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HETEROGENEITY IN PLACE EFFECTS ON HEALTH:
THE CASE OF TIME PREFERENCES AND ADOLESCENT OBESITY

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ABSTRACT

We leverage a natural experiment in combination with data on adolescents' time preferences to assess whether there is heterogeneity in place effects on adolescent obesity. We exploit the plausibly exogenous assignment of military servicemembers, and consequently their children, to different installations to identify place effects. Adolescents' time preferences are measured by a validated survey scale. Using the obesity rate in the assigned installation county as a summary measure of its obesity-related environments, we show that exposure to counties with higher obesity rates increases the likelihood of obesity among less patient adolescents but not among their more patient counterparts.

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1. Introduction

Efforts to reign in the obesity epidemic in the U.S. have had limited success. Obesity rates among adults and children in the U.S. are at an all-time high at 42% among adults and 19% among children ages 2-18 years (Fryar, Carroll, and Afful 2020; Hales et al. 2020). The thinking behind what drives obesity, and consequently how to address it, has evolved considerably over the last four decades. Obesity prevention efforts have shifted from their initial focus on individual-level factors, such as lifestyle choices, to place-based environmental factors. The shift was due, in part, to evidence of limited effectiveness of behavior modification interventions focused at the individual level (Minkler 1999). Since then, a large literature has studied the role of place-based factors, such as built, social, economic and policy environments, on obesity and related behaviors (Diez Roux and Mair 2010; Diez Roux 2001; Arcaya et al. 2016; Tseng et al. 2018; Lam et al. 2021; Kim, Cubbin, and Oh 2019). However, this literature too has found limited effectiveness even among efforts to alter the built, policy, and economic environments through, for example, the introduction of supermarkets and green spaces, taxation of sugary beverages, or through other community- and school-based interventions (Dubowitz et al. 2015; Bleich et al. 2013; Lam et al. 2021; Mayne, Auchincloss, and Michael 2015; Fletcher, Frisvold, and Tefft 2010a; Fletcher, Frisvold, and Tefft 2010b).

The apparent limited success of obesity prevention efforts may be attributed, at least in part, to two empirical challenges. First, our understanding of the causal effects of place-based environmental factors on obesity remains limited due to the methodological challenges resulting from self-selection of individuals into places. It is difficult to disentangle correlation from causation in observational data – an issue that has been highlighted most recently in surveys of the literature on place effects on health (Couillard et al. 2021; Deryugina and Molitor 2021;

Chyn and Katz 2021). These surveys have highlighted a subset of studies that leverage movers to assess the causal effects of place, although they focus primarily on adults and non-health outcomes. Moreover, with the exception of the Moving to Opportunity housing mobility experiment, the concern regarding potential endogeneity of moving itself, and of moving to specific places, remains a hurdle in this literature.

The second challenge is that the focus on "one size fits all" strategies ignores potential heterogeneity in place effects on obesity. In other words, place-based factors may not influence all individuals equally and this heterogeneity may explain the small or null effects observed at the population level. Correlational studies suggest heterogeneity with respect to sociodemographic characteristics such as gender, race-ethnicity, and socioeconomic status. These studies often find stronger associations of place with obesity in females versus males but find few consistent patterns with respect to other socio-demographic characteristics (Tcymbal et al. 2020; Duncan et al. 2012; Kranjac et al. 2021; Kranjac et al. 2019; Daniels et al. 2021; Galvez, Pearl, and Yen 2010; Kim, Cubbin, and Oh 2019; Jia et al. 2019). However, efforts to assess heterogeneity are absent from causal studies, and consequently, we have little understanding of how the effects of place might vary by individual. Identifying the sources of heterogeneity within a causal framework can offer insights into developing tailored interventions for obesity prevention instead of a one-size-fits-all approach.

In this paper, we assess whether time preferences represent an important source of heterogeneity in understanding the effect of place on obesity. Healthy behaviors typically involve intertemporal tradeoffs. For example, eating healthy often means forgoing tempting, unhealthy foods in lieu of more healthy options today, but the health benefits of such choices often accrue later in life. Indeed, research suggests that individuals who are more patient are more likely to engage in healthy behaviors and have better health outcomes, such as lower body mass index and/or obesity (Golsteyn, Grönqvist, and Lindahl 2014; Seeyave et al. 2009; Courtemanche, Heutel, and McAlvanah 2015; Sirois 2004). The intuition is that less patient individuals, who place relatively greater weight on immediate gratification, may be less likely to engage in the healthy choices offered in their environments because those choices provide largely delayed benefits. If time preferences influence how individuals respond to their environments, this may help explain more generally why interventions, programs and policies designed to increase healthy behaviors may not appear to be successful at the population level.

We use a natural experiment in combination with data on adolescents' time preferences to assess heterogeneity in place effects on adolescent obesity. To our knowledge, this paper provides the first quasi-experimental evidence on this issue. Adolescence represents a particularly compelling age to study this question. It is a crucial stage for developing a sense of self and identity and their preferences, goals, motivations, and behaviors evolve towards independence and autonomy (Becht et al. 2016; Meeus et al. 2005). Further, adolescent obesity rates have quadrupled during the past thirty years, making the study of how to reduce adolescent obesity particularly policy-relevant (Ogden et al. 2014; NCHS 2012).

To identify the causal effects of place on adolescent obesity, we leverage the plausibly exogenous assignment of military families to different locations. Specifically, we measure adolescents' exposure to obesity-related environments using the obesity rate in the county where their military parent's assigned installation is located. The county obesity rate is a summary, or realized, measure of all environmental influences on obesity in that county. We combine this natural experiment with data we collected on time preferences from adolescents using a validated survey scale. Taken together, this data provides novel empirical evidence on whether adolescents with less patient time preferences face a greater risk of obesity as a result of exposure to obesogenic environments relative to their more patient counterparts.

Our data come from the Military Teenagers Environments, Exercise and Nutrition Study (M-TEENS), a cohort study of adolescents in military families. In prior work, we analyzed baseline data from this cohort at ages 12-13 years and showed that adolescents in military families "assigned" to counties with higher obesity rates were more likely to be overweight or obese, although this effect was small (Datar and Nicosia 2018). In a related study with the same baseline data, we also found that some environmental features, specifically the neighborhood food environment, were unrelated to adolescents' dietary behaviors or BMI (Shier, Nicosia, and Datar 2016), suggesting that food environments may not matter for obesity prevention. One explanation for these small and null effects, both in our studies and in the literature more broadly, is that average effects may mask heterogeneity. Therefore, we examine heterogeneity on the basis of time preferences using newly collected data from the same cohort in a subsequent wave.

Our results indicate that time preferences are critical to understanding place effects on adolescent obesity. On average, a 10 percentage point increase in the obesity rate of the installation county is associated with a 5 percentage point higher probability of being obese. As predicted, this relationship becomes stronger among adolescents with less patient time preferences, suggesting that the adverse impacts of obesogenic environments are amplified for less patient adolescents. Specifically, the probability of being obese is as much as 7 percentage points higher for adolescents at the 25th percentile of the time preference distribution, but is only 2 percentage points higher for those at the 75th percentile. In fact, patience almost completely offsets the adverse effects of obesogenic environments for adolescents near the 90th percentile of the time preference score distribution. These findings are robust to several sensitivity analyses, including alternate measures of exposure to obesogenic environments, instrumental variables estimation, and corrections for bias in self-reports of height and weight. Finally, in exploratory analyses decomposing the overall place effects into those attributable to the built, social and economic environments separately suggest that heterogeneity based on time-preferences may be strongest for place-based features relating to the built environment.

The remainder of the paper is organized as follows. Section 2 discusses the relevant literatures, including neighborhood effects on obesity, and the link between time preferences and health. Section 3 describes the data and measures, Section 4 describes the empirical approach, which leverages our natural experiment for identification. And Sections 5 and 6 report the results and conclusions, respectively.

2. Background

Literature on Place Effects on Obesity

A large literature, predominantly in the public health and epidemiology disciplines, has examined the effects of place spanning the built, socioeconomic, and policy contextual environments on obesity.[1] This literature has been reviewed elsewhere and suggests a limited

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[1] A separate literature in the economics and sociology disciplines has studied neighborhood effects on social, educational, economic and other health outcomes (Bilger and Carrieri 2013; Damm 2014; Deutscher 2020; Ludwig et al. 2008; Chetty, Hendren, and Katz 2016; Chetty and Hendren 2018) and has been surveyed most recently in Deryugina and Molitor (2021) and Chyn and Katz (2021).

role for environments in influencing obesity (Arcaya et al. 2016; Diez Roux and Mair 2010; Ding and Gebel 2012; Feng et al. 2010; Mayne, Auchincloss, and Michael 2015; Tseng et al. 2018; Lam et al. 2021). However, the majority of this work is based on observational study designs that are limited in their ability to draw causal inferences.

Here, we briefly review a smaller economics literature that has employed quasi-experimental or experimental approaches that are more amenable to causal identification. For example, an instrumental variables approach has been used to assess effects of a specific feature of the built environment, such as access to retail food outlets such as fast food, restaurants, and supermarkets. These studies exploit variation in the expansion of such outlets (e.g. Walmart supercenters), timing of exposure to these outlets, or geographic features near these outlets (e.g. proximity to highways) to identify their impacts on obesity. Some studies find significant effects of proximity to these outlets (Currie et al. 2010; Courtemanche and Carden 2011; Dunn 2010) while others do not find any effects (Anderson and Matsa 2011; Dunn 2010; Allcott et al. 2019), which raises concerns about whether heterogeneity plays a role in the mixed findings.

