Eating Patterns and Weight Status: Evidence from the American Time Use Survey

Eating Patterns and Weight Status: Evidence from the American Time Use Survey

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Table of contents

List of figures……………………………………………………………………………………4
List of tables…………………………………………………………......................................5

Abstract………………………………………………………………………………………….. 6

1. Introduction………………..………………………………………………………………………7
    1.1 Background…………………………………………………………………………….. 9
    1.2 Measuring body weight: the Body Mass Index……………………….............................. 12

2. Materials and methods…………………………………………………………………………. 15
    2.1 Data source……………………………………………………….......…………..15
    2.2 Data description………………………………………………………....................... 23
    2.3 Empirical model…………………………………………………………………………33

3. Results……………………………………………………………………………………..39

4. Summary and conclusions……………………………………………………………………... 45

5. References………………………………………………………………………………………48

6. Appendix A……………………………………………………….……………………………53

List of figures

Figure 1. Mean BMI and % of overweight/obese respondents between 18 and 65 years old………… 14
Figure 2. Histogram and of BMI by gender and EH wave…………………………………………….. 24
Figure 3. Mean time use by eating category………………………………………………………… 26
Figure 4. Percentage of zero values by eating category………………………………………………...28
Figure 5. Standardized Mean Differences by eating category between weekend and weekdays……… 28
Figure 6. Mean Time Spent exercising and walking/biking including (uncensored) and excluding (censored) zero values ……………………………………………………………………….………29
Figure 7. Percentage of zero values in exercise and active travel time use (source: ATUS data, own elaboration)…………………………………………………………………………………..……… 30
Figure 8. Mean Time Spent Working From Home (WFH) and Working Away from Home (WAFH) including (uncensored) and excluding (censored) zero values………………………………………… 31
Figure 9. Percentage of zero values in Working From Home (WFH) and Working Away from Home (WAFH) time use……………………………………………………………………………………32

List of tables

Table 1. Weight Categories Based on BMI Thresholds ……………………………………………..13
Table 2. Example of Three-Tiered Classification of Time Allocation in ATUS ……………………...16
Table 3. Non-response Rates for Self-Reported Height and Weight ………………………………..18
Table 4. Data cleaning process………………………………………………………………………19
Table 5. Eating time: explanatory variables …………………………………………………………20
Table 6. BMI mean values and standardized mean differences (SMD) by gender and EH waves …… 25
Table 7. Weighted mean values of time spent eating, other variables of interest and incidence of 0 values…………………..………………………………………………………………………… 27
Table 8. Control variables..……………………………………………………………………………35
Table 9. Weighted mean values (control variables)………………………………………………… 36
Table 10. OLS results, effects of eating time and exercise on corrected BMI…………….....……..… 40
Table 11. IV results, effects of eating time and exercise on BMI ……………………………………. 43
Table 12. Predicted on BMI by scenario ………………………………………………………………44

Abstract

Overweight and obesity rates are a source of increasing concern for the long-term health and well-being of the US population. This work examines the relationship between eating time and Body Mass Index (BMI) using a representative sample of US respondents from the American Time Use Survey data. Different eating modalities (primary and secondary) and locations (at home and away-from-home) are analyzed to provide evidence on how slow and fast eating may affect the weight status when controlling for physical exercise. Lewbel's instrumental variables are used to account for potential omitted variable and reverse causality bias. The set of instruments is also complemented by dummy variables indicating whether respondents worked from home or away from home in the diary day. Primary eating time is associated with lower BMI values in 2006-08 during weekdays, but the relationship between eating time and BMI is no longer significant in 2014-16. Physical exercise remains the only factor showing a strong negative association with BMI.

1. Introduction

More than one third of the world population may be classified as obese or overweight. Obesity rates have increased during the last decades and doubled worldwide since 1980, with the American and European continents being the ones where obesity rates are consistently higher than in the rest of the world (Chooi et al., 2019). In 2021, 34% of people in the U.S. were overweight and 33% of them were obese, which makes only 1/3 of the U.S. population classified within the normal weight range.

In many countries, being obese or overweight is associated with a higher health risk, as obesity and overweight status are related to a series of diseases and chronic conditions that can negatively affect the quality and the duration of life, such as diabetes (Singh et al., 2013), cancers (Lauby-Secretan, 2016; Friedenreich et al., 2021), and cardiovascular diseases (Czernichow, 2011). Being obese or severely overweight can adversely affect fetal brain development in pregnant women (Cirulli et al., 2020). In addition, obesity has a bidirectional relationship with mental health conditions such as depression or anxiety (Fulton et al., 2022). Avila et al. (2015) mention how people who already struggle with depression, bipolar disorder, abuse or consequences from high stress and traumatic events have been associated with a greater risk of gaining weight and physical inactivity in multiple studies. Conversely, there is scientific evidence that being overweight or obese increases the likelihood of experiencing stress, depression, anxiety, or emotional problems (Hyungserk et al., 2017; Tyrrel et al., 2019).

Obesity and overweight in adults may be caused by the occurrence or combination of multiple determinants such as lack of sleep (Chaput and Dutil, 2016), stress (Tomiyama, 2019), lack or inadequate physical activity, or unhealthy dietary choices (Carbone et al., 2019). There are also socio-economic determinants of obesity which may directly or indirectly impact weight status such as income or gender (Ameye and Swinnen, 2019) or poor food choices (Cohen et al., 2011), and the rates of incidence of these conditions differ among racial and ethnic groups (Agbim et al., 2019). Some factors may be genetically determined (Sanghera et al., 2018), and sometimes previous illnesses or chronic conditions may be contributing factors (Taylor et al., 2012). A healthy lifestyle is negatively correlated with weight gain and helps prevent obesity or overweight status (Bullò et al., 2011). There is considerable research evidence concerning behaviors that may foster a healthy lifestyle to promote individuals' well-being. For instance, adhering to a sustainable dietary plan (Huo et al., 2014) or maintaining a daily level of physical activity aimed at burning at least 200 kcal (Myers et al., 2016).

However, the time devoted to good practices aimed at maintaining a satisfactory quality of life (e.g., sport, healthy eating) may be limited, depending on the competing life commitments such as presence of kids, time devoted to work and/or commuting and so on. Working hours and location may actively affect the time spent on different activities, which is therefore reflected in the long-run physical health status. In their recent work, Restrepo and Zeballos (2022) showed how working from home (WFH) or working away from home (WAFH) during the pandemic period had a different impact on multiple activities such as sleeping, childcare, socializing, housework, and particularly stimulated additional eating time from home. Even without considering the unconventional disruption of the typical work routine during 2020, WFH has been associated with greater time spent eating from home in previous years (Restrepo and Zeballos, 2022).

This thesis investigates the linkage between behavioral patterns and obesity levels using the American Time Use Survey (ATUS) data and its extra modules. More specifically, it is based on the ATUS Eating and Health module (surveyed over the 2006-08 and 2014-16 periods), which contains self-reported height and weight data as well as time spent on 'secondary eating' – what Daniel Hamermesh terms as "grazing" that is, the time spent eating while carrying on a main activity (e.g., watching TV, working, traveling, etc.). Identifying the relationships between time use and obesity levels may increase awareness of what habits should be reinforced or discouraged to achieve a healthy, balanced lifestyle to prevent obesity, overweight and their consequences. In focusing on the connection between eating time and the weight status of US citizens, this work accounts for how WFH and WAFH may potentially affect eating (and grazing) time at home and away from home as well as time spent exercising.

Previous research on related topics was carried on Courtemanche et al. (2021), mostly investigating the amount of time spent either exercising or engaging in active travel. This work expands the range of their research to the amount of time spent eating in different modalities. Primary and secondary eating time use and their association with BMI has been investigated by Hamermesh (2010). However, his work only included data from the first ATUS EH wave and did not consider endogeneity issues, nor the differentiation between eating at home versus away from home. Furthermore, the study by Hamermesh (2010) analyzes the relationship between eating activities and BMI using self-reported height and weight measures without any correction to account for underreporting or overreporting. In this work, the mentioned measures will instead be appropriately corrected using the methodology later proposed by (Courtemanche et al., 2015).

1.1 Background

Obesity-related studies span across multiple disciplines. Economists have extensively explored the issue of obesity from various perspectives, highlighting its association with higher medical costs per individual (Cawley and Meyerhoefer, 2012) and contribution to wage discrimination (Cawley, 2004). Therefore, understanding the determinants and consequences of obesity is crucial in defining appropriate policy interventions. Time use analyses can provide valuable information on the relationship between lifestyle and obesity by identifying specific behaviors that may contribute to this condition. Given the limited 24 hours in a day, time allocation is indeed an economic problem, and the major time-use activities can significantly affect our well-being (Hamermesh, 2020) and physical health status (Patel et al., 2016).

The duration and variety of activities can affect health outcomes. For instance, sleeping less than 7 hours per night may potentially contribute to an increase in obesity (Tajeu and Sen, 2016), watching TV (Patel et al., 2016) and motorized vehicle commuting time has also been linked to adverse health outcomes (Yang and French, 2013). Spending time engaging in physical activity through exercise or active modes of transportation, such as biking or walking, has been associated with weight loss (Courtemanche et al., 2021). Eating patterns can also significantly impact health outcomes. Hamermesh (2010) utilized an economic model to investigate the relationship between time use, and health outcomes, specifically regarding eating behaviors. The study aimed to identify the empirical determinants of eating and grazing (i.e., primary and secondary eating time) and to investigate how these habits relate to the physical health status of respondents and their BMI. Controlling for the total amount of time spent eating and sociodemographic factors, individuals who consume a greater number of meals tend to have better health outcomes, while secondary eating (grazing) time has a negative correlation with the Body Mass Index (BMI). Temporal eating patterns have also been identified as important factors affecting health outcomes. Studies have shown that evenly spaced and balanced meals are associated with a lower BMI (Aqeel et al., 2017), while irregular eating patterns (e.g., skipping breakfast, late-night eating) are associated with a higher BMI (St-Onge et al., 2017).

Additionally, certain sociodemographic segments are more prone to overweight or obesity than others: compared to other women and men, low-income mothers have a higher likelihood of being overweight or obese (Gouch et al., 2019; Martin et al., 2022). Similarly, eating behaviors can also vary according to certain characteristics: Senia et al. (2017) has indicated that food at home and food away from home consumption controlling for food prices is different for low-income households, which tend to spend more time eating at home.

Despite knowing that a healthy lifestyle is associated with lower levels of BMI, other activities may interfere with this successful outcome: Kalenkoski and Hemrick (2013) have argued that time-poor individuals are less prone to engage in active exercise and travel and more prone to purchasing fast food (that is one way of eating food away from home). Time poverty may be dictated by having specific life necessities (necessary time[1]) and commitments (committed time) that restrict personal discretionary (or leisure) time. Time-poor individuals have different eating patterns than others: they tend, perhaps surprisingly to purchase less fast-food meals, but they also eat less frequently within a day, which makes them subjected to higher risk of obesity and overweight. Additionally, time poor individuals engage less frequently than non-time poor ones in active travel or exercise (Kalenkoski and Hemrick, 2013).

The workplace is also associated with different eating patterns: people who work from home spent more time eating at home before and during the pandemic period (Restrepo and Zeballos, 2022), suggesting that not only working time, but working location affects eating time and, indirectly, the weight status of the respondents.

The combined findings from the existing literature suggest the following hypothesis:

Hypothesis. Primary (PE) and secondary (SE) eating time at home (FAH) and away from home (FAFH) are associated with BMI. More specifically, the following coefficient signs are expected:

Eating time use	**Expected direction**
Primary eating at home (FAH PE)	-
Primary eating away from home (FAFH PE)	+
Secondary eating at home (FAH SE)	+
Secondary eating away from home (FAFH SE)	+

The expected direction of the marginal effects of eating time on BMI is suggested by research findings on whether and how the eating speed can affect the weight status (Sasaki et al., 2003; Leong et al., 2011; Sonoda et al., 2018), because slow eating can help minimize the likelihood of excessive food intake (Almiron-Roig et al., 2015). ATUS data have been previously used to investigate this relationship between BMI primary vs secondary eating by Hamermesh (2010), who found how primary eating time

[1] Examples are grooming, sleeping, health-related self-care.

is indeed negatively associated with BMI without differentiating for whether respondents were eating at home or away from home. However, considering that food away from home consumption includes food purchased at restaurants and other establishments, this work hypothesizes that it may be positively associated with BMI values. The positive sign attributed to both secondary eating components is derived from the inherent nature of grazing, which is performed while engaging in other activities and may lead to neglecting both the quality and quantity of what is being consumed.

