1]
Time-of-day sensitivity		**32.4 [23.7; 41.1]**			**22.6 [6.6; 38.6]**	**23.6 [4.7; 42.4]**
Day-of-week sensitivity			**28.7 [19.95; 37.5]**		7.7 [-7.2; 22.8]	10.5 [-7.4; 28.4]
Month-of-year sensitivity				**29.5 [21.01; 37.9]**	4.83 [-11.2; 20.9]	0.997 [-17.9; 19.9]
Degree						3.9 [-21.02; 28.8]
Degree+						-7.8 [-34.7; 19.1]
Low income (below £25,000 per household)						**62.3 [6.9; 117.7]**
Medium income (between £25,000 and £100,000 per household)						51.2 [-0.24; 102.7]
Adjusted R^2	0.035	0.074	0.07	0.069	0.078	0.082
N	1,410	1,307	1,293	1,353	1,177	867