Other studies have taken the approach of looking at the impact of neighborhoods as a whole instead of focusing on specific features. The most well-known among these is the Moving to Opportunity (MTO) housing experiment. MTO randomized individuals from very low-income neighborhoods to receive housing vouchers to move into higher income neighborhoods. The study's findings indicated that moving to a higher income neighborhood was associated with improved mental and physical health, including lower risk of extreme obesity and diabetes (Ludwig et al. 2011; Sanbonmatsu et al. 2012). However, another study that further explored the mechanisms underlying the observed effects on obesity in the MTO experiment found that they were not explained by neighborhood-level factors such as food prices, restaurant and food store availability, the availability of physical activity facilities, the prevalence of crime, or population density, suggesting that other factors might be at play (Zhao, Kaestner, and Xu 2014).[2]

Most relevantly, our own prior work, using the same natural experiment as this study, assesses the effects of place as a whole as well as those of specific environmental features on obesity. Military installation assignments generate plausibly exogenous variation in exposure to places, and its associated obesogenic environments, that we used to identify place effects on adolescents' and parents' obesity. With the adult obesity rate in the county of the servicemember's assigned installation as a "realized" or summary measure of all obesogenic environments in the community, we found that adolescents ages 12-13 years and their parents assigned to installations in counties with higher obesity rates were more likely to be obese (Datar and Nicosia 2018). Since time at installation is also plausibly exogenous because the military determines the timing and length of stay at an installation, we also examined whether this relationship varied by time at installation and found that it was stronger among families who had been at the assigned installation longer and, as should be expected, was absent for families who had recently arrived at the assigned installation. These results support the idea that the obesogenic environment, as a whole, has a causal effect on obesity, although the estimated effect

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[2] In another related study aiming to identify the impact of neighborhoods as a whole, (Ou 2019) used data from the California Health Interview Survey and exploited variation in the number of years individuals had lived in their neighborhood to identify neighborhood effects on adult BMI. The study found no relationship between neighborhood exposure and adult BMI. However, unobserved individual level characteristics that are correlated with both BMI and moving may limit causal identification.

size was small. We also explored what specific environmental features contributed to obesity in that study and in a series of additional papers published using the same data (Datar and Nicosia 2018; Richardson et al. 2020; Shier, Nicosia, and Datar 2016; Datar et al. 2015; Datar and Nicosia 2017). The food and physical activity related environments in the installation county, residence neighborhood, and schools (e.g., types of food outlets, fitness and recreation facilities, policies regulating access to unhealthy foods) had either no association, or at best a small association, with BMI and obesity outcomes. However, we did find support for the role of social influence on adolescent obesity (Datar and Nicosia 2018; Nicosia and Datar 2020; Datar, Mahler, and Nicosia 2020) – adolescents exposed to communities with higher obesity reported a higher ideal body type, suggesting social norms related to body size as a potential mechanism.

Understanding whether these findings suggest a limited role for environments or whether they mask important heterogeneity in the environments' effects is critical for determining the nature of obesity prevention efforts. Heterogeneity can lead to inconclusive or misleading findings regarding place effects (Brand and Thomas 2013). Despite its importance, it remains poorly understood in this literature. Heterogeneity in place effects has mainly been assessed with respect to sociodemographic characteristics such as gender, race-ethnicity, and socioeconomic status. These studies have tended to find stronger associations in females than males but few consistent patterns have emerged with respect to other socio-demographic characteristics (Tcymbal et al. 2020; Duncan et al. 2012; Kranjac et al. 2021; Kranjac et al. 2019; Daniels et al. 2021; Galvez, Pearl, and Yen 2010; Kim, Cubbin, and Oh 2019; Jia et al. 2019). This may be because there is considerable variation in the specific environmental feature being studied (e.g. food environment, walkability, safety, socioeconomic context), the geographic coverage of the study samples (e.g. national versus regional, urban versus rural), and methodologies, which complicates the ability to draw strong conclusions from this literature. But perhaps even more concerning, these studies are based on observational studies and focus primarily on sociodemographic rather than behavioral characteristics. Identifying the critical sources of heterogeneity in a quasi-experimental setting can offer important insights into developing tailored interventions for obesity prevention instead of a one-size-fits-all approach.

Literature on Time Preferences and Health Behaviors

Preferences, particularly time-preferences, are emerging as likely contributors to heterogeneity given the well-documented link between patience and health behaviors and outcomes. In a series of studies, time preferences have been elicited using laboratory methods and then linked to real-world outcomes including health behaviors. Among adults, time preferences predict health, smoking, drinking and drug abuse behaviors (Kirby, Petry, and Bickel 1999; Harrison et al. 2005; Khwaja, Sloan, and Salm 2006; Chabris et al. 2008; Weller et al. 2008; Bradford et al. 2017), and demand for medical screening tests or vaccines (Chapman and Coups 1999; Picone, Sloan, and Taylor 2004). Importantly, a higher level of impatience in childhood and/or adolescence has been linked to greater expenditures on alcohol and cigarettes (Sutter et al. 2013), a greater number of disciplinary referrals at school (Castillo et al. 2011), lower high school completion rates (Castillo, Jordan, and Petrie 2019) and adverse labor market outcomes in adulthood.

Directly relevant to our work is evidence from recent studies that have found that higher impatience in childhood and adolescence is associated with higher BMI (Seeyave et al. 2009; Sutter et al. 2013; Caleza et al. 2016; Samek et al. 2021). Recent studies also show that individuals (including adolescents) with low future-orientation (i.e. low self-control) make poor diet and exercise choices (Conell-Price and Jamison 2015; de Ridder et al. 2012; Wills et al. 2007; Sutter et al. 2013) and have higher BMI (Borghans and Golsteyn 2006). And most recently, time preferences also explained why food purchase decisions made for immediate consumption were less healthy than those made for future consumption (Sadoff, Samek, and Sprenger 2020).

While there is emerging evidence linking time preferences to BMI and related behaviors, whether they influence place effects on obesity and related behaviors remains largely unexplored. An exception is Courtemanche and colleagues' analysis of panel data from the National Longitudinal Study of Youth (NLSY), which finds that impatient adults exhibit the largest weight gain when food prices fall (Courtemanche, Heutel, and McAlvanah 2015). Thus, preliminary evidence suggests that time preferences can be important moderators of the impact of the environment on obesity-related behaviors, albeit in observational data. This finding is consistent with an emerging literature, which shows that time preferences are important moderators with respect to effects other outcomes involving intertemporal tradeoffs, such as educational achievement.[3]

3. Data

[3] Time preferences have also been assessed with respect to effects on educational achievement and other outcomes. For example, researchers have found that impatient children are more affected by incentives for better grades than their patient counterparts because they are more motivated by immediate rewards (Oswald and Backes-Gellner 2014).

The Military Teenagers Environment Exercise and Nutrition Study (M-TEENS) was designed to leverage the natural experiment generated by the periodic relocation of military families, to assess how place-based environments affect obesity in children. Military servicemembers are periodically reassigned to different installations, typically every 3-4 years, based on the needs of the military. According to Army Regulation 614-200, "the primary goal of the enlisted personnel assignment system is to satisfy the personnel requirements of the Army". Thus, the primary consideration when assigning a servicemember is their "current qualification and ability to fill a valid requirement". In exceptional circumstances (e.g. specialized medical needs of a family member, military couples), a servicemember may be assigned among a subset of installations that meets their special needs. As a result, the assignment of servicemembers to installations at a given point in time is arguably exogenous to the outcome of interest, obesity.

Between Spring 2013 and Summer 2014, M-TEENS recruited just over 1,100 children ages 12-13 years from Army enlisted families located primarily at 10 large divisional posts and 2 medium-sized installations spread across all Census regions. Families were eligible to participate if: 1) the service member did not intend to leave the military within the coming year, 2) the child resided with the enlisted parent at least half-time, and 3) the child was enrolled in public or Department of Defense Education Activity schools. Families were recruited between Spring 2013 and Summer 2014 via the military parent's email and mailing addresses obtained from the Army's personnel records. The focal child and one parent were invited to complete surveys online at baseline and in three follow-up waves.

Our analysis sample uses data from the 2017-2018 wave, which collected data on adolescents' time preferences for the first time. In this wave, 491 adolescents completed the survey. The analysis sample was further restricted to adolescents whose school and residence counties were within 100 miles of the installation and lived with their parents at least some of the time. This restriction was necessary to ensure that adolescents' would be potentially exposed to the parent's assigned installation. This yielded a final analysis sample of 400 adolescents with complete data.[4] Table 1 reports summary statistics for this sample (mean age =17 years, 39% white, 21% Black, 25% Hispanic, 47% have at least one parent with a 4-year college degree).

The study was approved by the Institutional Review Boards at RAND, University of Southern California, and the Army's Human Research Protection Office. Parent consent and child assent were obtained online prior to participation.

Measures

BMI and Obesity

Adolescents' height and weight information was collected primarily via self-reports because it was the most cost-effective way of collecting this data from a geographically-dispersed sample. However, to address concerns about potential measurement error in self reports, a subsample (N=216) of adolescents were also measured by trained staff using guided videoconference sessions using measurement equipment shipped to respondents, an approach

[4] We compared baseline data for adolescents who were included in our sample to those were not and found no systematic differences in their sociodemographic characteristics, BMI, or their assigned installation county's obesity rate at baseline. These results are reported in Appendix Table 1.

that yielded high accuracy in a pilot study (Ghosh-Dastidar, Nicosia, and Datar 2020)[5]. This subsample was used as a validation sample to correct for bias in self-reports of adolescents' height and weight for the full sample using regression calibration (Ghosh-Dastidar et al. 2016). The self-reported and "corrected" height and weight were used to construct age- and gender-specific BMI z-scores and BMI percentiles based on the 2000 BMI-for-age and gender growth charts issued by the Centers for Disease Control and Prevention. A child was classified as obese if the BMI percentile was greater than or equal to 95. In our sample, 13% of adolescents were classified as obese based on the age- and sex-specific growth charts (Table 1).

Installation County Obesity Rate

Exposure to obesogenic environments was measured using the adult obesity rate in the county where the family's current installation was located. The installation county obesity rate (*InstaCOR*) is a useful summary (or realized) measure of all potential obesogenic influences in the county. Installation county, instead of residence county, was used to construct our primary exposure measure (akin to an intent-to-treat analysis) because, as explained later, residential choice at a given installation may be less exogenous. Moreover, military families regularly access the installation for work, health care, shopping (e.g. Commissary, Post-Exchange), recreation (e.g. Youth programs), or education and so are exposed to the installation county regardless of where they live.

[5] Pilot study participants were measured by trained staff using the same study-provided equipment immediately after the guided videoconference sessions.

The “assigned” installations of the study sample were spread across 30 states, 57 counties, in all Census regions. County obesity rates for each of these installation counties were obtained from the Robert Wood Johnson Foundation’s County Health Rankings data[6] and were linked to the M-TEENS sample by installation. The county obesity rates are from the 2018 release of the County Health Rankings data, which are based on estimates computed by the US Centers for Disease Control and Prevention by pooling the 2013-2015 Behavioral Risk Factor Surveillance System dataset. The lagged county obesity data were preferred because of the typical length of time at installation for our sample.

Descriptive statistics for the installation and composite COR measures are provided in Table 1. The mean (SD) of *installation COR* in our sample was 30% (4.2%) and ranged from 18.3% (Arlington county, VA) to 37.1% (Christian county, KY).

Time Preferences

Our time preference measure is a validated 12-item survey called the Consideration of Future Consequences (CFC) scale (Strathman et al. 1994). In the survey, adolescents rated how characteristic each statement was of them on a 5-point Likert scale, including statements such as “Often I engage in a particular behavior in order to achieve outcomes that may not result for many years” and “I only act to satisfy immediate concerns, figuring the future will take care of itself.” The responses were averaged over the 12 questions (with higher numbers generally indicating more patience, but reverse-coding statements like “I only act to satisfy immediate

[6] https://www.countyhealthrankings.org/explore-health-rankings/measures-data-sources. Last accessed 2/25/21.

concerns."). The time preference scores ranged from 1.8 to 4.7 with a mean (SD) of 3.28 (0.61) (Table 1).