1.2 Measuring body weight: the Body Mass Index

The Body Mass Index (BMI) is a widely used metric for determining whether an individual is overweight or obese. The BMI was developed in 1972 by Keys et al. to update previous body measures and has been extensively used in the past decade as an indicator of the physical health status of the population. The BMI was designed to normalize the body mass distribution at each level of height and reduce the effect of variance in height on the weight/height relationship, while maintaining the simplicity of calculation. Previously used indicators were biased by leg length, while most of the body fat is located in the trunk. However, despite its widespread use, Keys et al. (1972) and following studies (Prentice and Jebb, 2001) also pointed out that the BMI is a poor representation of a person's percent of body fat, and it should be used in conjunction with other measures to get a more accurate representation of an individual's physical health status.

The BMI can be computed as:

$$BMI = \frac{weight\ (kg)}{height^2\ (m)}$$

Or, alternatively, as:

$$BMI = 703 \cdot \frac{weight\ (lbs)}{height^2\ (in)}$$

Despite the limitations of the BMI that have been outlined over the last decade, it continues to be a widely used metric for determining whether an individual is overweight or obese because of its ease of computation. Nuttal (2015) highlights how usually the BMI distribution is skewed to the right, as extremely lower values of this indicator would pose a short-term threat to a person's survival, while it is still possible to maintain life with body fat accumulation.

Table 1. Weight Categories Based on BMI Thresholds

BMI	**Status**
< 18.5	Underweight
18.5 – 24.9	Normal weight
25.0 – 29.9	Pre-obesity (overweight)
30.0 – 34.9	Obesity – Class I
35.0 – 39.9	Obesity – Class II
> 40.0	Obesity – Class III

The World Health Organization (WHO) has adopted the BMI as one of the main indicators[2] for determining obesity. WHO Weight categories based on BMI thresholds[3] are displayed in Table 1.

An additional criticism of the BMI is that it does not take into account various demographic factors that influence an individual's physical state, as it is purely based on Caucasian standards that do not suit more ethnically diverse groups (Prentice and Jebb, 2001). Despite this indicator being partly deficient, many studies and international institutions still employ BMI because it is calculated using easily accessible data. For instance, Dunton et al. (2009) have highlighted the positive association between the amount of time spent in sedentary activities and higher Body Mass Index values.

The analysis of time-use data may enhance our understanding of what people do on a daily basis and how time spent in specific sedentary activity can impact physical and mental well-being. Leisure and

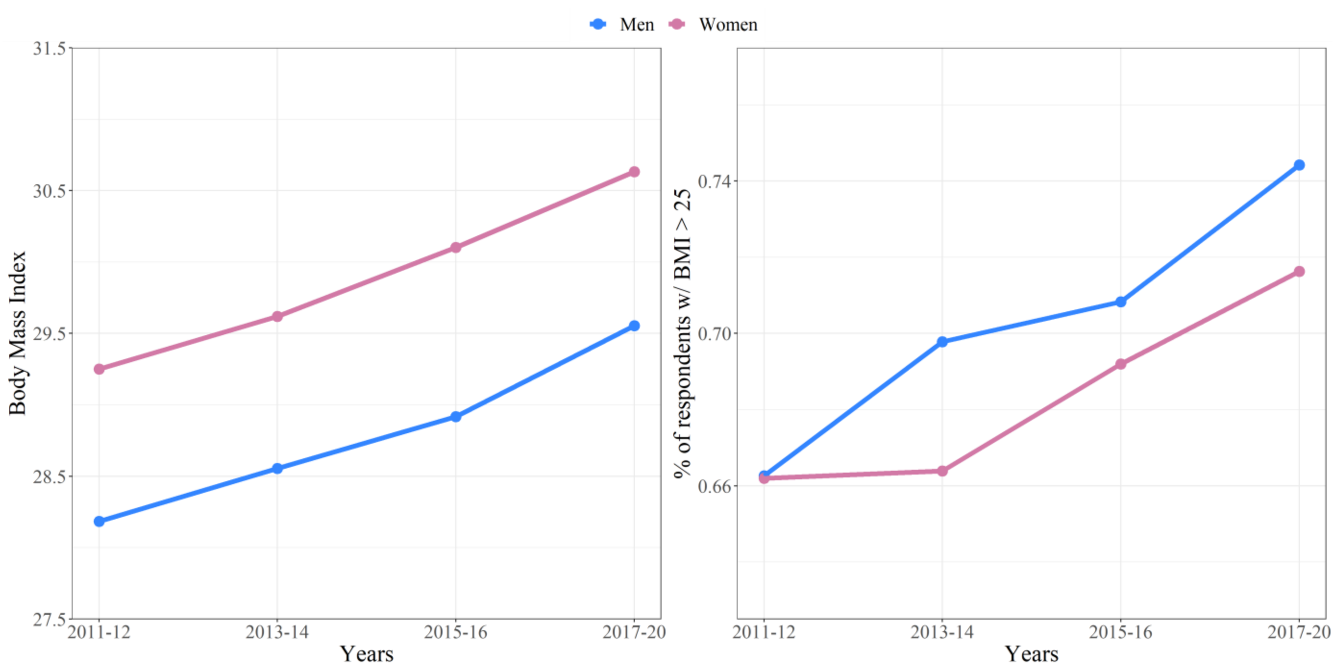
[2] Along with the waist circumference and the waist-to-hip-ratio, that are sometimes considered better measures to assess the risk of cardiovascular events (Schneider et al., 2007).
[3] https://www.who.int/europe/news-room/fact-sheets/item/a-healthy-lifestyle---who-recommendations

active transportation—walking and biking, for example—are also associated with lower BMI levels, while watching TV and computer games are positively correlated with higher BMI outcomes. Hamermesh (2010) analyzed the correlation between the amount of time spent on eating as a primary and secondary activity and BMI. Despite acknowledging the limitations of BMI as an obesity indicator, it is often the only variable available to conduct statistical analysis of a representative sample from publicly available datasets.

The National Health and Nutrition Examination Surveys (NHANES) collects weight and height data from a sample of US respondents and releases it every two years.

Figure 1 shows how the average BMI falls within the overweight and obesity range, with more than 60% of the respondents being overweight or obese, with a BMI greater than 25.

Figure 1. Mean BMI and % of overweight/obese respondents between 18 and 65 years old (source: NHANES data, own elaboration using measured height and weight of respondents)



Additionally, the figure shows how there has been a slow but steady increase in BMI and the number of overweight or obese individuals between 2011 and 2020. Although the sample of participants in the NHANES survey is limited, the data are consistent with the scientific and medical literature illustrated in the previous paragraphs and reflect a concerning situation that has apparently worsened during the pandemic period.

2. Materials and methods

2.1 Data

The way in which individuals allocate their 24 hours each day can have a significant impact on their financial stability, health, and well-being, as well as their overall happiness levels (Hamermesh et al., 2005). Unlike other resources, such as income, time cannot be replenished and is considered the ultimate limited resource (Hamermesh, 2019). The American Time Use Survey (ATUS) provides valuable insights into how people allocate their time and can be used to better understand the potential implications of daily time allocation decisions.

The ATUS survey is an ongoing monthly survey administered using computer-assisted telephone interviewing, which ensures accuracy and consistency in data collection over time. It captures detailed information about how individuals spend their time throughout the day, including activities like paid work, household chores, leisure activities and many others. Respondents are drawn from the Current Population Survey (CPS) and assigned a specific diary day. They receive an advance mailer informing them that they have been selected for the ATUS sample, along with an indication of the designated interview date. They are thus made aware of the interview's content and are instructed to report their time use from the previous 24 hours before the interview. Respondents must be a minimum of 15 years old. The CPS interview and the ATUS interview can be conducted anywhere from two to five months apart.

Data provided by the Bureau of Labors Statistics (BLS) from CPS interviews can be accessed to supplement ATUS data. At the time of the ATUS interview some socio-demographic variables and additional information are updated from the CPS data files.

In the ATUS phone interview, people are asked to report the way they allocated their time during the previous twenty-four hours, specifying who was present during each activity and where they took place (except that for sleeping and grooming, whose 'who' and 'where' codes are not recorded). Interviewers then register and classify each activity according to a three-tier coding scheme going from major aggregated activities to the most detailed ones.

Table 2 exemplifies this classification scheme. All household activities are aggregated under the major tier 02 and subsequently divided into intermediate and detailed ones. The middle tier refers to the intermediate activity groups such as general housework, food and drink preparation, house maintenance and others. Additional details are included in the last tier, which articulates time use differentiating among specific activities within each intermediate group such as laundry, interior cleaning, food preparation and so on.

Table 2. Example of Three-Tiered Classification of Time Allocation in ATUS

Tier 1	**Tier 2**	**Tier 3**
02 (Household activities)	02-01 (Housework)	02-01-01 (Interior cleaning)
		02-01-02 (Laundry)
		…
	02-02 (Food & Drink Preparation, Presentation, & Clean-up)	02-02-01 (Food and drink preparation)
		…
		02-02-03 (Kitchen and food clean-up)
		…
	…	…
	02-04 (Exterior Maintenance, Repair & Decoration)	02-04-01 (Interior arrangement, decoration, & repairs)
		02-04-02 (Building and repairing furniture)
	…	…

The ATUS multi-year data files contain 17 tier-1 codes, 105 tier-2 codes and more than 400 tier-3 codes. When respondents forget, refuse, or do not provide enough information for a specific activity, the corresponding time use is reported under tier 50 (Unable to code) and its respective sub-tiers.

The ATUS main survey is periodically integrated with additional modules for specific purposes. For instance, the Leave Module includes questions about wages, salaries, work leave, and work schedules. This module was administered in 2011, 2017, and 2018. Additionally, the Well-Being Module measures how people feel during various activities, and has been conducted in 2010, 2012, 2013, and 2021. The Eating and Health (EH) Module, sponsored by the U.S. Department of Agriculture's Economic Research Service, provides information about respondents' eating habits, including the occurrence and duration of secondary eating times and self-reported height and weight. EH data are available for the 2006-08 and 2014-16 periods and are used in the following analysis. In subsequent discussion, these will be referred to as Wave 1 and Wave 2 of the EH modules.

The ATUS data are complemented with land area and population estimates by Metropolitan Statistical Area (MSA) from the U.S. Census Bureau, and potentially with additional data from the Quarterly Census of Employment and Wages (QCEW) which provides the quarterly number of establishments per industry type by MSA. The QECW data use the North American Industry Classification System (NAICS) to classify business establishments according to their industry sector. NAICS restaurant codes (7221, 722511) are used to combine the number of full-service restaurant establishments in every MSA, along with the number of limited-service restaurants (7222, 722513) which also includes cafeterias and snack bars (722514, 722515).

The full EH sample contains 69,880 observations of which 37,832 pertain to the first wave (2006-08) and 32,048 to the second wave (2014-16). Non-response rates in both waves are low and respondents who have refused to say, or don’t know if they engaged in any sort of secondary eating (n = 697) are excluded from the sample. Similarly, respondents who say they are engaged in secondary eating but don't know or refuse to say for how long (n = 260) are excluded. Pregnant women (n = 574) at the time of the interview are also excluded from the sample as the pregnancy status affects their BMI and their eating habits. BMI can be computed by relying on ATUS respondents' self-reported height and weight from the EH module. Table 3 summarizes the pattern of missing values for height and weight by gender, highlighting how female respondents systematically avoid self-reporting their physical measurements, particularly when it comes to weight.

Besides EH nonresponses and pregnant women, all observations with missing weight and/or height measures (n = 2,859) are excluded from the analysis. Age is restricted excluding respondents outside the 18-65 age limits[4] (n = 15,668).

