CULTURALLY-INHERITED PATIENCE AND HARMFUL HEALTH BEHAVIORS

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This paper investigates whether culturally transmitted time preferences influence health behaviors. Using panel data on U.S.-born second-generation immigrants, we analyze the impact of long-term orientation in individuals' countries of ancestry on a range of outcomes, including substance use, body mass index, and sexual health behaviors. We find that culturally inherited long-term orientation has a significant effect on health behaviors. These results are robust across alternative measures of cultural time preference, including one based on linguistic structure, and after controlling for individual time preferences, risk aversion (including a genetic marker), and origin-country characteristics. We also implement a Heckman-type correction for parental selection into migration, which indicates that unobserved parental traits that promote migration are negatively correlated with unobserved traits of their offspring that predispose them to engage in harmful health behaviors. Overall, the findings highlight the role of cultural transmission of preferences in shaping health behaviors and contributing to intergenerational persistence in outcomes.

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I. Introduction

In this paper we investigate the extent to which culturally-inherited patience is a determinant of health behaviors. We use a panel that follows U.S.-born second-generation immigrants from adolescence into adulthood and contains detailed information on their health behaviors and health outcomes, including smoking, alcohol and marijuana consumption, body mass index, and unplanned pregnancies. In addition to personal characteristics — including a measure of individual patience— the data contain information on each individual's country-of ancestry. Employing a widely-used measure of time preference for ancestral country, we show that long-term orientation, as an inherited cultural attribute, has a significant impact on health behaviors. Using an alternative measure of cultural time preference, based on linguistic structure of the county-of-origin, provides the inference.

We observe respondents in three waves of the panel, when their average ages are 17, 22, and 29. While inherited cultural long-term orientation is time-invariant, the panel structure of the data allows us to analyze how cultural time preference influences health behaviors as respondents age. Furthermore, even though our focus is on cultural time preference, we are also able to investigate the impact of induvial time preference. Information on individuals' own time preference (which may in part be impacted by culturally-inherited time preference) is collected in all three waves of the panel, enabling us to analyze the evolution of the revealed impatience over time. Although we remain agnostic about the specific form of the time-discounting process underlying observed behaviors, the availability of these repeated measures allows us to assess the stability of individual time preference.[1]

Another novel attribute of the data is the availability of a genetic marker of risk aversion, generated from saliva samples collected from respondents. This biological marker,

[1] In contrast, existing studies that employed longitudinal data typically analyzed outcomes over time as a function of a time-preference measured at a single point in the panel. For example, Golsteyn et al. (2014) used Swedish panel data (Stockholm Birth Cohort) to study the impact of time preference measured at age 13 on school performance, labor supply, income, and health over subsequent decades. Similarly, Cadena and Keys (2015), using the NLSY, examined the propensity to drop out of college and later labor market outcomes, measuring impatience based on interviewers' assessments when respondents were young adults.

together with a self-reported measure of risk preference, allows us to control for individuals' proclivity for risk-taking and to estimate the impact of time preference net of risk aversion.

We recognize and address potential sources of confounding. For example, first-generation immigrants (parents of the individuals we analyze) may have selected into neighborhoods with amenities aligned with their time preferences. More patient parents—whether due to cultural background or individual traits—may have chosen schools that cultivate patience and expose their children to similarly patient peers. Our data allow us to mitigate this concern as we observe multiple individuals from each high school. By including high school fixed effects in our regression models, we compare individuals who attend (and previously attended) the same high school but whose parents migrated to the United States from different countries of origin.

We also acknowledge that country-of-origin time preference, as a cultural attribute, may be correlated with other important origin-country characteristics, such as individualism versus collectivism as an ancestral trait, and dimensions of prosperity—measured by average educational attainment and the U.N. Human Development Index. We show, however, that cultural time preference has an independent impact on health behaviors.

Finally, we account for parents' self-selection into migration. Using information from Hanushek et al. (2017) on the percentiles of the origin-country skill distributions from which immigrants to the U.S. are drawn, we implement a Heckman-type selection correction. The results indicate that unobserved parental attributes that motivate migration are negatively correlated with unobserved traits of their offspring that predispose them to engage in harmful health behaviors.