We chose to use the CFC scale rather than alternative measures of time preferences for a few reasons. First, the CFC Scale has been widely used in the psychology literature to study self-regulating behaviors in health and finance. Second, the CFC scale has been shown to be correlated with personality traits associated with self-control (Joireman et al. 2008; Joireman, Anderson, and Strathman 2003; Joireman, Strathman, and Balliet 2006). A recent meta-analysis also showed that the CFC scale correlates well with a host of health-related behaviors including diet and exercise (Murphy and Dockray 2018; Samek et al. 2021). Third, in a separate study aimed at understanding the effectiveness of different ways to elicit time preferences in our sample of adolescents, we showed that time preferences elicited using the CFC were associated with BMI and health-related behaviors (Samek et al. 2021).[7] In contrast, time preferences elicited using monetary trade-off tasks commonly used in the experimental economics literature did not correlate with BMI in our sample (Samek et al., 2021). One benefit of the CFC scale over questions about monetary trade-offs is that it is easier to explain and therefore easier to implement remotely. The CFC is similar to the "preference survey module" – a survey with questions on risk, time and social preferences that has been proposed by Falk et al. (Falk et al. 2016) and is gaining widespread use in economics (Falk et al. 2018).

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[7] This related study used the same set of data that we use here, but did not examine the association of neighborhood environments with obesity, nor did it consider time preferences as a mediator for obesity.

Covariates

Covariates included adolescents' gender and race-ethnicity, parents' marital status, military parent's rank, indicator for military parent's active duty status[8], annual household income, time at installation, and on-installation residence.[9] Besides adolescent's gender and race-ethnicity, which was reported by the respondent, all other covariates were parent-reported. Covariates also included the adolescent's risk preferences, as measured by a single question where respondents were asked to rate their willingness, in general, to take or avoid risk on a scale of 1 (very unwilling to take risks) to 10 (very willing to take risks). Time preferences are closely linked to risk preferences, since choosing to wait for a reward also assumes some level of risk taking. As such, in our preferred regression specifications, we also control for risk preferences. Descriptive statistics for these covariates are reported in Table 1.

4. Empirical Approach

[8] We controlled for active duty status to account for that fact that some portion of military parents in our cohort would experience retirement due to their natural career progression. The vast majority of those who were retired at the time of survey had done so within the last two years and had remained at their last duty assignment. Sensitivity analyses on the active duty sample yielded similar results, but reduced precision due to smaller sample size ($p<0.10$).

[9] Adolescent's age was not included since the distribution of age in our sample was very narrow. The cohort was recruited as 12-13 year olds and, moreover, BMI z-scores are already age and gender normed.

Our estimation model is shown by the linear regression in Eq (1), where $Obese_{ic}$ is an obesity indicator for adolescent *i* in county *c*; *InstaCORc* is the obesity rate for the installation county; $TimePref_i$ is the CFC scale score for adolescent *i*, the vector *X* includes individual and family level covariates described earlier, and ε_{ic} is the error term. The variables *InstaCOR* and *TimePref* are de-meaned for easier interpretation of the estimates. The coefficient β_1 captures the effect of *InstaCOR* on obesity risk for an adolescent with time preferences at the mean. We expect β_1 to be greater than zero i.e. exposure to more obesogenic counties should increase the adolescent's risk for obesity. The coefficient β_2 captures the effect of time preferences on obesity risk for adolescents in counties with obesity rates at the mean. We expect β_2 to be less than zero, as adolescents with higher time preference scores (i.e. more patient) would be less likely to be obese. The coefficient of interest, β_3, captures whether the effect of *InstaCOR* on adolescent's obesity risk varies by time preference. We hypothesize that β_3 will be less than zero as patient adolescents would be less adversely affected by exposure to obesogenic environments.

$$Obese_{ic} = \beta_1 InstaCOR_c + \beta_2 TimePref_i + \beta_3 InstaCOR_c * TimePref_i + \gamma X_i + \varepsilon_{ic} \qquad (1)$$

Identification in our model comes from the fact that assignment to installations is based on the Army's needs.[10] This assignment creates plausibly exogenous variation in exposure to obese

[10] This identification approach has been used in prior studies to estimate the effect of air pollutants on child health (Lleras-Muney 2010), the effect of parental absences on children's academic achievement (Lyle 2006), and the effect of moves on marriage (Carter and Wozniack forthcoming).

communities, proxied by the obesity rate in the county where the assigned installation is located. We provide support for this claim in Table 2, which compares the sociodemographic characteristics of adolescents assigned to installation counties with above-median (>=30%) versus below-median (<30%) *InstaCOR*.[11] We find that the composition of adolescents does not vary systematically by *InstaCOR*. We also estimate models with and without covariates given that stability in the estimates for the effect of *InstaCOR* across adjusted and unadjusted models would lend further support to the exogeneity of *InstaCOR*.

While most military families are exposed to the installation county, the majority of families live in surrounding communities off-base (Buddin et al. 1999; Bissell, Crosslin, and Hathaway Feb 2010; MilitaryOneSource 2020) (75% of our sample), some of whom choose to live outside the installation county, exposing them to those counties as well.[12] Likewise, adolescents who attend schools in counties that are different from the installation and/or the

[11] We use 30% at the cutoff for high versus low *InstaCOR* as it is the median *InstaCOR* in our sample as well as the median COR in the U.S. across all counties.

[12] Military servicemembers that have moved up in rank (e.g. mid- and senior enlisted personnel) have the option to live in military housing on-base or live in privatized military housing or private housing off-base. On-base military housing often has a waitlist and is sometimes perceived to be of lower quality, therefore, most military families prefer to live off-base. For those who choose to live off-base, the military provides a base housing allowance.

residence county, are exposed to those counties as well (Department of Defense 2015).[13] To account for exposure to obesogenic environments across up to three different counties (installation, residence, and school), we construct a composite measure of the obesity rates in the three counties as an alternate measure of the obesogenic environment. The composite COR is constructed in several different ways. First, we take a simple average of the COR in the three counties (*MeanCOR*). Second, we compute a weighted average of the COR in the three counties, where the weights are based on the proportion of waking hours spent in the three locations (*WgtmeanCOR*)[14]. Since adolescents spend a sizeable fraction of their waking time at school, we assign 50% of the weight to the school county and divide the rest equally between installation and residence.[15] Third, we use the maximum obesity rate of the three counties as the composite measure (*MaxCOR*). And finally, we use an indicator for whether the COR for any of the three counties was greater than 30% (*AnyCORabove30*), which is the mean and median in the sample.

Table 3 compares the adult obesity rates for the installation, residence, and school counties. Concordance between school and residence county obesity rates is highest – 90% of the sample goes to school in the same county as their residence. In comparison, the concordance is 58%

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[13] Although the Department of Defense Education Activity (DoDEA) operates school on base, there are only About 80% of children in military families attend public schools, which are located off-base (Department of Defense, 2015).

[14] Note that if the installation and residence county is the same, i.e. if the family lives on base, then the installation COR would get half the weight in the simple mean composite.

[15] In wave 4, we did not ask adolescents who lived off base how often they came to the base or how much time they spent.

between school and installation county obesity rates, and is 55% between residence and installation county obesity rates.[16]

While the composite measures encompass more of the environment that adolescents are actually exposed to, they are likely to be endogenous because, while installation county is exogenously assigned, families can choose where to live and attend school around the assigned installation. To address this concern, we also estimate two-stage least squares models that use the assigned *InstaCOR* as an instrument for the composite COR. Our identification of the interaction effect of COR and time preferences relies similarly on the assumption that time preferences are not affected by assignment to installation. This assumption is consistent with the long-standing tradition in economics of assuming that preferences are predetermined and stable, at least in adults (Meier and Sprenger 2015).[17]

Because time preferences were collected after assignment to installation, we need to assess the plausibility of our assumption. To do so, we examine whether time preferences are associated with COR. Specifically, we estimate models that regress time preferences on *InstaCOR* or composite measures of COR. Since both are measured contemporaneously, a significant

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[16] 57% of adolescents attend school in the same county as the installation and 55% live in the same county as the installation.

[17] Chuang and Schecter (2015) provide an excellent review of the empirical evidence on stability of experimental and survey measures of economic preferences. They find that recent work is consistent with the notion that preferences tend to remain stable over time among adults. Further, they suggest that survey-based measures such as those we use here may be more reliable than experimental measures.

association between time preferences and COR may indicate that preferences are shaped by environments. In contrast, an insignificant association would be consistent with the idea that preferences are likely stable and not affected by environments, which would reduce concerns about endogeneity of the *TimePref* variable in our models. Furthermore, an insignificant association would provide further evidence that the natural experiment does, in fact, balance the sample with respect to preferences, and that there is no sorting of adolescents into places based on preferences.

5. Results

Effect of County Obesity Rate on Adolescent Obesity

Table 4 reports results from estimating Equation (1) using linear probability models for obesity based on the child's self-reported height and weight.[18] Corresponding results using the obesity indicator based on height and weight data "corrected" for measurement error are reported in Appendix Table 3. For ease of interpretation, *InstaCOR* and *TimePref* variables were centered on their respective means.

In the unadjusted model with only *InstaCOR* as the covariate, a 10 percentage point increase in *InstaCOR* increases the likelihood of obesity by 5 percentage points (Column 1). Adding the full set of sociodemographic covariates to the model does not change this estimate (Column 2), as expected if the natural experiment effectively randomizes adolescents to different *InstaCORs*.

The effect of time preferences, and of their interaction with *InstaCOR*, on obesity is estimated starting in Column 3, first without covariates (Column 3) and then with the addition of

[18] Estimates for all coefficients in the models are reported in Appendix Table 2.

controls for risk preferences (Column 4) and sociodemographic covariates (Column 5). Since *InstaCOR* and *TimePref* are de-meaned, each of their coefficients capture the effects on obesity for an adolescent with *TimePref* and *InstaCOR* at their respective means. The estimated effects of *InstaCOR*, *TimePref*, and their interaction remain stable across all columns, indicating that inclusion of covariates and risk preference does not alter the estimates. An increase in the time preference score, which indicates greater patience, is consistently associated with a lower probability of being obese. Estimates in column 5, the fully specified model, indicate that a 1 standard deviation increase in the time preference score (0.6) is associated with a 3.5 percentage point (=-0.058*0.6) decrease in the likelihood of being obese.