Table 3. Non-response Rates for Self-Reported Height and Weight (excluding EH non-respondents and pregnant women)

	Women	**Men**	**Total**
Missing Height only	386	135	521
Missing Weight only	1,679	207	1,886
Missing Weight & Height	270	182	452
Total	2,335	524	2,859

Additionally, observations with missing data are excluded. The raw sample includes respondents with no MSA code information (n = 14,344) and/or missing income information (n = 4,977) which are omitted. Respondents who did not pass the interviewer quality check[5] (n = 388) are also dropped. Certain

[4] Age restrictions are applied for two main reasons: first, the thesis investigates how working time affects eating behaviors, with the focus being on respondents who are in the labor force. Second, BMI measures are corrected according to the methodology proposed in Courtemanche et al., (2015) which also consider the same age range for their analysis.
[5] The quality check is executed at the end of any ATUS phone call. ATUS interviewers are required to ask the following questions: ": is there any reason this interview should not be used?" and "why do you think the data should not be used?". These questions may indicate whether a respondent was purposely or accidentally misreporting their time use during the interview process.

observations may exhibit missing data across multiple variables, such as respondents with incomplete information in more than one area. Table 4 provides a comprehensive summary of the data cleaning methodology employed, delineating sample size after eliminating respondents at each step with the corresponding fraction of retained observations.

The final sample consists of 37,579[6] observations which includes 19,252 observations from the first EH wave and 18,327 from the second one.

Table 4. Data cleaning process

Data cleaning step	**Sample size**	**Fraction retained**
Initial sample	69,880	-
Exclusion criteria:		
Respondent did not participate in the EH interview	69,183	99.00
Respondent did not provide secondary eating time information	68,923	98.63
Respondent is pregnant	68,352	97.82
Missing height/weight information	65,493	93.72
Age not between 18 – 65 years old	50,455	72.20
Missing MSA information	40,374	57.78
Missing income information	37,743	54.01
Respondent did not pass the interviewer quality check	37,579	53.78

The EH module allows for the classification of eating time based on the location where respondents eat and on whether eating is considered a primary or secondary activity. The ATUS survey enables respondents to specify where they eat, allowing for more than 30 distinct locations.

[6] The number of observations decreased from 69,880 to 37,579, representing a reduction of 46.22%. Despite the low non-response rate in the ATUS data (mostly due to missing height and/or weight), the CPS data files do not report information for some sociodemographic data such as MSA code and income, which drastically reduces the number of observations. Additionally, the age restrictions applied here further restrict the final sample. This is common in other studies using the ATUS EH modules, with a percentage reduction from raw to clean data ranging from 14% (Martin et al., 2022) to 71% (Senia et al., 2017) depending on the specific restrictions and research objectives implemented.

Table 5. Eating time: explanatory variables

Variable	Description	Data source
FAH – PE	Food at Home, classified as primary eating (TEWHERE = 1)	ATUS
FAFH – PE	Food Away from Home, classified as primary eating (TEWHERE ≠ 1)	ATUS
FAH – SE	Food at Home, classified as secondary eating (TEWHERE = 1)	ATUS EH
FAFH – SE	Food Away from Home, classified as secondary eating (TEWHERE ≠ 1)	ATUS EH

For the purposes of this study, eating is classified as either 'Food at Home' (FAH) or 'Food Away from Home' (FAFH). If respondents engage in primary eating (PE) as their main activity, they indicate it in the base ATUS survey when allocating their time during the diary day. If they engage in secondary eating (SE) time, they indicate it in the EH module and define how much time they spent eating while doing something else. Secondary eating time is also defined as 'grazing' (Hamermesh, 2010). The combination of PE vs SE and FAH vs FAFH allows to define four different eating categories, summarized in Table 5.

In this work, FAH is defined as the eating time that takes place at home (TEWHERE = 1) and FAFH identifies every eating time that takes place away from home. However, home delivery and food takeaway are not included in the FAH time use: if the respondent orders food[7] and then consumes it at home within the following two hours, that eating time is attributed to the FAFH category because the food was prepared away from home.

Working a main job is classified at the second-tier level (activity code 05-01). Dummy variables are defined depending on whether respondents worked from home (WFH), worked away from home (WAFH), or both in the interview day. The data also allow for the identification of exercise or active travel time. A dummy variable is defined to account for these time uses: the variable is equal to one if respondents engaged in active exercise (second tier activity code 13-01) for at least 15 minutes, or if they walk or bike for at least 20 minutes in a row[8].

[7] Tier 3 code 07-01-03.
[8] Similarly to the approach used by Kalenkoski and Hamrick (2013).

The final data sample of 35,579 observations includes data for both weekdays and weekends. Besides controlling for whether the diary day was a holiday, eating habits and other behaviors such as physical activity and working may follow different patterns depending on the day of the week (e.g., people may not work/exercise on weekends). The cleaned sample contains data for 18,641 respondents interviewed on weekdays (Monday to Friday) and 18,938 respondents interviewed on Saturdays and Sundays. This is the result of the sampling methods used in the ATUS Survey, which purposely oversamples weekends during the data collection process and the almost exact split between weekends and weekdays is similarly noticeable in the raw data sample. The descriptive statistics and the following estimations will be therefore conducted on both the pooled sample of all seven days and two separate ones—weekdays vs weekends—to appropriately detect any behavioral differences between weekdays and weekends. The EH survey sampling weights are applied when calculating descriptive statistics and estimating regression analysis.

Self-reported height and weight are used to compute the BMI for each ATUS EH respondent. Obtaining accurate data on weight and height on a large scale is challenging. Most nationally representative surveys are administered by telephone interviews and can exclusively rely on self-reported weight and height, which often leads to measurement errors in the BMI calculation as respondents may not know, refuse, or purposely underreport or overreport their body measures. Ideally, in-person medical examinations of respondents should prevent weight and heigh misreporting but such measures are not available in the ATUS data. However, examination data is available in the U.S. National Health and Nutrition Examination Surveys (NHANES). The NHANES is a comprehensive study aimed at evaluating the well-being and nutritional state of adults and children. The survey combines both interview sessions followed by physical exams, providing a new representative sample of respondents every two years. Self-reported weight and height can be compared with measured weight and height to reveal any discrepancies. NHANES is the only nationally representative survey that allows such comparison.

The NHANES data have been used as a validation dataset by Courtemanche et al. (2015) to correct self-reported weight and height in surveys that do not physically measure respondents. While previously available correction methods were obtained by regressing the measured height and weight on their self-reported values and their squares (Cawley, 2004), Courtemanche et al. (2015) based their correction on the percentile rank of self-reported height and weight. The percentile rank is generated within the gender ("female", "male") and race ("white", "black", "other") subgroups. Measured height and weight are then regressed on race and gender dummies, a cubic polynomial function of age, and the cubic b-spline of the percentile rank variable. B-splines are used to estimate the nonlinear relationship between self-reported and measured values by approximating the percentile rank variable with a series of polynomial segments passing through certain control points ("knots")[9]. Courtemanche et al. (2015) results show that the estimated prevalence of obesity and class II/III obesity is higher when using their correction compared to self-reported measures. The self-reported weight and height the ATUS EH modules are therefore adjusted using the b-spline approach. NHANES data refers to two years of measurements, while ATUS data is collected annually. For this reason, two subgroups of NHANES data on which to perform b-spline correction have been identified: the first refers to the years 2005-06, 2007-08, and the second to the years 2013-14, 2015-16, in order to create the best possible match between NHANES data and the first (2006-08) and second (2014-16) waves of ATUS data. Corrected weight and height are then used to compute the corrected BMI of every respondent. See Figure 1 and Table 5 for a comparison of the self-reported and the corrected BMI in the cleaned data sample.

[9] Following Courtemanche et al. (2015), knots are set at the following percentiles: 0, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 1. B-splines are computed following the Stata routine written by Roger Newson (see documentation).

2.2 Data description

Figure 2 graphs the BMI distribution across the two EH waves by gender subgroups. Both subsamples exhibit a rightward shift in the corrected BMI, especially in the second wave. Although men's corrected BMI shows only a slight (but noticeable) shift to the right, the difference between self-reported and corrected women's BMI is already more pronounced in the first wave, suggesting a higher tendency among women to underreport physical measures.

Table 6 contains a comparison of self-reported and corrected BMI measures in Wave 1 and Wave 2, reported as both unweighted and weighted averages. Weights have been drawn from the EH data. A standardized mean difference (SMD) has been calculated to compare the average difference between the two time periods.

The SMD is extensively used in the medical propensity-score matching literature to measure the mean difference between the treatment and the control samples and to assess whether the two groups are comparable. SMD effects for continuous variables are computed following the approach indicated by Austin (2009):

$$SMD = \frac{|\bar{X}_{treatment} - \bar{X}_{control}|}{\sqrt{\frac{s^2_{treatment} + s^2_{control}}{2}}}$$

where $\bar{X}$ is the sample mean (of the treatment and the control group respectively), and s^2 the sample variance. SMD does not depend on sample sizes as opposed to other commonly used statistical tests (e.g., the t-test) and it does not make any assumption regarding the variances of the two groups being compared. Rather, it measures the average difference between means expressed in standard deviation units. SMD measures in Table 5 are computed considering the first wave of the EH survey (2006-2008) as the control group and the second wave (2014-2016) as the treatment group. There are only minor differences between the unweighted and weighted average BMI, but these differences persist across both waves and gender groups. The standardized mean difference (SMD) in BMI between the first and second EH waves appear to be small when considering self-reported values, but more than doubles when accounting for corrected weights, supporting the findings of Courtemanche et al. (2015). The corrected BMI SMD for men is 0.14. For women, the corrected BMI SMD is 0.25. The overall BMI trend is consistent with the medical literature, which shows a continual increase in obesity over the past few decades, despite the short time interval (6-10 years) between the two surveys.

Figure 2. Histogram and of BMI by gender and EH wave (Source: ATUS EH module, own elaboration)

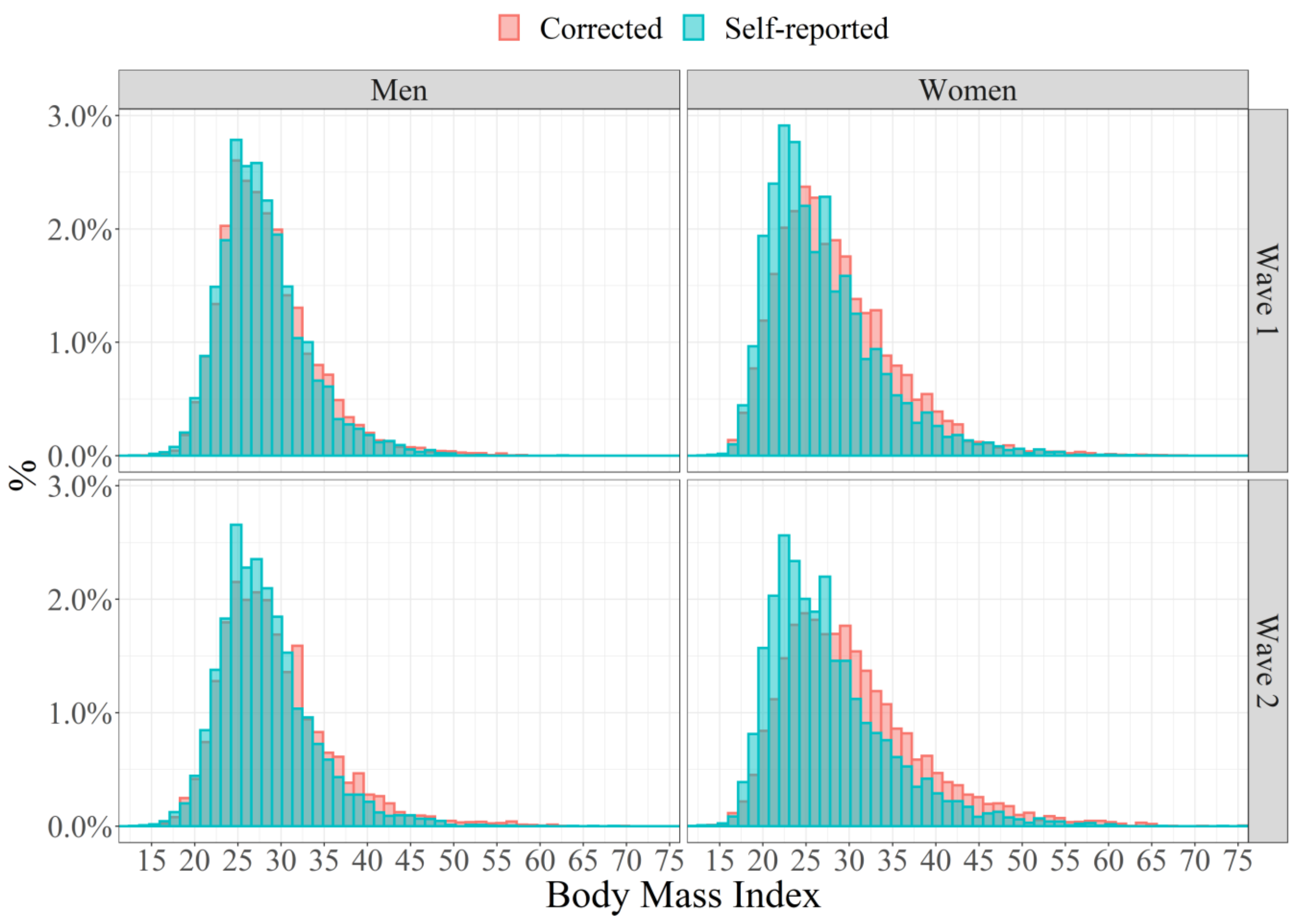


Table 6. BMI mean values and standardized mean differences (SMD) by gender and EH waves.