The paper contributes to several research areas, including the root causes of intergenerational persistence in behaviors and outcomes, the transmission of cultural preferences from parents to children, and the determinants of unhealthy behavior.

The positive correlation between parents and their offspring in behaviors and outcomes—ranging from educational attainment and occupational choice to health, criminal activity, income, and wealth—has long been documented, giving rise to a large literature that seeks to understand its determinants.[2] More recent contributions to this literature have focused on identifying the root causes of intergenerational persistence. One strand examines

[2] Examples include Charles and Hurst (2003), Haeck and Laliberté (2025), Hjalmarsson and Lindquist (2013), Mazumder (2005), and Solon (1992).

the relative importance of nature versus nurture -- the transmission of genetic attributes versus the influence of the home environment and resource—(Barth, Papageorge, and Thom, 2020; Björkegren et al., 2006; Black et al., 2017; Barne et al. 2010; Cronqvist and Siegel, 2015; Fagereng, Mogstad, and Rønning, 2021).[3] Another strand investigates the transmission of preferences from parents to children (Brenøe and Epper, 2022; Cappelen et al., 2020; Chowdhury et al., 2022; Dohmen et al., 2012; Mocan and Orak, 2025).

Two additional related lines of research are also informative for understanding intergenerational persistence. The first emphasizes the role of location and geography. For example, the places where individuals spend their childhood and adolescence have been shown to affect adult income and patterns of intergenerational mobility (Chetty et al., 2016; Chetty and Hendren, 2018a,b; Deutscher, 2020). The second examines the role of cultural traits in shaping behaviors and their transmission across generations.

A related literature studies how time preferences influence a wide range of economic behaviors, including educational attainment, consumption of addictive goods, financial decisions, and labor market outcomes (e.g. Angerer et al., 2023; Golsteyn et al., 2014; Hanushek et al., 2022). This work connects naturally to the intergenerational persistence literature, as it considers both the responsiveness of time preferences to factors such as education (Becker and Mulligan 1997; Alan and Ertac 2018) and the extent to which patience is transmitted across generations through parenting styles and preferences (Cappelen et al., 2020; Kosse et al., 2020).

In this context, our paper contributes to this body of work by analyzing the impact of long-term orientation, as a culturally transmitted trait, on behaviors with harmful health consequences.

[3] Identifying the separate impacts of nature (the genetic component) and nurture (the family environment) on behaviors and outcomes has been a difficult challenge not only in economics, but also in domains, ranging from psychology to medicine. Adoption studies provide arguably the clearest evidence on the relative roles of nature and nurture. Linking adopted children to both their biological and adoptive parents, large administrative datasets allowed researchers to separate the influence of inherited prebirth (genetic) factors from the effects of the family environment during childhood. Evidence from these studies show that both sets of factors contribute to intergenerational transmissions. For example, an analysis of roughly 7.5 million individuals in Sweden, including all adoptees, found that male adoptees are more likely to engage in criminal behavior if their biological parents have criminal records, yet the criminal history of adoptive parents also affects their likelihood of offending. (Hjalmarsson et al., 2013) Other research on Swedish adoptees demonstrates that genetic inheritance from biological parents and characteristics of adoptive parents both shape the transmission of earnings and educational attainment across generations. (Bjorlund et al., 2006).

II. Conceptual Framework and Empirical Implementation

Following the seminal theoretical work of Grossman (1972) on the concept of health capital, the demand for health and the derived demand for health investment, a vast literature has examined several dimensions encompassed by the Grossman model, such as the production of health, and the demand for medical care.[4] A substantial branch of this literature has focused on individuals' choices in unhealthy behaviors such as smoking, alcohol consumption, and drug use, with an emphasis on the impact of prices and government policies (Saffer and Grossman 1987; Coate and Grossman 1988; Grossman and Chaloupka 1998; Gruber and Zinman, 2001; Colman et al. 2003; Kenkel et al. 2014; Carpenter and Sansone 2021). The focus of our paper is the impact of impatience on health behaviors, culturally-inherited impatience being a key determinant.