Importantly, the interaction effect indicates that the effect of *InstaCOR* is smaller for adolescents with more patient time preferences. A 10 percentage point increase in *InstaCOR* increases the likelihood of obesity by 5 percentage points for an adolescent with time preferences at the mean. The likelihood of obesity increases by 7 percentage points for an adolescent with a time preference score at the 25th percentile, but increases by only 2 percentage points for an adolescent with a time preference score at the 75th percentile. These results are statistically significant at the 10% level in all models, and statistically significant at the 5% level in the model that incorporates all controls.

Table 5 reports estimates from alternate specifications where *InstaCOR* is replaced with composite measures of the obesogenic environment that capture environments from the installation county, the school county, and the residence county.[19] Results from specifications

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[19] Corresponding results using the "corrected" BMI and obesity measures are reported in Appendix Table 4.

that use the *mean COR*, *weighted mean COR*, and *MaxCOR* measures are qualitatively similar to the main models. When using *AnyCORabove30*, for example, adolescents exposed to a county with obesity rate above 30% are 5.3 percentage points more likely to be obese and this association is smaller among more patient adolescents.

Table 6 reports results from 2SLS models, which instrument the different composite measures of obesogenic environment and their interaction with time preferences using *InstaCOR* and *InstaCORxTimePref*.[20] The first stage tests show a strong positive association between *InstaCOR* and composite COR measures; the F-statistic for excluded instruments ranged from 25.8-35.8. The second stage results show that the IV estimate of the effect of weighted mean COR on obesity is 0.008 (SE=0.004). The interaction effect is -0.008 (SE=0.004). Results for the models that instrument for the other composite CORs are similar. The IV estimates using the composite COR measures are slightly larger than the OLS estimates, suggesting a downward bias in the OLS estimates.

Effect of County Obesity Rate on Time Preferences

Table 7 reports results from models that estimate the relationship between the county obesity rate and adolescents' time preferences. There is no significant association between *InstaCOR* and preferences, which may have two implications given that both measures are collected contemporaneously. One implication may be that there is no systematic sorting of adolescents into more versus less obesogenic communities based on their time preferences. This would

[20] Corresponding results using the "corrected" BMI and obesity measures are reported in Appendix Table 5.

provide further support to our identification assumption that the assignment to installations is exogenous. In addition, the null findings may also imply that obesogenic environments have no impact on adolescents' time preferences. This would be consistent with the long-standing tradition in economics of assuming that preferences are predetermined and stable, at least in adults (Meier and Sprenger 2015; Chuang and Schechter 2015). There is emerging evidence that time preferences evolve substantially during childhood (Bettinger and Slonim 2007; Angerer et al. 2015; Kosse et al. 2020; Sutter, Yilmaz, and Oberauer 2015; Andreoni et al. 2019), but there is not much evidence about whether time preferences respond to environmental changes. In their survey of the literature, Chuang and Schecter (2015) find mixed evidence about whether events like economic shocks or natural disasters affect time preferences, potentially due to the difficulties with collecting such data.

Decomposing the Effect of County Obesity Rate

The results presented thus far indicate that time preferences play an important role in understanding the effects of obesogenic environments on adolescent obesity. Here, we explore what features of the environment interact with time preferences to influence adolescent obesity. Because we lack the power to assess the role of specific environmental factors (e.g. fast food restaurants, access to parks), we focus on the role of broad categories of environments via some exploratory analyses. Using a county-level regression of COR on built and social environment measures (Appendix table 7), we partition COR into three components: a) the portion predicted by the built environment, b) the portion predicted by the socioeconomic environment, and c) the residual, defined as the difference between actual COR and that predicted by the built and social environment measures.[21] We then interact these three components of COR with the time preference measure to estimate their interactive effects on adolescent obesity (Appendix Table 8). Similar to our own and other prior studies, we find little support for an average effect of the built environment on obesity (column 1). However, results from the interaction do support an effect of the built environment on impatient adolescents (Column 2). Or put another way, patience offers significant protection against obesogenic built environments, which may explain the fact that many studies find little or no effect, *on average*. With respect to social environment, we find no evidence of an effect on obesity, on average, or that it varies by adolescent time preferences. Lastly, we find a significant impact of the residual component, which, following Datar and Nicosia (2018) and Datar, Mahler, and Nicosia (2020), may be interpreted as a social contagion effect: for example, seeing more obese people may influence adolescents' own likelihood of obesity via changes in social norms about body type, behavior mirroring or other social influence mechanism. In contrast to the built environment, social contagion appears to be equally important for all adolescents regardless of time preferences. Overall, these results suggest that understanding the role of time preferences is important for understanding the effects of some features of the environment more so than others.

6. Conclusion

This paper provides the first quasi-experimental evidence on heterogeneity in place effects on adolescent obesity with respect to time preferences. Specifically, we examine whether

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[21] Bivariate correlations between each of the county level measures used in the COR prediction model are reported in Appendix Table 6.

adolescents with more patient time preferences are less affected by their obesogenic environments compared to their less patient counterparts.

Our results show that exposure to obesogenic environments has a greater effect on obesity among less patient adolescents. For an adolescent with time preferences at the mean, a 10 percentage point increase in the county obesity rate for the assigned installation increases the likelihood of obesity by 5 percentage points. This effect varies considerably across adolescents with varying time preferences. For example, the likelihood of obesity increases by 7 percentage points for an adolescent with a time preference score at the 25th percentile, but only increases by 2 percentage points for an adolescent with a time preference score at the 75th percentile. In fact, patience almost completely offsets the adverse effects of obesogenic environments for adolescents near the 90th percentile of the time preference score distribution. Finally, while exploratory, our analyses also suggest that adolescents' time preferences appear to be most important for protecting against the adverse effects of built environments on obesity. Such heterogeneity should be explored in more detail in future research.

Overall, our findings have several implications. First, they may explain why obesity prevention interventions, policies, and programs may appear to have small or no effects, when estimated on average (Tseng et al. 2018; Wang et al. 2015; Bramante et al. 2019). They may also explain why childhood obesity rates have continued to rise despite significant efforts to reverse the trends (Skinner et al. 2018). Efforts to address adolescent obesity may benefit from assessing time preferences during childhood and adolescence and targeting interventions towards those at higher risk. Second, our findings suggest a greater role for interventions that seek to alter adolescents' time preferences. In our analysis, we treat time preferences as a stable trait, and show that time preferences are not affected by place. However, a relatively new area of research examines whether (and how) children's time preferences can be modified via targeted interventions. For example, Alan and Ertac (2014) find that a program targeted at helping children imagine their future selves yields more patient time preferences in a separately-elicited laboratory task. And, Luhrmann et al. (2014) find that a financial education program administered with adolescents affects time preferences by making treated subjects less present-biased. Our research implies that such interventions, by making children more patient, could also shield children from the potentially harmful effects of an obesogenic environment. Finally, our findings speak to the literature on socioeconomic disparities in obesity. Low income families are not only more likely to live in obesogenic neighborhoods (Lovasi, Hutson, Guerra, & Neckerman, 2009) but there is also a growing literature suggesting that poverty is linked to impatience (Haushofer and Fehr 2014). Therefore, our findings suggest that the combination of time preferences and obesogenic environments might exacerbate socioeconomic disparities in obesity.

TABLES

Table 1: Descriptive Statistics

Variables	Mean	SD	Min	Max
Dependent Variable				
Obese (self-report)	0.125	(0.33)	0	1
Obese (corrected)	0.133	(0.34)	0	1
Preferences				
Time Preference	3.28	(0.61)	1.33	4.67
Risk Preference	5.89	(2.27)	1	10
Obesogenic Environment				
InstaCOR (%)	30.03	(4.11)	18.3	37.1
Mean COR (%)	29.97	(3.65)	20.27	36.53
Weighted Mean COR (%)	29.96	(3.71)	19.1	37.58
Max COR (%)	30.97	(4.23)	20.6	40.7
AnyCORabove30	0.70	(0.47)	0	1
Covariates				
Female	0.445	(0.50)	0	1
Male	0.555	(0.50)	0	1
White	0.3925	(0.49)	0	1
Black	0.2075	(0.41)	0	1
Hispanic	0.2475	(0.43)	0	1
Other	0.1525	(0.36)	0	1
Live on installation	0.2475	(0.43)	0	1
Time at installation >=2 years	0.3475	(0.48)	0	1
Parent rank>=E7	0.4725	(0.50)	0	1
Military parent active duty	0.5875	(0.49)	0	1
Household income>$70k	0.3525	(0.48)	0	1

Notes: N=400. COR: County Obesity Rate. InstaCOR: Installation County Obesity Rate. Weighted Mean COR: Weighted mean of the obesity rates for the installation, residence, and school counties. Max COR: maximum obesity rate of the installation, residence, and school counties. AnyCORabove30: Indicator for whether the obesity rate for installation, residence, or school county is above the median rate of 30%.

Table 2: Balance table

Variables	Installation County Obesity Rate (*InstaCOR*) Below Median[a] (n=176)	At or Above Median (n=224)	Difference
Dependent Variable			
Obese (self-report)	0.091	0.152	-0.061
Obese (corrected)	0.091	0.165	-0.074**
Covariates			
Time preference score	3.295	3.272	0.023
Risk preference score	5.716	6.018	-0.302
Female	0.466	0.429	0.037
Male	0.534	0.571	-0.037
NH-White	0.409	0.379	0.030
NH-Black	0.182	0.228	-0.046
Hispanic	0.284	0.219	0.065
Other	0.125	0.174	-0.049
Live on the installation	0.284	0.219	0.065
Time at installation >= 2 years	0.358	0.339	0.019
Parent Rank E7 or higher	0.426	0.509	-0.083
Parent Active Duty	0.540	0.625	-0.085
Household annual income <=$70,000	0.653	0.643	0.011
Household annual income >$70,000	0.347	0.357	-0.011

** p<0.05, [a] Median value of *InstaCOR* is 30%

Table 3: Comparison of Adult Obesity Rates for Installation, School, and Residence Counties

		Difference in COR (percentage points)		
	% of Sample	Minimum	Median	Maximum
School COR < Installation COR	29%	-10.7	-2.0	-0.2
School COR = Installation COR	58%			
School COR > Installation COR	13%	0.1	5.3	12.5
Residence COR < Installation COR	29%	-10.7	-2.0	-0.2
Residence COR = Installation COR	55%			
Residence COR > Installation COR	15%	0.1	5.1	12.5
Residence COR < School COR	4%	-10.9	-2.7	-0.4
Residence COR = School COR	90%			
Residence COR > School COR	6%	0.4	2.6	10.7

COR: County Obesity Rate

Table 4: Effect of Installation County Obesity Rate and Time Preferences on Adolescent Obesity