	Unweighted			*Weighted*		
BMI	**2006-08**	**2014-16**	**SMD**	**2006-08**	**2014-16**	**SMD**
Self-reported	27.38	27.85	0.08	27.30	27.71	0.07
Women	26.90	27.55	0.10	26.72	27.30	0.07
Men	27.94	28.20	0.05	27.84	28.13	0.05
Corrected	28.41	29.77	0.20	28.28	29.58	0.19
Women	28.40	30.22	0.25	28.26	30.00	0.24
Men	28.41	29.25	0.14	28.30	29.15	0.14

SMD greater than 0.2 (Austin, 2009) indicates less overlap between the compared distributions. Table 5 suggests that there has been a pronounced increase between the two waves for women's corrected BMI measures. The overall sample's SMD for corrected BMI is 0.19 and therefore very close to the 0.2 threshold, while there is not a pronounced difference for men's BMI corrected values between the two considered time periods.

Figure 3 summarizes the average time spent on each eating activity using both uncensored and censored (only positive values of time) data. The percentage of zero values in each category is reported in Figure 4. Primary eating appears to be the activity with the longest duration in both at-home (FAH_PE) and away-from-home (FAFH_PE) modalities.

Excluding zeros, it is interesting to note that eating away from home predominates, almost doubling the uncensored average time spent eating away from home in a day in the, indicating that even though half of the respondents do not eat out, those who do spend much more time doing so. On the other hand, the incidence of zeros in time spent eating at home is much lower (less than 25% of the cleaned sample). As for secondary eating time, eating at home or away from home does not seem to differ much in terms of duration, which remains low. However, most respondents do not engage in these activities (around 70% of zero values). For the minority of respondents who grazed during the interview day, whether at home or away from home, the average duration of time spent on these activities rises to 40 minutes per day.

The difference between weekdays and weekends appears to be more pronounced in the averages calculated on censored data, with the weekend average eating duration for primary eating at home and away from home being higher than on weekdays, by around 15 and 10 minutes respectively. There is little difference in grazing time between weekdays and weekends. Table 7 presents summary statistics of the eating time variables.

Figure 3. Mean time use by eating category (source: ATUS data, own calculation)

The SMD for these categories between weekdays and weekends indeed shows that there is a pronounced difference (greater than 0.2 for censored primary eating activities, while the difference for grazing time is less pronounced, even in censored data (see Figure 5). This provides further justification (along with the sampling technique and composition) to segment the data and the results between weekends and weekdays.

Table 7. Weighted mean values of time spent eating, other variables of interest and incidence of zero values.

		2006-08			**2014-16**		
		Uncensored	*Censored*	*% of zeros*	*Uncensored*	*Censored*	*% of zeros*
Weekdays	FAH Primary	33.54	43.51	22.32	34.68	44.00	21.00
	FAFH Primary	30.81	51.43	41.39	25.77	48.70	47.09
	FAH Secondary	10.72	38.24	71.00	6.29	23.02	71.45
	FAFH Secondary	15.92	43.30	62.90	11.43	31.11	63.01
	Exercise	15.18	87.25	83.06	16.68	79.33	79.67
	Active travel	1.63	55.93	97.40	1.73	56.04	97.04
	WAFH	394.20	483.40	18.14	381.37	480.23	20.27
	WFH	26.11	170.13	83.08	36.16	202.98	79.56
Weekends	FAH Primary	39.97	52.56	23.48	39.34	52.24	24.03
	FAFH Primary	32.06	66.04	51.71	30.44	64.59	53.48
	FAH Secondary	13.96	39.52	63.84	10.67	30.40	64.30
	FAFH Secondary	11.71	41.99	72.15	8.27	31.76	73.46
	Exercise	20.53	120.07	83.65	21.76	112.23	81.04
	Active travel	1.77	62.12	97.41	1.86	59.50	97.15
	WAFH	101.49	402.10	75.63	100.05	406.21	77.40
	WFH	16.04	121.83	85.53	17.05	126.93	84.92

Figure 4. Percentage of zero values by eating category (source: ATUS EH, own elaboration).

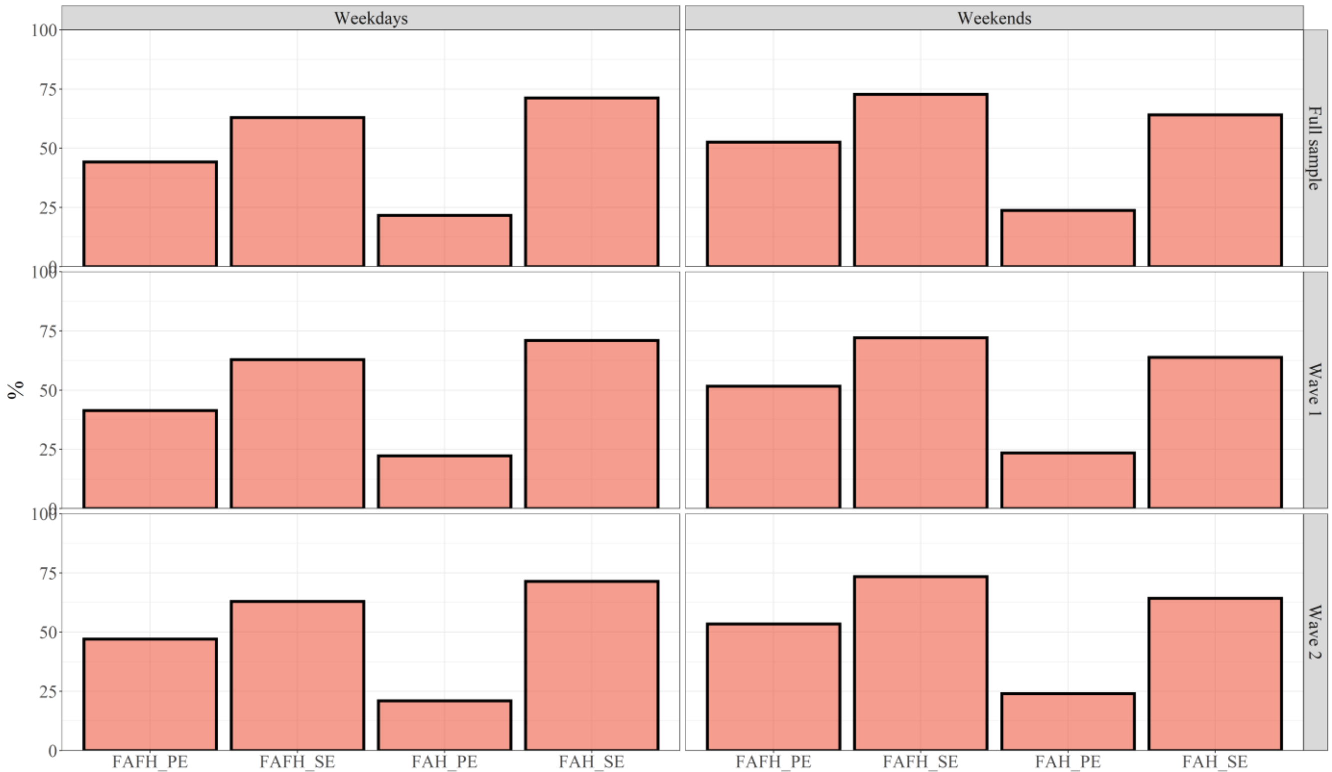
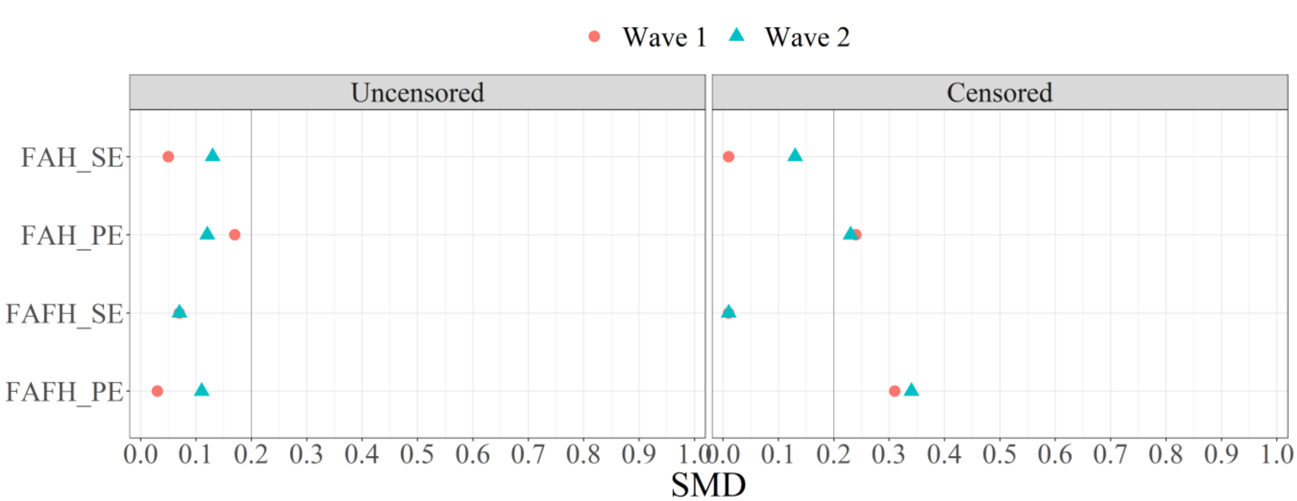


Figure 5. Standardized Mean Differences by eating category between weekend and weekdays (source: ATUS data, own elaboration).



The average time spent exercising or walking/biking (active travel) and the percentage of people who engaged in such activities is reported in Figure 6 and Figure 7 respectively.

Figure 6. Mean Time Spent exercising and walking/biking including (uncensored) and excluding (censored) zero values (source: ATUS data, own elaboration).