A burgeoning literature in economics examines the role of cultural attributes in shaping individual behavior. The standard approach links second-generation immigrants—born and raised in a destination country—to their country of origin and studies how cultural characteristics of those origin countries, that are transmitted from first-generation immigrant parents to their children, influence these individuals' decisions, behaviors, and outcomes. Examples include the impact of country-of-origin attributes on women's work and fertility behavior in the United States (Fernández and Fogli, 2009), labor supply in Europe (Mocan, 2019), educational performance of students in Florida (Figlio et al., 2019), student achievement across counties measured by PISA test scores (Hanushek et al. 2022), stock market participation in the United States (Osili and Paulson, 2008), law-breaking propensity of U.N. diplomats (Fisman and Miguel, 2007) household savings behavior in Germany (Fuchs-Schündeln et al., 2020), and firm productivity in Sweden (Ek 2024). Similarly, Alesina et al. (2015) show that individuals who inherit stronger family ties are less geographically mobile, earn lower wages, and have a higher likelihood of unemployment. Alesina and Giuliano (2011) demonstrate the impact of culturally transmitted family ties on political participation among immigrants across countries.[5]

[4] Examples of this vast literature include Almond et al. (2005), Auer and Kunz (2025), Corman et al. (1987), Cygan-Rehm and Karbownik (2022), Dardanoni and Wagstaff (1990), Gilleskie (1993), Grossman and Joyce (1990), Mocan et al. (2004), Picone et al. (1998), and Rosenweig and Schultz (1983).

[5] A parallel branch of this literature examines the extent to which cross-country differences in cultural attributes help explain variation in outcomes across countries, ranging from economic growth to international trade; from innovation to government regulation, from savings rates to accumulation of

Within this framework, consider Equation (1) below.

$$Y_{icsgt} = \alpha + \beta\, LTO_c + X_{it}\Gamma + \rho_g \,.\, \rho_s + \tau_t + \varepsilon_{icsgt} \qquad (1)$$

where Y_{icsgt} denotes a health behavior/health outcome of individual i, with ancestral country c, who attended school s, and was in grade g during the first wave of the panel survey. LTO_c denotes the long-term orientation of origin country c, which intends to capture the extent to which a society emphasizes future rewards and delayed gratification, as opposed to short-term considerations and immediate benefits. We employ two alternative measures of LTO. The primary measure, which is widely used in the literature, assigns to every country a score reflecting its position on the spectrum from short-term orientation (impatience) to long-term orientation (patience). The alternative measure of LTO is a dichotomous indicator of long-term orientation, based on the language structure of the origin country.

X_{it} is a vector of individual controls, including age, gender, and maternal and paternal educational attainment.[6] As described in the data section below, the first wave of the Survey was registered during the 1994-95 academic year when the respondents were in grade 7 to 12, of 145 different schools across the U.S. The specification includes grade-by-school fixed effects ($\rho_g \,.\, \rho_s$) to absorb unobservable factors shared by students in the same school-grade in 1994-95 such as teacher influences, school resources, and other contextual attributes. They also capture neighborhood and peer effects. This is important because parents from countries of origin with long term orientation might sort into better neighborhoods and schools. Thus, conditioning on grade-by-school fixed effects mitigates the concern of selection into schools and allows us to compare second-generation immigrants who share the same school-cohort environment. The model also includes wave-of-the-survey fixed effects (τ_t) to control for cohort effects.

Although grade-by-school fixed effects mitigate concerns about sorting of children from high-LTO ancestral origins into schools that foster delayed gratification, other forms of selection may still be present. For example, suppose first-generation immigrants in the U.S. are positively selected from their countries of origin (rather than being a random draw), in terms of time preference. Put differently, they could be more patient than the average person in their country of origin. Suppose further that individual time preference is positively

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physical capital and productivity (Gorodnichenko and Roland, 2017; Tabellini, 2010; Algan and Cahuc, 2010; Guiso et al., 2009).