	Obese				
	(1)	(2)	(3)	(4)	(5)
InstaCOR	0.005**	0.006*	0.005*	0.005*	0.005*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
TimePref			-0.061***	-0.061***	-0.058***
			(0.020)	(0.019)	(0.020)
InstaCOR x TimePref			-0.005*	-0.005*	-0.006**
			(0.003)	(0.003)	(0.003)
Controls					
Covariates	No	Yes	No	No	Yes
Risk Preferences	No	No	No	Yes	Yes
R-squared	0.004	0.034	0.018	0.018	0.047
Observations	408	406	404	402	400

Estimates in Panel A are from OLS models and those in Panel B are from linear probability models. Robust standard errors in parentheses. *InstaCOR* and *TimePref* are centered on their respective means. *InstaCOR*: Installation County Obesity Rate; *TimePref*: Time preference score; higher value indicates more patience.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of Composite County Obesity Rate Measures on Adolescent Obesity

		(1) Obese	(2) Obese	(3) Obese	(4) Obese
A.	*Mean COR*	0.005			
		(0.004)			
	TimePref	-0.056**			
		(0.021)			
	Mean COR x TimePref	-0.009**			
		(0.004)			
B.	*Weighted Mean COR*		0.005		
			(0.004)		
	TimePref		-0.056**		
			(0.022)		
	Weighted Mean COR x TimePref		-0.009**		
			(0.004)		
C.	*Max COR*			0.005	
				(0.003)	
	TimePref			-0.046**	
				(0.023)	
	Max COR x TimePref			-0.009***	
				(0.003)	
D.	*AnyCORabove30*				0.042*
					(0.024)
	TimePref				-0.005
					(0.027)
	AnyCORabove30 x TimePref				-0.077**
					(0.033)
	Observations	400	400	400	400
	R-squared	0.047	0.048	0.049	0.048

Robust standard errors in parentheses. *COR*: County Obesity Rate. *Mean COR* is the average obesity rate of the installation, school, and residence counties. *Weighted mean COR* is the weighted average of the obesity rate of the three counties. Max COR is the highest obesity rate of the three counties. *AnyCORabove30* is an indicator for whether any of the three counties (installation, residence, school) have an obesity rate above 30%, which is the mean county obesity rate in our sample and is also the mean and median obesity rate across all counties in the U.S. *TimePref*: Time preference score; higher value indicates more patience. *COR*, *Mean COR*, *Weighted mean COR* and *TimePref* are all centered on their respective means. All models include the full set of covariates.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Instrumental Variables Regression for the Effect of Composite County Obesity Rate on Adolescent Obesity

VARIABLES	(1) Obese	(2) Obese	(3) Obese
Mean COR	0.007*		
	(0.004)		
TimePref	-0.057***		
	(0.021)		
Mean COR x TimePref	-0.009**		
	(0.004)		
Weighted mean COR		0.007*	
		(0.004)	
TimePref		-0.055***	
		(0.021)	
Weighted mean COR x TimePref		-0.009**	
		(0.004)	
Max COR			0.007*
			(0.004)
TimePref			-0.047**
			(0.021)
Max COR x TimePref			-0.008*
			(0.004)
First Stage Tests			
F-stat of excluded instruments	35.78 (p=0.0000)	27.78 (p=0.0000)	34.57 (p=0.0000)
Andersen Rubin Wald test (Chi-2)[b]	8.04 (p=0.0179)	8.04 (p=0.0179)	8.04 (p=0.0179)
Sanderson and Windmeijer multivariate F-test	71.11 (p=0.0000)	55.23 (p=0.0000)	65.79 (p=0.0000)
Test of exogeneity of instruments[a]: Robust F-stat (p-value)	0.545 (p=0.583)	0.479 (p=0.622)	0.332 (p=0.719)
Observations	400	400	400
R-squared	0.047	0.047	0.049

Robust standard errors in parentheses. The estimates reported are from two-stage least squares regressions where the composite COR measure and its interaction with time preference are instrumented with *InstaCOR* and

InstaCORxTimePref. All models include the full set of covariates. [a] The F-stat reported here is a robust score test (Wooldridge 1995) equivalent of the Durbin-Wu-Hausman test. [b] The Andersen Rubin Wald Chi-2 statistic tests the joint significance of endogenous regressors in main equation.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Regression of Time Preferences on County Obesity Rate

VARIABLES	(1) *TimePref*	(2) *TimePref*	(3) *TimePref*
InstaCOR	-0.004		
	(0.008)		
Weighted mean COR		-0.007	
		(0.008)	
Max COR			-0.003
			(0.008)
Observations	400	400	400
R-squared	0.046	0.047	0.049

Robust standard errors in parentheses. All models include the full set of covariates

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1: Comparison of baseline characteristics of adolescents who participated in Wave 4 (stayers) versus those who did not (Attritors)

Variable	**Stayers (n=400)**	**Attritors (n=1109)**	**Difference**	**p-value**
Overweight or obese	0.2437	0.2745	-0.0308	0.2352
Obese	0.0779	0.1007	-0.0228	0.1831
BMI z-score	0.3951	0.3974	-0.0023	0.9702
Female	0.455	0.4914	-0.0364	0.2115
Live on installation	0.4462	0.446	0.0001	0.9968
Parent married	0.9184	0.8898	0.0285	0.1119
Total children in household	2.4046	2.4027	0.0019	0.9636
Race-ethnicity				
White Non Hispanic	0.3959	0.3983	-0.0024	
Black Non Hispanic	0.2157	0.2192	-0.0035	0.995
Hispanic/Latino	0.2462	0.2453	0.0009	
Other	0.1421	0.1371	0.005	
Military parent’s rank				
E4 or less	0.1147	0.113	0.0017	
E5	0.1493	0.1967	-0.0474	
E6	0.3413	0.298	0.0433	0.283
E7	0.2773	0.2775	-0.0002	
E8 or more	0.1173	0.1149	0.0024	
Annual household income				
40,000 or less	0.1943	0.2153	-0.021	
40,001 to 50,000	0.1995	0.2027	-0.0032	0.425
50,001 - 85,000	0.5078	0.4633	0.0445	
85,001 or more	0.0984	0.1187	-0.0203	
Months at installation				
24 months or less	0.3832	0.3748		

Appendix Table 2: Full Regression Results for Models in Table 4

	Obese (self-report)					Obese (corrected)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
InstaCOR	0.005**	0.006*	0.005*	0.005*	0.005*	0.005**	0.006*	0.005*	0.005*	0.006*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
TimePref			-0.061***	-0.061***	-0.058***			-0.060***	-0.062***	-0.059***
			(0.020)	(0.019)	(0.021)			(0.019)	(0.019)	(0.021)
InstaCOR x TimePref			-0.005*	-0.005*	-0.006**			-0.005	-0.005	-0.006**
			(0.003)	(0.003)	(0.003)			(0.003)	(0.003)	(0.003)
Risk Preference Score				0.000	0.001				0.005	0.006
				(0.007)	(0.007)				(0.006)	(0.007)
Male		-0.031			-0.040		-0.027			-0.038
		(0.034)			(0.033)		(0.035)			(0.034)
Non-Hispanic Black		-0.016			-0.026		-0.027			-0.035
		(0.056)			(0.058)		(0.062)			(0.063)
Hispanic		-0.012			-0.008		-0.014			-0.010
		(0.036)			(0.037)		(0.036)			(0.037)
Other Race-ethnicity		-0.003			0.000		-0.015			-0.010
		(0.048)			(0.051)		(0.054)			(0.056)
Live on installation		-0.008			-0.011		-0.016			-0.021
		(0.051)			(0.051)		(0.053)			(0.054)
Time at base >= 24 months		-0.058*			-0.058*		-0.068*			-0.068*
		(0.033)			(0.033)		(0.036)			(0.035)
Military parent rank		-0.050			-0.046		-0.046			-0.041
		(0.035)			(0.036)		(0.035)			(0.036)
Military parent active duty		-0.021			-0.021		-0.016			-0.017
		(0.038)			(0.039)		(0.039)			(0.041)
Annual household income>$70,000		-0.064**			-0.056**		-0.069***			-0.063**
		(0.026)			(0.028)		(0.026)			(0.028)
Constant	0.122***	0.228***	0.124***	0.125***	0.232***	0.130***	0.241***	0.132***	0.132***	0.245***
	(0.013)	(0.050)	(0.013)	(0.013)	(0.051)	(0.017)	(0.053)	(0.017)	(0.017)	(0.054)

Observations	408	406	404	402	400	408	406	404	402	400
R-squared	0.004	0.034	0.018	0.018	0.047	0.004	0.036	0.018	0.019	0.049

Appendix Table 3: Effect of Installation County Obesity Rate and Time Preferences on Adolescent Obesity (based on corrected BMI)

	(1)	(2)	(3)	(4)	(5)
	Obese	Obese	Obese	Obese	Obese
Panel A: Continuous Specification					
InstaCOR	0.005**	0.006*	0.005*	0.005*	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
TimePref			-0.060***	-0.062***	-0.059***
			(0.019)	(0.019)	(0.021)
InstaCOR x TimePref			-0.005	-0.005	-0.006**
			(0.003)	(0.003)	(0.003)
R-squared	0.004	0.036	0.018	0.019	0.050
Panel B: Binary Specification					
InstaCORabove30	0.071**	0.081**	0.073**	0.072**	0.079**
	(0.030)	(0.034)	(0.030)	(0.031)	(0.034)
TimePref			-0.032	-0.034	-0.026
			(0.021)	(0.021)	(0.017)
InstaCORabove30 x TimePref			-0.052	-0.052	-0.066**
			(0.035)	(0.035)	(0.030)
R-squared	0.004	0.036	0.018	0.019	0.050
Controls					
Covariates	No	Yes	No	No	Yes
Risk Preferences	No	No	No	Yes	Yes
Observations	408	406	404	402	400

Robust standard errors in parentheses. InstaCOR: Installation County Obesity Rate; TimePref = Time preference score, InstaCORabove30 = Installation County obesity rate is above 30%, which is the mean county obesity rate in the sample and in the U.S. InstaCOR and TimePref are centered on their respective means. Higher values of TimePref indicate more patience.

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4: Effect of Composite County Obesity Rate Measures on Adolescent Obesity (Based on corrected BMI)

	(1)	(2)	(3)	(4)
VARIABLES	Obese	Obese	Obese	Obese
Mean COR	0.005			
	(0.004)			
Mean COR x TimePref	-0.008*			
	(0.004)			
Weighted mean COR		0.005		
		(0.004)		
Weighted mean COR x TimePref		-0.008*		
		(0.004)		
Max COR			0.005*	
			(0.003)	
Max COR x TimePref			-0.008***	
			(0.003)	
anyCORabove30				0.053*
				(0.029)
anyCORabove30 x TimePref				-0.075**
				(0.032)
TimePref	-0.059**	-0.059**	-0.050**	-0.008
	(0.023)	(0.023)	(0.024)	(0.026)
Observations	400	400	400	400
R-squared	0.049	0.049	0.052	0.052

Each column represents a separate regression. Robust standard errors in parentheses. COR: County Obesity Rate. Mean COR is the average obesity rate of the installation, school, and residence counties. Weighted mean COR is the weighted average of the obesity rate of the three counties. Max COR is the highest obesity rate of the three counties. AnyCORabove30 is an indicator for whether any of the three counties have an obesity rate above 30%. All models include the full set of covariates.