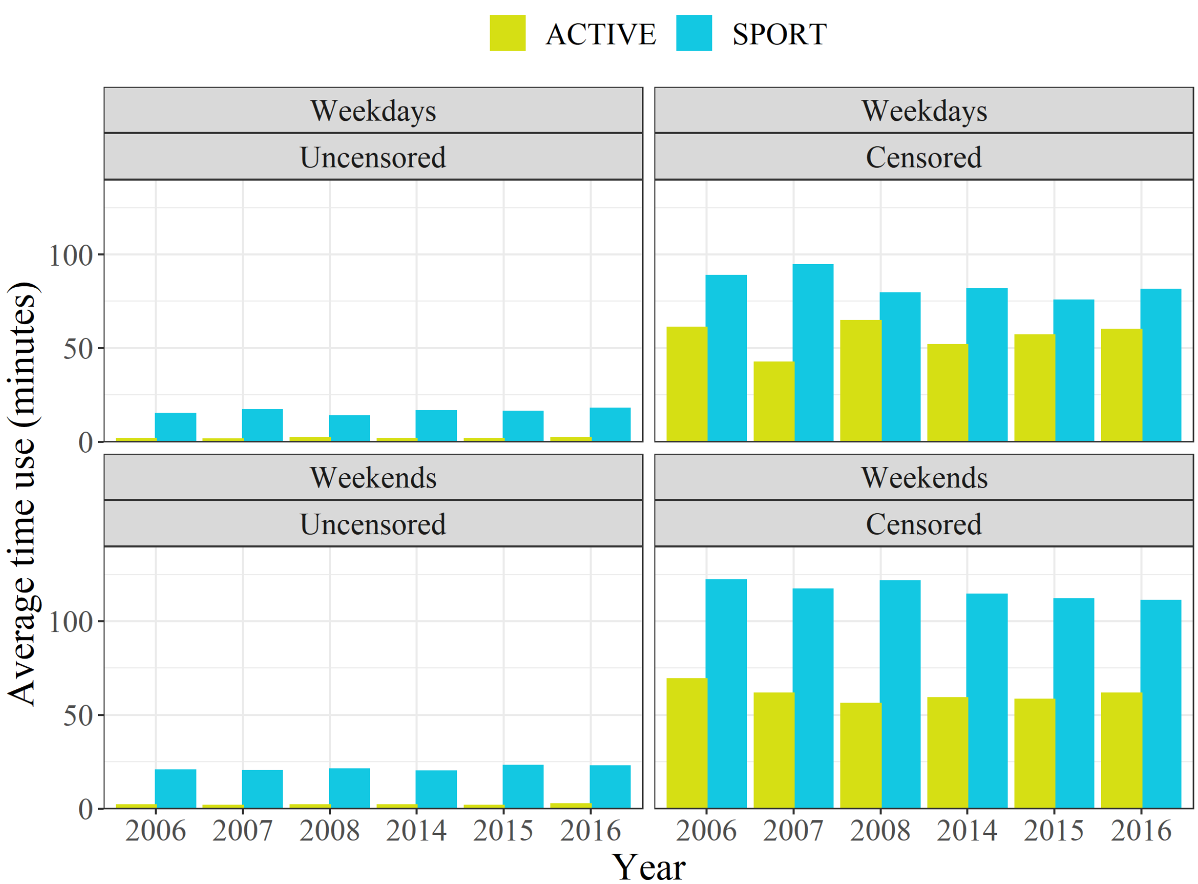
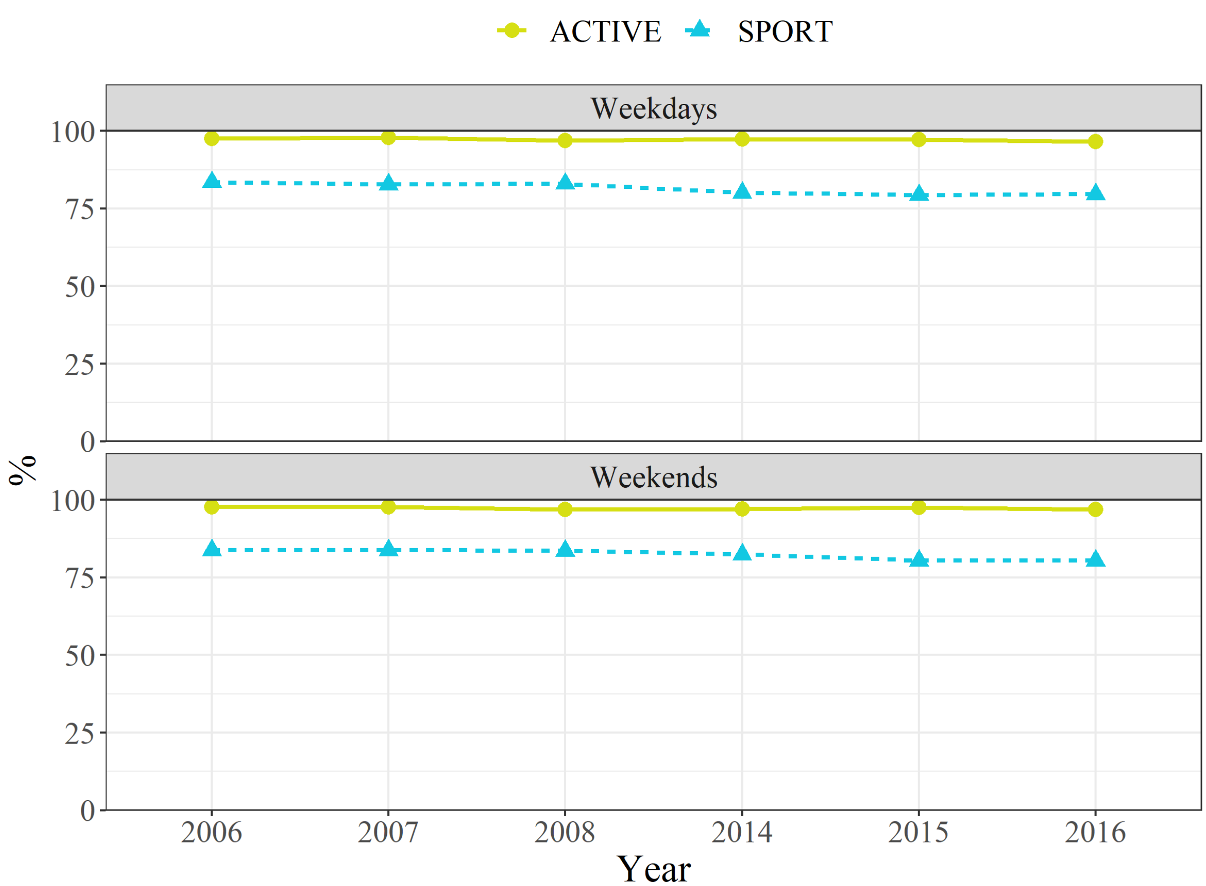


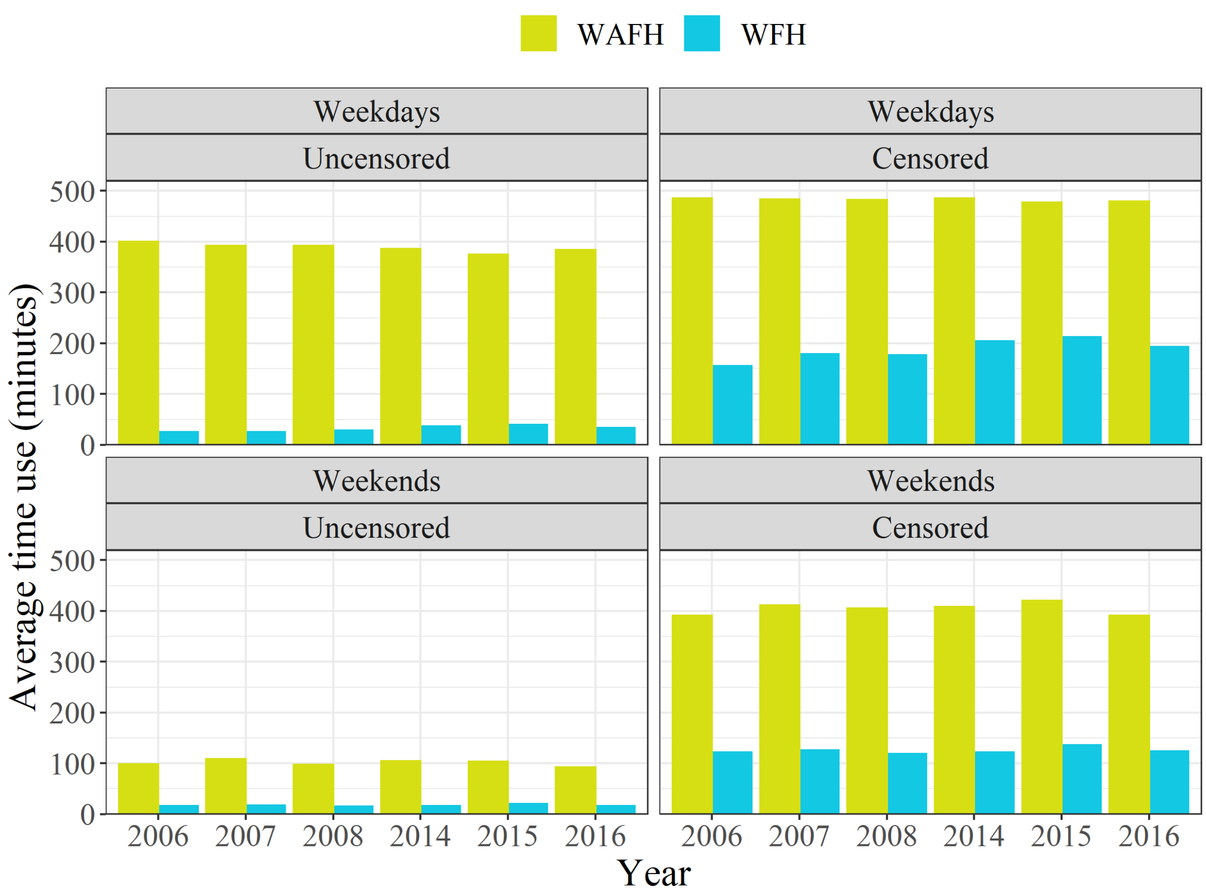
Figure 6 already suggests that the incidence of people note the incidence of people engaging in any kind of active travel and exercising is low, given the difference between uncensored and censored means. There is a general decrease time spent exercising from the first wave (2006-08) and the second one (2014-16) during weekdays and a slight but visible decreasing trend of exercise time during weekends. The data also suggests that the number of people who engage in some form of sports or physical exercise is greater than the number of people who cycle or walk. Overall, the situation would appear to be concerning because the incidence of 0 values in both variables exceeds 75% for exercise time and 96% for active travel.

Figure 7. Percentage zero values in exercise and active travel time use (source: ATUS data, own elaboration).



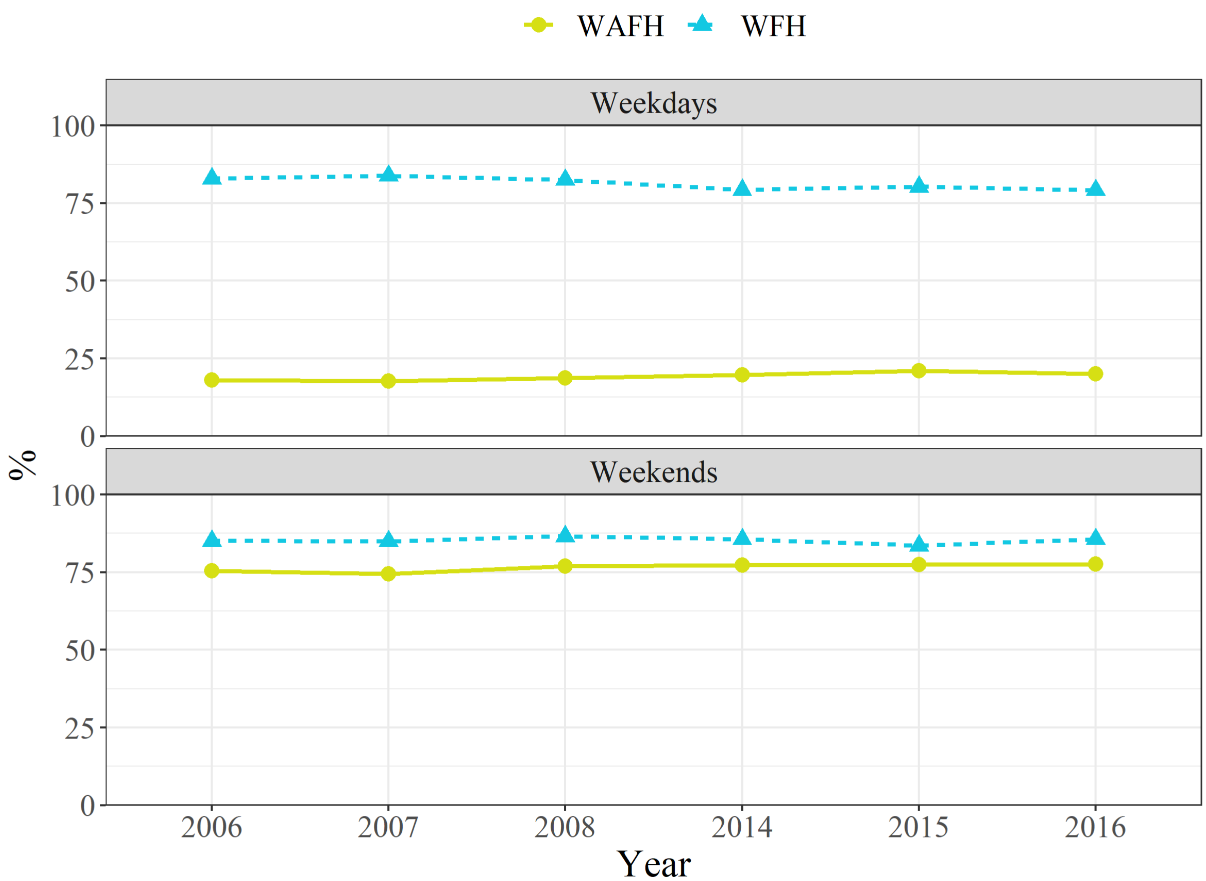
Lastly, working patterns are also analyzed and reported in Figure 8. Mean working time use refers to the main job[10] only, when present. The difference between time spent working from home and away from home is visible, even if slightly less pronounced when excluding people who did not work during the interview day.

Figure 8. Mean Time Spent Working From Home (WFH) and Working Away from Home (WAFH) including (uncensored) and excluding (censored) zero values (source: ATUS data, own elaboration). Unemployed respondents excluded.



[10] Tier 3 code 05-01-01.

Figure 9. Percentage of zero values in Work From Home (WFH) and Work Away from Home (WAFH) time use (source: ATUS data, own elaboration). Unemployed respondents excluded.



The percentage of zero values in the WFH category is between 80-90% in all years. The percentage of zero values in the WAFH categories is equal to or lower than 20% of the working respondents during weekdays, and close to the WFH trend during weekends. The data suggests that most respondents working away from home follow a standard working routine with days off on weekends.

2.3 Empirical model

The main objective of this work is to quantify the impact of eating time on BMI. the following OLS regression model is specified:

$$BMI_i = \boldsymbol{X_i} \cdot \boldsymbol{\alpha} + \boldsymbol{EAT_i} \cdot \boldsymbol{\beta} + \gamma \cdot ACT_i + \varepsilon_i \qquad i = 1, \dots, n$$

where $\boldsymbol{X}$ indicates sociodemographic characteristic, $\boldsymbol{EAT}$ includes four different categories of eating time by place and modality (primary eating at home and away from home, secondary eating at home and away from home) and a dummy variable (ACT) indicates whether respondents engaged in physical exercise or active travel in the interview day. ε_i is the error term.

Selected sociodemographic variables are summarized in Table 8 and include gender, race, relationship status, educational attainment, employment status, income, and age of the respondents. The race variables are defined using three categories following Courtemanche et al. (2015): “white”, “black” and “other”. The income variable refers to the whole household and is classified according to the base ATUS dictionary, which defines 16 different income brackets (included as separate dummies). The employment dummy variable is equal to 1 if the respondent is employed, and equal to 0 if the respondent is on leave, unemployed or not in the labor force. The education variable is categorical and includes the following levels: less than a high school diploma, high school diploma (or GED), some college, college/professional degree or more. To capture the non-linear relationship between age and the outcome variable, age^2 is also included. Presence of own-household children[11] is acknowledged by using multiple dummy variables to indicate their main age groups. These groups are defined as 0-2, 3-5, 6-10, 11-13, and 14-18 years old, which correspond to different periods of education, including pre-school, elementary, middle, and high school. Accounting for the age of children is important because of the potential impact of parenting on BMI status, especially for parents of younger children. Research has

[11] Own children who are under 18 years old and live in the same household.

shown that parents tend to face more time constraints and have less time for physical activity (Gaston et al., 2014) which can contribute to weight gain and poor BMI outcomes. Additionally, previous research has demonstrated that pregnancy can also affect the long-term postpartum weight (Gunderson, 2010). The models also account for the presence of at least one person over 75 years of age in the household (excluding partners), which may limit the amount of discretionary time for exercising. A dummy variable has been established for whether the diary day was a holiday. An additional control is defined to account for whether respondents slept for at least seven hours during the diary day as lack of sleep has previously been associated with potentially unhealthy eating patterns (Tajeu and Sen, 2016) and obesity (Patel et al., 2016). Lastly, this work takes into account whether respondents engaged in tobacco and/or drug use during the diary day[12] as previous research outlined the negative correlation between appetite and tobacco use (Gonseth et al., 2011). All categorical variables have been broken down into dummies. The weighted proportion of respondents falling within each category are reported in Table 9.

The main limitation of the specified model is that BMI values are attributed to activities (eating, exercising) recorded in a specific interview day. However, BMI values are most likely dependent on long-term behavior, for which there is no data available, and tend to change slowly, especially when compared with time use that may vary on a daily basis. Additionally, the ATUS does not collect data on the daily nutritional intake of respondents, resulting in a potential omitted variable bias. Not having data on what people eat also introduces some degree of measurement error in the econometric model, as eating time at home or away from home only acts as a proxy for the nutritional intake. Missing data on genetics, medical or physical factors may also lead to an omitted variable bias. Time use should therefore be treated as endogenous given that observed or unobserved factors may affect the amount of time people spend

[12] Tier 3 code 12-03-02.

eating and exercising, not to mention the reverse causality issues: as Courtemanche et al. (2021) indicated, higher BMI values may negatively affect an individual's ability to exercise and vice versa.

Table 8. Control variables.

Variable	**Description**
Gender	= 1 if female
Race	= 1 if white = 2 if black = 3 if other
Relationship status	= 1 if spouse or unmarried partner present
Educational attainment	= 1 if less than a high school diploma = 2 if high school diploma (or GED) = 3 if some college = 4 if college/professional degree or more
Income	16 different income brackets as per ATUS dictionary
Employment status	= 1 if respondent is employed and not on leave
Age, Age^2	Continuous variables for age
Presence of children	= 1 if presence of children in the following age ranges: a) 0-2 b) 3-5 c) 6-10 d) 11-13 e) 14-18
Presence of senior family members	= 1 if family member above 75 years old is present
Tobacco/drug use	= 1 if tobacco/drug use during diary day
Sleeping time	= 1 if sleeping time greater than 7 hours
Year of the interview	Dummy variables for 2007, 2008 in the first wave (2006 as the base category) and 2015, 2016 in the second wave (2014 as the base category)
Holiday	= 1 if diary day was a holiday (New Year's Day, Easter, Memorial Day, the Fourth of July, Labor Day, Thanksgiving Day, Christmas Day)

Table 9. Weighted mean values (control variables).

	Variable	**2006-08**	**2014-16**		**Variable**	**2006-08**	**2014-16**
	Age	40.274	41.136	*Employment*	Has a main job	0.750	0.721
		(*median* = 43)	(*median* = 43)	*Educational attainment*	Less than high school	0.116	0.097
Gender	Women	0.487	0.500		High school diploma	0.271	0.262
	White	0.814	0.785		Some college	0.193	0.186
Race	Black	0.119	0.132		College degree	0.421	0.455
	Other	0.068	0.083	*Household income*	Less than $5,000	0.022	0.021
	Partner present	0.613	0.590		$5,000 to $7,499	0.014	0.011
Presence of children	Toddler	0.116	0.096		$7,500 to $9,999	0.015	0.015
	Pre-school	0.111	0.093		$10,000 to $12,499	0.022	0.022
	Elementary	0.157	0.147		$12,500 to $14,999	0.018	0.018
	Middle school	0.104	0.093		$15,000 to $19,999	0.031	0.034
	High school	0.137	0.127		$20,000 to $24,999	0.045	0.042
	Employed	0.750	0.721		$25,000 to $29,999	0.049	0.046
Diary day	Monday	0.141	0.144		$30,000 to $34,999	0.055	0.046
	Tuesday	0.142	0.147		$35,000 to $39,999	0.054	0.047
	Wednesday	0.139	0.145		$40,000 to $49,999	0.092	0.079
	Thursday	0.145	0.140		$50,000 to $59,999	0.087	0.084
	Friday	0.143	0.140		$60,000 to $74,999	0.119	0.109
	Saturday	0.148	0.143		$75,000 to $99,999	0.149	0.137
	Sunday	0.142	0.141		$100,000 to $149,999	0.137	0.155
	Holiday	0.018	0.014		$150,000 and over	0.091	0.134
Senior member	Above 75 years old	0.025	0.032		Exercise/Act. travel	0.196	0.227
Smoking	Smoke during diary day	0.024	0.018	*Sleeping*	Sleep $\geq$ 7 hours	0.784	0.820

Frazis and Stewart (2012) have provided an accurate examination of why OLS estimation when time use is treated as an independent variable in conjunction with a long-term dependent variable (such as BMI) may result in inaccurate coefficient estimates. This issue is usually addressed accounting for the endogeneity in the time-use variables.

A second model is estimated where eating time and physical activity are indicated as endogenous. A common approach used when dealing with endogeneity is using instrumental variables. Such instruments should be correlated with the endogenous variables on the right-hand side of the model but not with the dependent variable, and they must be excluded from the main model so that their effect on the dependent variable is indirect.

Even when assuming that short-term time use values may be used as a proxy for long-term behaviors (Frazis and Stewart, 2012) finding appropriate instrumental variables may be difficult as they should reflect long-term factors (e.g., seasonal weather changes) instead than short-term ones (e.g., daily weather fluctuations). Selection of instrumental variables follows the approach used in Courtemanche at al. (2021), which relies on the method developed by Lewbel (2012).

Lewbel's method relying on heteroskedasticity (2012) can be used when instrumental variables are not available or to supplement the already identified external instruments. This method relies on heteroskedasticity of the endogenous variables (such as eating time uses) to construct artificial additional instruments $Z_j = (X_j - \bar{X}) \cdot \varepsilon$ where ε indicates the residuals of an 'auxiliary first-stage' regression of some (or all) exogenous variables on the endogenous variables. Lewbel's (2012) approach is used twice: first, all exogenous variable and potential additional external instruments are used to construct the artificial ones in the auxiliary first-stage. Second, all exogenous variables besides the selected external instruments are used to construct the Lewbel's instruments.

External instruments include annual MSA population estimates, a dummy for whether respondents worked from home, away from home or both on the diary day, and dummies which account for the interview season[13]. MSA population estimates are included as in Courtemanche et al. (2021). They also include the number of full service and limited-service restaurants and the number of fitness centers from the QCEW data, which were originally part of the preliminary model estimation. However, there is a very high correlation between population estimates and number of eating establishments (> 0.9) therefore these variables are not included in the final specification of the model. Using dummies for Work from home and away from home dummies as instruments deserves further explanation. While it may be argued that working time in the 24-hour time span preceding the interview may be endogenous, working time is the results of a standard and repeated commitment over time. That the data refers to past years (2006-08 and 2014-16) where flexible working accommodation was not as widely spread as during and after the pandemic. Additionally, as reported in Figure 5, working accommodations remained overall stable among the two waves with working away from home being the preferred option for most respondents. Seasonal dummies are used in absence of external instruments to account for weather data at the MSA level as in Courtemanche et al. (2021).

Table A1 in Appendix A shows the χ^2 statistics for the Breusch-Pagan used to assess the presence of heteroskedasticity in all the endogenous dependent variables. The test is performed following a regression model using all the exogenous control variables in $\boldsymbol{X}$ and the above-mentioned external instruments. Every performed test supported the presence of heteroskedasticity in the eating time use and exercise variables, hence the Lewbel's instruments for those variables can be constructed.

[13] Spring: March, April, May; Summer: June July, August; Fall: September, October, November; Winter: December, January, February.

3. Results

Table 10 presents estimation results using OLS, not accounting for endogeneity. These results outline whether the Hypothesis 1 holds. Columns 1 and 4 show results for the full clean sample in the first and second wave respectively, columns 2 and 5 show results for weekdays and columns 3 and 6 for weekends. The dependent variable is the corrected BMI measure. All models are estimated controlling for the socio-demographic characteristics and using the ATUS EH sample weights. Parameter estimates for socio-demographic variables are included in appendix A.