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 5: Instrumental Variables Regression for Effect of Composite COR on Adolescent Obesity (based on corrected BMI)

	(1) Obese	(2) Obese	(3) Obese
Mean COR	0.008*		
	(0.004)		
Mean COR x TimePref	-0.008*		
	(0.004)		
Weighted mean COR		0.008*	
		(0.004)	
Weighted mean COR x TimePref		-0.008*	
		(0.004)	
Max COR			0.007*
			(0.004)
Max COR x TimePref			-0.008*
			(0.004)
TimePref	-0.059***	-0.058***	-0.050**
	(0.022)	(0.022)	(0.022)
First Stage Tests			
F-stat of excluded instruments	35.78 (p=0.0000)	27.78 (p=0.0000)	34.57 (p=0.0000)
Sanderson and Windmeijer multivariate F-test for weak identification	71.11 (p=0.0000)	55.23 (p=0.0000)	65.79 (p=0.0000)
Andersen Rubin Wald test (Chi-2)[a]	7.22 (p=0.0271)	7.22 (p=0.0271)	7.22 (p=0.0271)
Test of exogeneity of instruments[b]: Robust F-stat (p-value)	0.562 (p=0.573)	0.476 (p=0.624)	0.398 (p=0.674)
Observations	400	400	400
R-squared	0.048	0.048	0.051

Robust standard errors in parentheses. The estimates reported are from two-stage least squares regressions where the composite COR measure and its interaction with time preference are instrumented with InstaCOR and InstaCORxTimePref. All models include the full set of covariates. [a] The Andersen Rubin Wald Chi-2 statistic tests the joint significance of endogenous regressors in main equation. [b] The F-stat reported here is a robust score test equivalent of the Durbin-Wu-Hausman test.

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6: Correlations between COR and measures of built and socioeconomic environment for counties where MTEENS sample is located (n=82)

COR	1						
Food Environment Index	-0.53	1					
Access to exercise opportunities	-0.59	0.45	1				
Teenage pregnancy rate	0.46	-0.65	-0.40	1			
Percent with some college	-0.43	0.28	0.43	-0.49	1		
Unemployment rate	0.28	-0.36	-0.19	0.40	-0.43	1	
Poverty rate	0.45	-0.65	-0.41	0.66	-0.61	0.47	1
Percent single parent households	0.46	-0.52	-0.28	0.46	-0.48	0.19	0.76

Appendix Table 7: Three-way partitioning of Installation County Obesity Rate (InstaCOR)

County-level Measures of Built and Socioeconomic Environment	InstaCOR
Built Environment Measures	
Food environment index	-0.926*
	(0.496)
Percent of population with access to exercise opportunities	-0.113***
	(0.028)
Socioeconomic Environment Measures	
Teenage pregnancy rate	0.034
	(0.039)
Percent with some college	-0.073
	(0.070)
Unemployment rate	0.251
	(0.228)
Poverty rate	-0.188*
	(0.099)
Percent of single parent households	0.186**
	(0.073)
Observations	82
R-squared	0.503

Standard errors in parentheses. Estimates are from a linear regression of InstaCOR on county-level measures of built and socioeconomic environment obtained from the RWJ CHR data for the 82 counties where the MTEENS sample was located. The dependent and explanatory variables are all centered on their respective means.

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8: Effect of Three Components of InstaCOR on Adolescent Obesity

Explanatory Variables	Obese (1)	Obese (2)
COR predicted from built environment (COR_BE)	0.003	0.003
	(0.006)	(0.006)
COR_BE x TimePref		-0.019**
		(0.007)
COR predicted from socioeconomic environment (COR_SE)	-0.013	-0.014
	(0.013)	(0.012)
COR_SE x TimePref		0.008
		(0.013)
Residual COR (COR_RES)	0.014*	0.013
	(0.008)	(0.008)
COR_RES x TimePref		0.000
		(0.008)
Time Preference Score (TimePref)		-0.034*
		(0.018)
Risk Preference Score		0.003
		(0.007)
Male	-0.032	-0.043
	(0.034)	(0.033)
Non-Hispanic Black	-0.015	-0.022
	(0.056)	(0.059)
Hispanic	-0.011	-0.006
	(0.036)	(0.038)
Other Race-ethnicity	0.007	0.016
	(0.048)	(0.051)
Live on installation	-0.011	-0.011
	(0.053)	(0.052)
Time at base >= 24 months	-0.058*	-0.058*
	(0.032)	(0.033)
Military parent rank	-0.046	-0.040
	(0.036)	(0.036)
Military parent active duty	-0.024	-0.025
	(0.038)	(0.040)
Annual household income>$70,000	-0.063**	-0.060**
	(0.026)	(0.028)
Constant	0.221***	0.224***
	(0.050)	(0.052)
Observations	406	400
R-squared	0.040	0.057

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

References

Allcott, H., R. Diamond, J. P. Dube, J. Handbury, I. Rahkovsky, and M. Schnell. 2019. "Food Deserts and the Causes of Nutritional Inequality." *Quarterly Journal of Economics* 134 (4):1793-1844. doi: 10.1093/qje/qjz015.

Anderson, M. L., and D. A. Matsa. 2011. "Are Restaurants Really Supersizing America?" *American Economic Journal-Applied Economics* 3 (1):152-188. doi: 10.1257/app.3.1.152.

Andreoni, J., M. A. Kuhn, J. A. List, A. Samek, K. Sokal, and C. Sprenger. 2019. "Toward an understanding of the development of time preferences: Evidence from field experiments." *Journal of Public Economics* 177. doi: 10.1016/j.jpubeco.2019.06.007.

Angerer, S., P. Lergetporer, D. Glatzle-Rutzler, and M. Sutter. 2015. "How to measure time preferences in children: a comparison of two methods." *Journal of the Economic Science Association-Jesa* 1 (2):158-169. doi: 10.1007/s40881-015-0016-0.

Arcaya, Mariana C., Reginald D. Tucker-Seeley, Rockli Kim, Alina Schnake-Mahl, Marvin So, and S. V. Subramanian. 2016. "Research on neighborhood effects on health in the United States: A systematic review of study characteristics." *Social Science & Medicine* 168:16-29. doi: 10.1016/j.socscimed.2016.08.047.

Becht, A. I., S. A. Nelemans, S. J. Branje, W. A. Vollebergh, H. M. Koot, J. J. Denissen, and W. H. Meeus. 2016. "The quest for identity in adolescence: Heterogeneity in daily identity formation and psychosocial adjustment across 5 years." *Dev Psychol* 52 (12):2010-2021. doi: 10.1037/dev0000245.

Bettinger, E., and R. Slonim. 2007. "Patience among children." *Journal of Public Economics* 91 (1-2):343-363. doi: 10.1016/j.jpubeco.2006.05.010.

Bilger, M., and V. Carrieri. 2013. "Health in the cities: When the neighborhood matters more than income." *Journal of Health Economics* 32 (1):1-11. doi: 10.1016/j.jhealeco.2012.09.010.

Bissell, Kristie L., Robert L. Crosslin, and James L. Hathaway. Feb 2010. Military Families and their Housing Choices. LMI Government Consulting.

Bleich, S. N., J. Segal, Y. Wu, R. Wilson, and Y. F. Wang. 2013. "Systematic Review of Community-Based Childhood Obesity Prevention Studies." *Pediatrics* 132 (1):E201-E210. doi: 10.1542/peds.2013-0886.

Borghans, L., and B. H. H. Golsteyn. 2006. "Time discounting and the body mass index - Evidence from the Netherlands." *Economics & Human Biology* 4 (1):39-61. doi: 10.1016/j.ehb.2005.10.001.

Bradford, D., C. Courtemanche, G. Heutel, P. McAlvanah, and C. Ruhm. 2017. "Time preferences and consumer behavior." *Journal of Risk and Uncertainty* 55 (2-3):119-145. doi: 10.1007/s11166-018-9272-8.

Bramante, C. T., R. L. J. Thornton, W. L. Bennett, A. Zhang, R. F. Wilson, E. B. Bass, and E. Tseng. 2019. "Systematic Review of Natural Experiments for Childhood Obesity Prevention and Control." *American Journal of Preventive Medicine* 56 (1):147-158. doi: 10.1016/j.amepre.2018.08.023.

Brand, Jennie E., and Julie Simon Thomas. 2013. Causal Effect Heterogeneity. Morgan SL, ed. *Handbook* of Causal Analysis for Social Research: Springer.

Buddin, R., C.R. Gresenz, S.D. Hosek, M.N. Elliott, and J. Hawes-Dawson. 1999. An Evaluation of Housing Options for Military Families. Santa Monica, CA: RAND, MR-1020-OSD.

Caleza, C., R. M. Yanez-Vico, A. Mendoza, and A. Igiesias-Linares. 2016. "Childhood Obesity and Delayed Gratification Behavior: A Systematic Review of Experimental Studies." *Journal of Pediatrics* 169:201-+. doi: 10.1016/j.jpeds.2015.10.008.

Carter, SP, and A Wozniack. forthcoming. "Making Big Decisions: The Impact of Moves on Marriage Among U.S. Army Personnel." *Journal of Human Resources*.

Castillo, M., P. J. Ferraro, J. L. Jordan, and R. Petrie. 2011. "The today and tomorrow of kids: Time preferences and educational outcomes of children." *Journal of Public Economics* 95 (11-12):1377-1385. doi: 10.1016/j.jpubeco.2011.07.009.

Castillo, M., J. L. Jordan, and R. Petrie. 2019. "Discount Rates of Children and High School Graduation." *Economic Journal* 129 (619):1153-1181. doi: 10.1111/ecoj.12574.

Chabris, C. F., D. Laibson, C. L. Morris, J. P. Schuldt, and D. Taubinsky. 2008. "Individual laboratory-measured discount rates predict field behavior." *Journal of Risk and Uncertainty* 37 (2-3):237-269. doi: 10.1007/s11166-008-9053-x.

Chapman, G. B., and E. J. Coups. 1999. "Time preferences and preventive health behavior: Acceptance of the influenza vaccine." *Medical Decision Making* 19 (3):307-314. doi: 10.1177/0272989x9901900309.

Chetty, R., and N. Hendren. 2018. "The Impacts Of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects." *Quarterly Journal of Economics* 133 (3):1107-1162. doi: 10.1093/qje/qjy007.

Chetty, R., N. Hendren, and L. F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review* 106 (4):855-902. doi: 10.1257/aer.20150572.

Chuang, Y. T., and L. Schechter. 2015. "Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results." *Journal of Development Economics* 117:151-170. doi: 10.1016/j.jdeveco.2015.07.008.

Chyn, Eric, and Lawrence F. Katz. 2021. "Neighborhoods Matter: Assessing the Evidence for Place Effects." *Journal of Economic Perspectives* 35 (4):197-222. doi: 10.1257/jep.35.4.197.

Conell-Price, L., and J. Jamison. 2015. "Predicting health behaviors with economic preferences & locus of control." *Journal of Behavioral and Experimental Economics* 54:1-9. doi: 10.1016/j.socec.2014.10.003.

Couillard, Benjamin K., Christopher L. Foote, Kavish Gandhi, Ellen Meara, and Jonathan Skinner. 2021. "Rising Geographic Disparities in US Mortality." *Journal of Economic Perspectives* 35 (4):123-46. doi: 10.1257/jep.35.4.123.

Courtemanche, C., and A. Carden. 2011. "Supersizing supercenters? The impact of Walmart Supercenters on body mass index and obesity." *Journal of Urban Economics* 69 (2):165-181. doi: 10.1016/j.jue.2010.09.005.

Courtemanche, C., G. Heutel, and P. McAlvanah. 2015. "Impatience, Incentives and Obesity." *Economic Journal* 125 (582):1-31. doi: 10.1111/ecoj.12124.

Currie, J., S. DellaVigna, E. Moretti, and V. Pathania. 2010. "The Effect of Fast Food Restaurants on Obesity and Weight Gain." *American Economic Journal-Economic Policy* 2 (3):32-63. doi: 10.1257/pol.2.3.32.

Damm, A. P. 2014. "Neighborhood quality and labor market outcomes: Evidence from quasi-random neighborhood assignment of immigrants." *Journal of Urban Economics* 79:139-166. doi: 10.1016/j.jue.2013.08.004.

Daniels, K. M., L. H. Schinasi, A. H. Auchincloss, C. B. Forrest, and A. V. Diez Roux. 2021. "The built and social neighborhood environment and child obesity: A systematic review of longitudinal studies." *Prev Med* 153:106790. doi: 10.1016/j.ypmed.2021.106790.

Datar, A, A Mahler, and N Nicosia. 2020. "Association of Exposure to Communities With High Obesity With Body Type Norms and Obesity Risk Among Teenagers." *Jama Network Open* 3 (3). doi: 10.1001/jamanetworkopen.2020.0846.

Datar, A., and N. Nicosia. 2017. "The Effect of State Competitive Food and Beverage Regulations on Childhood Overweight and Obesity." *J Adolesc Health* 60 (5):520-527. doi: 10.1016/j.jadohealth.2016.09.003.

Datar, A., and N. Nicosia. 2018. "Assessing Social Contagion in Body Mass Index, Overweight, and Obesity Using a Natural Experiment." *JAMA Pediatr* 172 (3):239-246. doi: 10.1001/jamapediatrics.2017.4882.

Datar, Ashlesha, Nancy Nicosia, Elizabeth Wong, and Victoria Shier. 2015. "Neighborhood Environment and Children's Physical Activity and Body Mass Index: Evidence from Military Personnel Installation Assignments." *Childhood Obesity* 11 (2):130-138. doi: doi:10.1089/chi.2014.0094.

de Ridder, D. T. D., G. Lensvelt-Mulders, C. Finkenauer, F. M. Stok, and R. F. Baumeister. 2012. "Taking Stock of Self-Control: A Meta-Analysis of How Trait Self-Control Relates to a Wide Range of Behaviors." *Personality and Social Psychology Review* 16 (1):76-99. doi: 10.1177/1088868311418749.

Department of Defense, DODEA. 2015. Assistance to Local Educational Agencies for Defense Dependents' Education. Department of Defense.

Deryugina, Tatyana, and David Molitor. 2021. "The Causal Effects of Place on Health and Longevity." *Journal of Economic Perspectives* 35 (4):147-70. doi: 10.1257/jep.35.4.147.

Deutscher, N. 2020. "Place. Peers. and the Teenage Years: Long-Run Neighborhood Effects in Australia." *American Economic Journal-Applied Economics* 12 (2):220-249. doi: 10.1257/app.20180329.

Diez Roux, A. V. 2001. "Investigating neighborhood and area effects on health." *American journal of public health* 91 (11):1783-9 OD - 2001/10/31.

Diez Roux, Ana V., and Christina Mair. 2010. "Neighborhoods and health." *Annals of the New York Academy of Sciences* 1186 (1):125-145. doi: 10.1111/j.1749-6632.2009.05333.x.

Ding, Ding, and Klaus Gebel. 2012. "Built environment, physical activity, and obesity: What have we learned from reviewing the literature?" *Health & Place* 18 (1):100-105. doi: http://dx.doi.org/10.1016/j.healthplace.2011.08.021.

Dubowitz, Tamara, Madhumita Ghosh-Dastidar, Deborah A. Cohen, Robin Beckman, Elizabeth D. Steiner, Gerald P. Hunter, Karen R. Florez, Christina Huang, Christine A. Vaughan, Jennifer C. Sloan, Shannon N. Zenk, Steven Cummins, and Rebecca L. Collins. 2015. "Diet And Perceptions Change With Supermarket Introduction In A Food Desert, But Not Because Of Supermarket Use." *Health Affairs* 34 (11):1858-1868. doi: 10.1377/hlthaff.2015.0667.

Duncan, DT, MC Castro, SL Gortmaker, J Aldstadt, SJ Melly, and GG Bennett. 2012. "Racial differences in the built environment-body mass index relationship? A geospatial analysis of adolescents in urban neighborhoods." *International Journal of Health Geographics* 11. doi: 10.1186/1476-072X-11-11.

Dunn, R. A. 2010. "The Effect of Fast-Food Availability on Obesity: An Analysis by Gender, Race, and Residential Location." *American Journal of Agricultural Economics* 92 (4):1149-1164. doi: 10.1093/ajae/aaq041.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde. 2018. "GLOBAL EVIDENCE ON ECONOMIC PREFERENCES." *Quarterly Journal of Economics* 133 (4):1645-1692. doi: 10.1093/qje/qjy013.

Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. 2016. "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences." doi: doi.org/10.2139/ssrn.2725035.

Feng, Jing, Thomas A. Glass, Frank C. Curriero, Walter F. Stewart, and Brian S. Schwartz. 2010. "The built environment and obesity: A systematic review of the epidemiologic evidence." *Health & Place* 16 (2):175-190. doi: http://dx.doi.org/10.1016/j.healthplace.2009.09.008.

Fletcher, J. M., D. E. Frisvold, and N. Tefft. 2010a. "The effects of soft drink taxes on child and adolescent consumption and weight outcomes." *Journal of Public Economics* 94 (11-12):967-974. doi: 10.1016/j.jpubeco.2010.09.005.

Fletcher, JM, D Frisvold, and N Tefft. 2010b. "CAN SOFT DRINK TAXES REDUCE POPULATION WEIGHT?" *Contemporary Economic Policy* 28 (1):23-35. doi: 10.1111/j.1465-7287.2009.00182.x.

Fryar, CD, MD Carroll, and J Afful. 2020. Prevalence of overweight, obesity, and severe obesity among children and adolescents aged 2–19 years: United States, 1963–1965 through 2017–2018. NCHS Health E-Stats.

Galvez, M. P., M. Pearl, and I. H. Yen. 2010. "Childhood obesity and the built environment." *Curr Opin Pediatr* 22 (2):202-7. doi: 10.1097/MOP.0b013e328336eb6f.

Ghosh-Dastidar, Madhumita, Ann C. Haas, Nancy Nicosia, and Ashlesha Datar. 2016. "Accuracy of BMI correction using multiple reports in children." *BMC Obesity* 3 (1):37. doi: 10.1186/s40608-016-0117-1.

Ghosh-Dastidar, Madhumita, Nancy Nicosia, and Ashlesha Datar. 2020. "A novel approach to anthropometric assessment for geographically dispersed samples: A pilot study." *Preventive Medicine Reports* 19:101125. doi: https://doi.org/10.1016/j.pmedr.2020.101125.

Golsteyn, Bart H. H., Hans Grönqvist, and Lena Lindahl. 2014. "Adolescent Time Preferences Predict Lifetime Outcomes." *The Economic Journal* 124 (580):F739-F761. doi: 10.1111/ecoj.12095.

Hales, C. M., M. D. Carroll, C. D. Fryar, and C. L. Ogden. 2020. "Prevalence of Obesity and Severe Obesity Among Adults: United States, 2017-2018." *NCHS Data Brief* (360):1-8.

Harrison, Glenn, Morten Lau, Elisabet Rutstrom, and Melonie Williams. 2005. Eliciting Risk and Time Preferences Using Field Experiments: Some Methodological Issues. Field Experiments in Economics.

Haushofer, J., and E. Fehr. 2014. "On the psychology of poverty." *Science* 344 (6186):862-7. doi: 10.1126/science.1232491.

Jia, P., H. Xue, X. Cheng, Y. G. Wang, and Y. F. Wang. 2019. "Association of neighborhood built environments with childhood obesity: Evidence from a 9-year longitudinal, nationally representative survey in the US." *Environment International* 128:158-164. doi: 10.1016/j.envint.2019.03.067.

Joireman, J., J. Anderson, and A. Strathman. 2003. "The aggression paradox: Understanding links among aggression, sensation seeking, and the consideration of future consequences." *Journal of Personality and Social Psychology* 84 (6):1287-1302. doi: 10.1037/0022-3514.84.6.1287.

Joireman, J., D. Balliet, D. Sprott, E. Spangenberg, and J. Schultz. 2008. "Consideration of future consequences, ego-depletion, and self-control: Support for distinguishing between CFC-Immediate and CFC-Future sub-scales." *Personality and Individual Differences* 45 (1):15-21. doi: 10.1016/j.paid.2008.02.011.

Joireman, Jeff, Alan Strathman, and Daniel Balliet. 2006. "Considering Future Consequences: An Integrative Model." In *Judgments over time: The interplay of thoughts, feelings, and behaviors.*, 82-99. New York, NY, US: Oxford University Press.

Khwaja, A., F. Sloan, and M. Salm. 2006. "Evidence on preferences and subjective beliefs of risk takers: The case of smokers." *International Journal of Industrial Organization* 24 (4):667-682. doi: 10.1016/j.ijindorg.2005.10.001.