The expected signs and significance of the estimated coefficients do not completely corroborate the original expectations outlined in the initial hypothesis. More specifically, such expectations stated how primary eating away from home and all secondary eating components were supposed to positively affect BMI. However, results indicate that time spent eating is always negatively correlated with BMI. This indicates that a longer time spent eating corresponds to a better weight status. While this result may seem counterintuitive at first, it is backed up by previous research on this topic (Ohkuma et al., 2015), which states how high eating rates are positively associated with higher BMI even though the causal association between slow eating and BMI should be further investigated by clinical research.

It is interesting to note how primary eating for ‘All days’ during wave 1 (column 1) at home has the smallest coefficient (-0.0103) when compared to secondary eating away home (-0.00226). This means that the BMI is predicted to decrease by around 0.62 if respondents consistently spend 60 minutes eating at home. Conversely, the coefficients for secondary eating away from home is much smaller and would result in a lower BMI reduction of 0.14 per hour spent eating. Results show a similar pattern during wave 2 even if the gap between the two coefficients is reduced. When looking at weekdays (column 2 and 5) versus weekends (column 3 and 6), further differences are observed in both waves. The negative effect of primary eating time at home on BMI is always less pronounced on weekends, although the effect appears to decrease in intensity during the second wave.

Table 10. OLS results, effects of eating time and exercise on corrected BMI (coefficients of control variables[14] omitted).

	2006-08			**2014-16**		
	(1) All days	(2) Weekdays	(3) Weekends	(4) All days	(5) Weekdays	(6) Weekends
FAH Primary Eating	-0.0103***	-0.0123***	-0.00739***	-0.00806***	-0.008863**	-0.006561**
FAFH Primary Eating	-0.000526	-0.00180	0.00135	0.000892	0.0000618	0.00224
FAH Secondary Eating	-0.00125	-0.00159	-0.000466	-0.00325	-0.00179	-0.00520***
FAFH Secondary Eating	-0.00226**	-0.00208**	-0.00299***	-0.00349**	-0.00505***	0.00259
Exercise or active travel	-1.238***	-1.255***	-1.205***	-1.410***	-1.397***	-1.455***
Observations	19,252	9,439	9,813	18,327	9,202	9,125
R-squared	0.073	0.071	0.087	0.067	0.070	0.068

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The directions and magnitudes of the coefficients are overall consistent in both waves, but it is interesting to note a difference between weekends and working days in the second wave: while secondary eating time away from home is significant on weekdays, secondary eating time at home is significant with a similar magnitude on weekends, perhaps because people are more likely to eat and graze at home on weekends.

Despite the significant effect of time spent eating on BMI, physical activity appears to be the major driver for any BMI reduction as can be inferred by looking at the magnitude of the coefficients in Table 9. Engaging in physical exercise or active travel during the interview day for at least 15 or 20 minutes is always associated with lower BMI levels.

[14] Included controls are gender, age, age^2, race, presence of spouse or unmarried partner, age intervals of own household children, employment status, presence of senior members (+75 years old) in the household, household income (dummies), educational attainment, day of the week (interview day), holiday (interview day), interview year, tobacco use during diary day, sleep at least seven hours.

Table 11 shows the results of the IV estimation using Lewbel's instruments. More specifically, of using population estimation, working arrangements dummies and seasonal dummies as the base instruments, supported by additional ones built on the rest of the exogenous variables. The Hansen J statistics is also reported to assess the validity of the included instruments. The Hansen J test is used when the estimated model is overidentified (more instruments than endogenous variables) and it assesses if the instruments are independent from the error term (in other words, it assesses if the instruments only affect the dependent variable indirectly). If the error term is i.i.d., the Sargan test can be used instead. However, in the following models, IV-GMM estimation with robust standard errors has been used.

The Hansen J statistics indicate that instruments are not valid in model 1, therefore the following considerations will refer to column 2 to 6 in Table 11. Some eating modalities trigger different effects on BMI than the ones suggested by the OLS models.

Results are also strongly different between the two waves. In the first wave (columns 2, and 3), primary eating at home has a significant and negative impact on BMI. This result is consistent with previous work from Hamermesh (2010). Secondary eating time away from home is also significant with a negative coefficient, and secondary eating time at home is significant with a negative coefficient only in column 2 (weekdays). Physical activity (omitted in previous studies on the topic) has the predominant effect. However, the coefficients' size suggests that the BMI reduction triggered by primary eating time at home is always greater than the one triggered by secondary eating time. More specifically, weekdays estimates (column 2) indicate that the absolute value of the coefficients referred to secondary eating time at home and away from home respectively are almost four and six times smaller than the absolute value of the coefficient of primary eating time at home. Weekends estimates (column 3) show a similar pattern, with the absolute value of the coefficient of secondary eating time away from home being almost three times smaller than the absolute value of the coefficient of primary eating time at home. Results from the 2006-08 period suggest that the negative association between BMI and secondary eating time away from home is weaker than the negative association between BMI and primary eating time at home. Results seem to partially contradict the initial hypothesis, as a positive association between eating time away from home and BMI was initially expected, but they unequivocally tend to suggest that slow eating is preferred to fast eating independently of the eating location. Results seems to reinforce the outcomes discussed in Kolay et al. (2021), according to which a lower eating speed is associated with a lower BMI and vice versa.

Results for the 2014-16 period (column 4, 5, and 6) are unexpected and therefore suggest that over time, the impact of behaviors on BMI may have evolved. Physical activity has the stronger relationship with BMI and time spent eating is not significant except for secondary eating time at home in column 6.

The findings indicate that a greater amount of time spent on eating, irrespective of the modality (primary vs secondary) and location of consumption, is associated with lower BMI values. This relationship is stronger when the eating activity takes place during the primary eating time at home. Nevertheless, the impact of time spent eating on BMI is significantly attenuated in comparison to that of physical activity. Engaging in at least 15 minutes of exercise or 20 minutes of walking or biking appears to confer a better weight status overall.

Table 12 presents the predicted BMI values for a sample of constructed individuals. These individuals do not correspond to real respondents of the ATUS survey but are instead defined by selecting specific socio-demographic characteristics of interest. The baseline value of FAH and FAFH components is defined based on the average of these variables isolating respondents with the same characteristics as those selected.

Table 12 compares estimates from the first year of available data (2006) and the last one (2016), including a baseline scenario with no exercise or active travel (ACT = 0), a scenario in which the individual engages in exercise while keeping all other factors constant, and a scenario in which the primary eating time at home is doubled while halving the primary eating time away from home (here ACT = 0). Estimates are derived from models 2 and 5 (weekdays).

Table 11. IV results, effects of eating time and exercise on BMI (coefficients of control variables[15] omitted).

	2006-08			**2014-16**		
	(1) All days	(2) Weekdays	(3) Weekends	(4) All days	(5) Weekdays	(6) Weekends
FAH Primary Eating	-0.0127***	-0.0102**	-0.00906**	-0.00674	-0.00342	-0.00757
FAFH Primary Eating	-0.00339	-0.00416	-0.000277	-0.000747	0.000667	-0.000487
FAH Secondary Eating	-0.00132	-0.00273**	0.000546	0.00144	0.00652	-0.00537**
FAFH Secondary Eating	-0.00231*	-0.00172**	-0.00369***	-0.00299	-0.00285	0.00346
Exercise or active travel	-1.282***	-1.622***	-0.635*	-1.173***	-1.100**	-0.853*
Observations	19,252	9,439	9,813	18,327	9,202	9,125
Hansen J Stat.	261.725	219.017	204.125	2221.312	191.040	206.552
p-value	0.0113	0.1957	0.1856	0.3163	0.6992	0.1558
Degrees of freedom	212	202	187	212	202	187

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The 2016 predictions consist of a baseline scenario and a scenario in which the individual engages in physical exercise. Variations in FAH and FAFH are not considered due to the insignificance of the eating time coefficients. The predicted values tend to reflect the trend of increasing BMI from the first to the second wave: for the same socio-demographic characteristics, the predicted BMI for 2016 tend to be higher than the predicted values for 2006, except for the 5th individual. Most individuals fall into the "overweight" category, except for individual 2 and 7, who are predicted to be obese in both the first and second waves, and individual 1, who is predicted to be obese only in the second wave.

[15] Included controls are gender, age, age^2, race, presence of spouse or unmarried partner, age intervals of own household children, employment status, presence of senior members (+75 years old) in the household, household income (dummies), educational attainment, day of the week (interview day), holiday (interview day), tobacco use during diary day, sleep at least seven hours.

Table 12. Predicted BMI by scenario (overweight: BMI > 25, obese: BMI > 30)

		2006			2016	
	Individual	Baseline	w/ exercise	+FAH, -FAFH	Baseline	w/ exercise
1	Woman (Age 29) Race = White Partner = No Age kids = 0 – 2 Employed = Yes $30,000 to $34,999 Some college Sleep less than 7 hours	29.5	27.8	29.3	32.1	31.0
2	Woman (Age 35) Race = Black Partner = Yes Age kids = 3 – 5, 6 – 10 Employed = No $20,000 to $24,999 College degree	30.7	29.1	30.4	31.8	30.7
3	Man (Age 41) Race = White Partner = Yes Age kids = 14 – 18 Employed = Yes $100,000 to $149,999 College degree	28.3	26.7	28.0	29.7	28.6
4	Woman (Age 20), no kids Race = White Partner = No Employed = No $150,000 and over Some college	25.6	24.0	25.4	27.1	26.0
5	Man (Age 20), no kids Race = Other Partner = No Employed = No $100,000 to $149,999 Some college Sleep less than 7 hours	28.4	26.7	28.1	28.2	27.1
6	Man (Age 59) Race = White Partner = Yes Age kids = 14 – 18 Employed = Yes $150,000 and over College degree Smoker	26.7	25.1	26.3	28.3	27.2
7	Man (Age 43) Race = Black Partner = Yes Age kids = 11 – 13 Employed = Yes $75,000 to $99,999 High school diploma Smoker	30.4	28.8	30.1	33.1	32.0

Physical activity is the main driver of BMI reduction and therefore the best way to achieve a healthier lifestyle. In fact, several studies have highlighted the multiple benefits of weight loss. Even relatively small weight loss (starting from 2.5% of an individual's body weight) can lead to improvements in glycemic condition and therefore a lower risk of diabetes, as well as improvement in syndromes related to female reproductive systems such as polycystic ovary and infertility with potentially reduced healthcare and medication costs (Ryan and Yokey, 2017; Espeland et al., 2014). A 5% reduction in body weight can lead to additional benefits such as improvement in cardiovascular conditions, reduction in osteoarthritis pain, decreased risk of developing depressive symptoms, and improved mobility (Ryan and Yokey, 2017). For instance, individual 4 from Table 12 has a baseline BMI of 25.6 (in 2006). This may roughly correspond to, among other possible options, a person who is 5’3’’ tall and whose weight is 144.8 pounds. A 2.5% and 5% reduction of the body weight would therefore entail a 3.62 and a 7.24 lb reduction, which would translate in BMI values of 25.00 and 24.36. Hence, the BMI reduction corresponding to a 2.5% and 5% weight loss in individual 4 is equal to -0.6 and -1.24 respectively, which is smaller than the BMI reduction associated with some level of physical exercise in the 2006-08 period (-1.6) and close to the reduction associates with physical exercise in the 2014-16 period (-1.1).

4. Summary and conclusions

Overweight and obesity rates are a source of increasing concern for the long-term health and well-being of the world population, particularly in developed countries such as the US, where more than a third of citizens are obese and another third are overweight.

This work has examined how time spent eating and eating modalities affect the long-term weight status of US citizens using the main ATUS data and its Eating and Health extra module. The focus of this work was to assess the plausibility of one main hypothesis:

Hypothesis. Primary (PE) and secondary (SE) eating time at home (FAH) and away from home (FAFH) lead to changes in BMI. The following changes were expected:

Eating time use	**Expected change in BMI**
Primary eating at home (FAH_PE)	-
Primary eating away from home (FAFH_PE)	+
Secondary eating at home (FAH_SE)	+
Secondary eating away from home (FAFH_SE)	+

While primary eating time has been previously associated with a lower BMI and secondary eating time with a greater one (Hamermesh, 2010) in previous studies, the relationship between BMI and eating food at home or away from home has been less explored. Recent studies on BMI and physical activity (Courtemanche et al., 2021) have also outlined how time use may be endogenous when used as an explanatory variable. Therefore, both OLS and IV-GMM have been used to estimate econometric models with BMI as the main dependent variable, using working accommodation, seasonal dummies and population estimates ad external instruments.

Results do not completely support the original hypothesis: FAH and FAFH eating time coefficients all have a negative sign, meaning that eating for longer times is associated with lower BMI values no matter the location. Unexpectedly, there are no sign differences between primary and secondary eating time. Despite the unequivocal direction of these changes, the magnitude of the coefficient for primary and secondary eating time use is quite different, with primary eating being the smallest (therefore, the one associated with the greatest BMI reductions). All estimated models controlled for whether the respondents engaged in physical activity during the diary day and suggest that exercise and active travel have indeed a stronger negative association with BMI.

When using the IV regression model, time spent eating at home has a negative and significant effect on BMI in the first wave, but no effect in the second one. However, the effect of primary eating at home on BMI is stronger. Secondary eating does not frequently trigger any effect on BMI irrespective of eating modality. Results seem to suggest that primary eating time used to be more effective for BMI reduction, and prioritizing conscious eating over snacking could be considered a good strategy to attenuate weight gain during working days. Results for the first wave are also supported by previous findings from Hamermesh (2010). Unfortunately, this effect appears to have dissipated over the years and in more recent periods for which data is available, it is no longer possible to link weight status with eating time.

Physical activity defined as exercising for at least 15 minutes or walking/biking for at least 20 minutes during the diary day remains the only factor with a negative and significant effect on BMI, even if the magnitude of this coefficient has decreased over time.

There are many official sources to which one can refer for a healthier dietary lifestyle. Numerous guidelines are distributed for this purpose, such as the Dietary Guidelines for Americans issued by the Center for Diseases Control and Prevention. However, such guidelines do not appropriately address the health benefits of slow eating, which may have a limited but still positive effect on the weight status of U.S. citizens, as outlined by the results of this study. Additionally, further measures could be considered to promote physical activity. Exercise is an excellent way to effectively lose weight, but cycling or walking can be also effective. Reducing car dependency in metropolitan areas can help people become more engaged in active travel during or between their daily activities. This may be achieved by appropriate urban planning interventions such as the improved availability of sidewalks and bike paths in public areas. Such program and infrastructural interventions are more common in European countries and have proven themselves successful (Pucher et al., 2010).

The current study has some limitations. As previously mentioned, eating time at home and away from home is considered a proxy for the quantity and quality of food, but missing data on the nutritional value of meals leads to an omitted variable bias. Additionally, it is not possible to differentiate between full and limited-service restaurants regarding FAFH consumption, which may sell more or less healthy and nutritious meals depending on the establishment. Similarly, the study could only determine whether a food purchase was followed by eating or grazing at home, but it was not possible to identify eating occasions in which food was prepared at home and eaten elsewhere. To address the first issue, eating time at home with a previous food purchase was flagged as FAFH consumption (given that it was not prepared by the respondents). However, the second issue could not be addressed in this study due to data constraints. Previous studies (Tajeu and Sen, 2016) on time use and BMI were able to rely on data on secondary drinking for the 2006-08 period, but the same data was not collected during the 2014-16 period and hence was not included in the analysis. Future research should aim to fill this gap on secondary drinking. The data limitation arisen by the absence of long-term weather data has been partially addressed using seasonal dummies, which vary temporally but not geographically Long-term weather data capturing geographical variation could be incorporated as instruments in in future modeling. Finally, following up with previous ATUS respondents could also be beneficial: a second set of observations related to the same individuals could allow researcher to account for unobserved heterogeneity due to time-invariant factors such as genetics.

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Appendix A.

Table A1. χ^2 statistics from the Breusch-Pagan test for heteroskedasticity (d.o.f. = 1).

	2006-08			2014-16		
	All days	Weekdays	Weekends	All days	Weekdays	Weekends
FAH Primary	1,224.71	758.72	290.53	1,616.40	962.70	436.02
FAFH Primary	1,762.67	878.24	1,028.99	1,581.50	440.07	1,107.79
FAH Secondary	26,245.72	21,609.47	4,450.17	11,988.58	9,523.14	7,747.60
FAFH Secondary	12,368.78	7,092.02	8,214.10	6,268.66	3,320.86	12,010.26
Exercise/Active travel	816.77	393.38	545.19	808.98	419.66	453.67

Table A2. OLS results (control variables)

	2006-08			2014-16		
	All days	Weekdays	Weekends	All days	Weekdays	Weekends
Women	-0.238**	-0.171	-0.425***	0.768***	0.679***	0.987***
Age	0.308***	0.305***	0.307***	0.407***	0.421***	0.372***
Age^2	-0.00280***	-0.00283***	-0.00263***	-0.00406***	-0.00425***	-0.00357***
White	-0.427	-0.563	-0.0324	0.0111	-0.0800	0.232
Black	0.768**	0.477	1.486***	0.926***	0.899**	0.991**
Other	-	-	-	-	-	-
Partner present	0.284*	0.244	0.415**	0.159	0.0309	0.472*
Toddler	0.234	0.141	0.467**	0.339	0.407	0.232
Pre-school	0.00620	0.0146	-0.0454	-0.138	-0.0314	-0.396
Elementary	-0.154	-0.109	-0.241	-0.345*	-0.439*	-0.159
Middle school	-0.134	-0.149	-0.0665	-0.0333	-0.0711	0.0823
High school	0.0812	0.0336	0.201	0.283	0.517**	-0.263
Employed	-0.589***	-0.625***	-0.545***	-0.613***	-0.603**	-0.567**
Senior 75+	1.201***	1.029*	1.560***	0.950	1.154	0.420
Sleep < 7 hours	-0.419***	-0.430**	-0.344	-0.601	-0.403	-1.106
Smoking	-1.089***	-0.978**	-1.828**	-0.449**	-0.418*	-0.488
Less than $5,000	-	-	-	-	-	-
$5,000 to $7,499	0.545	0.203	1.291	0.984	1.418	0.115
$7,500 to $9,999	0.471	0.165	1.135	1.364*	1.807*	0.439
$10,000 to $12,499	1.524**	1.535*	1.283*	0.499	1.216	-1.199
$12,500 to $14,999	1.692**	1.590*	1.841**	1.295*	1.878**	0.170
$15,000 to $19,999	0.601	0.0665	1.814**	0.522	1.132	-0.783
$20,000 to $24,999	0.680	0.637	0.683	0.985*	1.538**	-0.221
$25,000 to $29,999	0.457	0.266	0.870	0.412	0.683	0.0730
$30,000 to $34,999	0.437	0.452	0.369	1.445**	1.837**	0.534
$35,000 to $39,999	0.475	0.323	0.749	1.300**	1.767**	0.322
$40,000 to $49,999	0.780	0.790	0.661	0.289	0.590	-0.287
$50,000 to $59,999	0.571	0.536	0.570	0.366	0.448	0.278
$60,000 to $74,999	0.349	0.221	0.550	0.0493	0.433	-0.724
$75,000 to $99,999	-0.0590	-0.187	0.124	0.427	1.053	-0.950
$100,000 to $149,999	-0.180	-0.327	0.0509	-0.379	0.0727	-1.345*
$150,000 and over	-1.168**	-1.438**	-0.665	-1.343***	-0.865	-2.295***
Less than high school	-	-	-	-	-	-
High school diploma	0.314	0.649**	-0.501	0.866***	1.258***	-0.0523
Some college	0.724***	1.036***	-0.0367	0.944***	1.271***	0.118
College degree	-0.749***	-0.457*	-1.441***	-0.140	0.170	-0.876**
Monday	-	-	-	-	-	-
Tuesday	0.178	0.189	-	0.110	0.116	-
Wednesday	0.0178	0.0319	-	0.0341	0.0279	-
Thursday	0.256	0.272	-	0.0388	0.0435	-
Friday	0.101	0.119	-	-0.331	-0.320	-
Saturday	-0.00462	-	-	0.131	-	-
Sunday	0.221	-	0.246	0.242	-	0.146
Holiday	0.650	0.883	0.147	0.243	0.518	-0.608
2007	0.268*	0.287	0.207	-	-	-
2008	0.267*	0.205	0.410**	-	-	-
2015	-	-	-	-0.0187	-0.0257	-0.00223
2016	-	-	-	0.0642	0.163	-0.144
Constant	22.09***	22.40***	21.51***	20.74***	19.92***	22.54***

Table A3. IV results (control variables)

	2006-08			2014-16		
	All days	Weekdays	Weekends	All days	Weekdays	Weekends
Women	-0.246**	-0.222	-0.400***	0.776***	0.690***	1.007***
Age	0.305***	0.273***	0.310***	0.408***	0.422***	0.380***
Age^2	-0.00276***	-0.00248***	-0.00264***	-0.00407***	-0.00427***	-0.00364***
White	-0.436	-0.453	-0.0685	0.0344	-0.0156	0.221
Black	0.717**	0.609*	1.447***	0.954***	1.027**	0.981**
Other	-	-	-	-	-	-
Partner present	0.293*	0.477***	0.444**	0.140	-0.00882	0.464*
Toddler	0.224	0.0294	0.491**	0.345	0.419	0.259
Pre-school	0.00605	-0.0532	-0.0397	-0.137	-0.0374	-0.382
Elementary	-0.157	-0.0726	-0.226	-0.340*	-0.422*	-0.156
Middle school	-0.139	-0.110	-0.0779	-0.0267	-0.0596	0.0811
High school	0.0742	0.0648	0.208	0.291	0.542**	-0.259
Employed	-0.592***	-0.469**	-0.543***	-0.545***	-0.474*	-0.562**
Senior 75+	1.206***	0.576	1.564***	0.926	1.113	0.397
Sleep < 7 hours	-0.427***	-0.526***	-0.339	-0.460**	-0.419**	-0.498
Smoking	-1.109***	-1.134***	-1.831***	-0.588	-0.364	-1.111
Less than $5,000	-	-	-	-	-	-
$5,000 to $7,499	0.518	0.173	1.321	1.014	1.498	0.118
$7,500 to $9,999	0.448	0.296	1.149	1.382*	1.920*	0.432
$10,000 to $12,499	1.526**	1.524**	1.265*	0.518	1.266	-1.187
$12,500 to $14,999	1.679**	1.050	1.873**	1.310*	1.882**	0.211
$15,000 to $19,999	0.579	0.156	1.821**	0.526	1.136	-0.740
$20,000 to $24,999	0.681	0.564	0.717	1.004*	1.556**	-0.182
$25,000 to $29,999	0.447	-0.0808	0.910	0.443	0.737	0.125
$30,000 to $34,999	0.426	0.0793	0.406	1.474**	1.892**	0.541
$35,000 to $39,999	0.472	0.0848	0.779	1.327**	1.793**	0.396
$40,000 to $49,999	0.775	0.265	0.706	0.320	0.641	-0.234
$50,000 to $59,999	0.564	0.213	0.572	0.397	0.529	0.329
$60,000 to $74,999	0.347	-0.184	0.573	0.0810	0.473	-0.708
$75,000 to $99,999	-0.0619	-0.489	0.130	0.455	1.103	-0.904
$100,000 to $149,999	-0.170	-0.740	0.0567	-0.350	0.112	-1.298*
$150,000 and over	-1.151**	-1.904***	-0.699	-1.323***	-0.836	-2.288***
Less than high school	-	-	-	-	-	-
High school diploma	0.324	0.596**	-0.489	0.875***	1.257***	-0.0311
Some college	0.738***	1.019***	-0.0175	0.945***	1.254***	0.136
College degree	-0.713***	-0.291	-1.449***	-0.154	0.120	-0.899**
Monday	-	-	-	-	-	-
Tuesday	0.181	0.222	-	0.121	0.126	-
Wednesday	0.0265	0.113	-	0.0416	0.0472	-
Thursday	0.262	0.303	-	0.0493	0.0550	-
Friday	0.123	0.198	-	-0.311	-0.310	-
Saturday	0.0284	-	-	0.139	-	-
Sunday	0.244	-	0.241	0.230	-	0.148
Holiday	0.665	0.360	0.132	0.277	0.507	-0.528
2007	0.268*	0.264	0.195	-	-	-
2008	0.265*	0.183	0.400**	-	-	-
2015	-	-	-	-0.0216	-0.0207	-0.0184
2016	-	-	-	0.0622	0.165	-0.161
Constant	29.27***	29.02***	28.89***	30.42***	30.12***	30.47***