Kim, Y., C. Cubbin, and S. Oh. 2019. "A systematic review of neighbourhood economic context on child obesity and obesity-related behaviours." *Obesity Reviews* 20 (3):420-431. doi: https://doi.org/10.1111/obr.12792.

Kirby, K. N., N. M. Petry, and W. K. Bickel. 1999. "Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls." *Journal of Experimental Psychology-General* 128 (1):78-87. doi: 10.1037/0096-3445.128.1.78.

Kosse, F., T. Deckers, P. Pinger, H. Schildberg-Horisch, and A. Falk. 2020. "The Formation of Prosociality: Causal Evidence on the Role of Social Environment." *Journal of Political Economy* 128 (2):434-467. doi: 10.1086/704386.

Kranjac, AW, C Boyd, RT Kimbro, BS Moffett, and KN Lopez. 2021. "Neighborhoods matter; but for whom? Heterogeneity of neighborhood disadvantage on child obesity by sex." *Health & Place* 68. doi: 10.1016/j.healthplace.2021.102534.

Kranjac, AW, JT Denney, RT Kimbro, BS Moffett, and KN Lopez. 2019. "Child Obesity and the Interaction of Family and Neighborhood Socioeconomic Context." *Population Research and Policy Review* 38 (3):347-369. doi: 10.1007/s11113-018-9504-2.

Lam, TM, I Vaartjes, DE Grobbee, D Karssenberg, and J Lakerveld. 2021. "Associations between the built environment and obesity: an umbrella review." *International Journal of Health Geographics* 20 (1). doi: 10.1186/s12942-021-00260-6.

Lleras-Muney, A. 2010. "The Needs of the Army Using Compulsory Relocation in the Military to Estimate the Effect of Air Pollutants on Children's Health." *Journal of Human Resources* 45 (3):549-590.

Ludwig, J., J. B. Liebman, J. R. Kling, G. J. Duncan, L. F. Katz, R. C. Kessler, and L. Sanbonmatsu. 2008. "What can we learn about neighborhood effects from the Moving to Opportunity experiment?" *American Journal of Sociology* 114 (1):144-188. doi: 10.1086/588741.

Ludwig, J., L. Sanbonmatsu, L. Gennetian, E. Adam, G. J. Duncan, L. F. Katz, R. C. Kessler, J. R. Kling, S. T. Lindau, R. C. Whitaker, and T. W. McDade. 2011. "Neighborhoods, obesity, and diabetes - A randomized social experiment." *New England Journal of Medicine* 365 (16):1509-1519. doi: 10.1056/NEJMsa1103216.

Lyle, DS. 2006. "Using military deployments and job assignments to estimate the effect of parental absences and household relocations on children's academic achievement." *Journal of Labor Economics* 24 (2):319-350. doi: 10.1086/499975.

Mayne, S. L., A. H. Auchincloss, and Y. L. Michael. 2015. "Impact of policy and built environment changes on obesity-related outcomes: a systematic review of naturally occurring experiments." *Obes Rev* 16 (5):362-75. doi: 10.1111/obr.12269.

Meeus, W., J. Iedema, G. Maassen, and R. Engels. 2005. "Separation-individuation revisited: on the interplay of parent-adolescent relations, identity and emotional adjustment in adolescence." *J Adolesc* 28 (1):89-106. doi: 10.1016/j.adolescence.2004.07.003.

Meier, S., and C. D. Sprenger. 2015. "TEMPORAL STABILITY OF TIME PREFERENCES." *Review of Economics and Statistics* 97 (2):273-286. doi: 10.1162/REST_a_00433.

MilitaryOneSource. 2020. "Housing Options for Service Members and Families." Military OneSource, accessed 3/8/21. https://www.militaryonesource.mil/moving-housing/housing/specialized-housing/housing-options-for-service-members-and-families/.

Minkler, M. 1999. "Personal responsibility for health? A review of the arguments and the evidence at century's end." *Health Education & Behavior* 26 (1):121-140. doi: 10.1177/109019819902600110.

Murphy, L., and S. Dockray. 2018. "The consideration of future consequences and health behaviour: a meta-analysis." *Health Psychology Review* 12 (4):357-381. doi: 10.1080/17437199.2018.1489298.

NCHS. 2012. National Center for Health Statistics. In *Health, United States, 2011: With Special Features on Socioeconomic Status and Health*. Hyattsville, MD: U.S. Department of Health and Human Services.

Nicosia, N, and A Datar. 2020. "The impact of state policies for school-based BMI/fitness assessments on children's BMI outcomes in rural versus urban schools: Evidence from a natural experiment." *Preventive Medicine* 141. doi: 10.1016/j.ypmed.2020.106257.

Ogden, C. L., M. D. Carroll, B. K. Kit, and K. M. Flegal. 2014. "Prevalence of childhood and adult obesity in the United States, 2011-2012." *JAMA* 311 (8):806-14. doi: 10.1001/jama.2014.732.

Oswald, Y., and U. Backes-Gellner. 2014. "Learning for a bonus: How financial incentives interact with preferences." *Journal of Public Economics* 118:52-61. doi: 10.1016/j.jpubeco.2014.06.003.

Ou, S. S. 2019. "Are some neighborhoods bad for your waistline? A test of neighborhood exposure effects on BMI." *Journal of Health Economics* 63:52-63. doi: 10.1016/j.jhealeco.2018.10.007.

Picone, G., F. Sloan, and D. Taylor. 2004. "Effects of risk and time preference and expected longevity on demand for medical tests." *Journal of Risk and Uncertainty* 28 (1):39-53. doi: 10.1023/b:risk.0000009435.11390.23.

Richardson, AS, N Nicosia, MB Ghosh-Dastidar, and A Datar. 2020. "School Food and Beverage Availability and Children's Diet, Purchasing, and Obesity: Evidence From a Natural Experiment." *Journal of Adolescent Health* 67 (6):804-813. doi: 10.1016/j.jadohealth.2020.03.004.

Sadoff, S., A. Samek, and C. Sprenger. 2020. "Dynamic Inconsistency in Food Choice: Experimental Evidence from Two Food Deserts." *Review of Economic Studies* 87 (4):1954-1988. doi: 10.1093/restud/rdz030.

Samek, Anya, Andre Gray, Ashlesha Datar, and Nancy Nicosia. 2021. "Adolescent time and risk preferences: Measurement, determinants and field consequences." 184 (1):460-488. doi: https://doi.org/10.1016/j.jebo.2020.12.023.

Sanbonmatsu, L., N. A. Potter, E. Adam, G. J. Duncan, L. F. Katz, R. C. Kessler, J. Ludwig, J. Marvakov, F. Yang, W. J. Congdon, L. A. Gennetian, J. R. Kling, S. T. Lindau, and T. W. McDade. 2012. "The Long-Term Effects of Moving to Opportunity on Adult Health and Economic Self-Sufficiency." *Cityscape* 14 (2):109-136.

Seeyave, D. M., S. Coleman, D. Appugliese, R. F. Corwyn, R. H. Bradley, N. S. Davidson, N. Kaciroti, and J. C. Lumeng. 2009. "Ability to Delay Gratification at Age 4 Years and Risk of Overweight at Age 11 Years." *Archives of Pediatrics & Adolescent Medicine* 163 (4):303-308. doi: 10.1001/archpediatrics.2009.12.

Shier, Victoria, Nancy Nicosia, and Ashlesha Datar. 2016. "Neighborhood and home food environment and children's diet and obesity: Evidence from military personnel's installation assignment." *Social Science & Medicine* 158:122-131. doi: http://dx.doi.org/10.1016/j.socscimed.2016.03.043.

Sirois, F. M. 2004. "Procrastination and intentions to perform health behaviors: The role of self-efficacy and the consideration of future consequences." *Personality and Individual Differences* 37 (1):115-128. doi: 10.1016/j.paid.2003.08.005.

Skinner, A. C., S. N. Ravanbakht, J. A. Skelton, E. M. Perrin, and S. C. Armstrong. 2018. "Prevalence of Obesity and Severe Obesity in US Children, 1999-2016." *Pediatrics* 141 (3). doi: 10.1542/peds.2017-3459.

Strathman, Alan, Faith Gleicher, David S Boninger, and C. Scott Edwards. 1994. "The consideration of future consequences: Weighing immediate and distant outcomes of behavior." *Journal of Personality and Social Psychology* 66 (4):742-752.

Sutter, M., M. G. Kocher, D. Glatzle-Rutzler, and S. T. Trautmann. 2013. "Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior." *American Economic Review* 103 (1):510-531. doi: 10.1257/aer.103.1.510.

Sutter, M., L. Yilmaz, and M. Oberauer. 2015. "Delay of gratification and the role of defaults An experiment with kindergarten children." *Economics Letters* 137:21-24. doi: 10.1016/j.econlet.2015.08.028.

Tcymbal, A., Y. Demetriou, A. Kelso, L. Wolbring, K. Wunsch, H. Wasche, A. Woll, and A. K. Reimers. 2020. "Effects of the built environment on physical activity: a systematic review of longitudinal studies taking sex/gender into account." *Environmental Health and Preventive Medicine* 25 (1). doi: 10.1186/s12199-020-00915-z.

Tseng, E., A. Zhang, O. Shogbesan, K. A. Gudzune, R. F. Wilson, H. Kharrazi, L. J. Cheskin, E. B. Bass, and W. L. Bennett. 2018. "Effectiveness of Policies and Programs to Combat Adult Obesity: a Systematic Review." *Journal of General Internal Medicine* 33 (11):1990-2001. doi: 10.1007/s11606-018-4619-z.

Wang, Y., L. Cai, Y. Wu, R. F. Wilson, C. Weston, O. Fawole, S. N. Bleich, L. J. Cheskin, N. N. Showell, B. D. Lau, D. T. Chiu, A. Zhang, and J. Segal. 2015. "What childhood obesity prevention programmes work? A systematic review and meta-analysis." *Obesity Reviews* 16 (7):547-565. doi: 10.1111/obr.12277.

Weller, R. E., E. W. Cook, K. B. Avsar, and J. E. Cox. 2008. "Obese women show greater delay discounting than healthy-weight women." *Appetite* 51 (3):563-569. doi: 10.1016/j.appet.2008.04.010.

Wills, T. A., C. R. Isasi, D. Mendoza, and M. G. Ainette. 2007. "Self-control constructs related to measures of dietary intake and physical activity in adolescents." *Journal of Adolescent Health* 41 (6):551-558. doi: 10.1016/j.jadohealth.2007.06.013.

Zhao, Zhenxiang, Robert Kaestner, and Xin Xu. 2014. "Spatial mobility and environmental effects on obesity." *Economics & Human Biology* 14:128-140. doi: http://dx.doi.org/10.1016/j.ehb.2013.12.001.