[6] Additional family attributes, including the number siblings, that may be endogenous controls, included in sensitivity analyses.

correlated with cultural time preference, indicating that a randomly drawn person from a country with high LTO is expected to be more patient from a person randomly chosen from another country with low LTO. This means that, on average, a positively selected immigrant from a high-LTO country is expected to be more patient than a positively selected immigrant from a low-LTO country. More formally, consider Equation (2)

$$TP_{ic} = \gamma\, LTO_c + \nu_{ic} \qquad (2)$$

where TP_{ic} represents individual's own time preference (patience), LTO_c is the extent of long-term orientation in the country of origin of the individual, and ν_{ic} stands for biological, environmental, and all other factors that impact own time preference. Positive selection implies that immigrants have high positive values for ν_{ic}. Under the reasonable assumption that $\gamma>0$, (i.e. the expected individual patience is higher for those from higher LTO countries), the inability to control for TP in Equation (1) would load both the direct and indirect effects of LTO on β, and would inflate its estimated value.

More specifically, if the proper model to explain health behaviors includes personal time preference (TP_{ic}), as depicted by Equation (3) below,

$$Y_{icsgt} = \alpha + \beta\, LTO_c + \delta\, TP_{ict} + X_{it}\Gamma + \rho_g \,.\, \sigma_s + \tau_t + u_{icsgt} \qquad (3)$$

then, the expected value of $\hat{\beta}$ in Equation (1) is $\beta + (\gamma\delta)$. If more patient individuals have lower propensity to engage in harmful health behaviors ($\delta<0$ in Equation 3), and if individual time preference is positively correlated with origin-country LTO ($\gamma>0$ in Equation 2), then β in Equation (1) will be overestimated (more negative).[7]

As mentioned in the previous section, a novelty of our data set is the availability of an indicator for individual impatience, which allows us to estimate Equations (2) and (3) to gain insights into (i) the role of cultural long-term orientation, holding constant individual time preference; (ii) the connection between individual time preference and cultural long-term orientation -as depicted by Equation (2); and (iii) the change in individual time preference over the duration of the panel, spanning from teenage years to adulthood.

Note that our analysis focuses on second-generation immigrants, while the migration decision was made by their parents. Time preference of individuals (TP) is likely correlated with their parents' time preference, but not perfectly so. Moreover, parents' decision to migrate depends on unobservable parental characteristics such as their ability, ambition,

[7] Note that β will be similarly biased if $\gamma=0$ and if immigrants are negatively selected from low-LTO countries, but positively selected from high-LTO countries, a condition which is not highly plausible.

skills, and risk tolerance. Given that such individual parent attributes (other than cultural long-term orientation) are transmitted from parents to children, these unobservable may also impact the behavior of their children.

Suppose $M_{jc}$is a dichotomous indicator for the probability that person (j) migrates to the U.S. from country c, determined by

$$M_{jc} = \pi K_j + m_{jc}, \qquad (4)$$

where $K_j$is a vector of migration determinants and $m_{jc}$is an error term. The fact that our dataset includes second-generation immigrants implies that their parents migrated to the U.S., and that for these parents $m_{jc} \geq -\pi K_j$. This, in turn, means that for the survey respondents the expected value of u_{ic} in Equation (3) is $E[u_{ic} \mid m_{jc} \geq -\pi K_j]$.

As shown by Heckman, if m_{jc} and u_{ic} are correlated—i.e., if unobserved parental characteristics that influence migration are correlated with unobserved characteristics of their children that affect health behavior—then this conditional expectation is not equal to zero. Consequently, the regressors in Equation (3) are correlated with the error term, leading to biased and inconsistent coefficient estimates.

We don't observe non-migrants (those who have not migrated, but remained in origin countries), which prevents us from estimating a migration-selection equation to correct for this potential selection bias. However, we draw on evidence from Hanushek et al. (2017), who document significant positive selection: immigrants from each origin country tend to come from the right tail of their country's skill distribution. The authors provide estimates of the skill percentiles within origin countries from which immigrants to the U.S. are drawn. This information allows us to generate a Heckman-style selection correction and create the inverse the Mill's ratio to include in Equation (3).

The argument is based on the observation that migrants are positively selected on human capital and related traits. Thus, to the extent that migration is primarily driven by individuals' position in the upper tail of the skill distribution, as shown by Hanushek et al. (2017), the relevant selection index (S_{jc}) for person j who migrated from origin country c can be approximated by the percentile rank from which immigrants originate in country c's skill distribution. Hanushek et. al (2017) provide for each origin country the percentile (S_c) above which immigrants are drawn from. Thus, if $\Phi^{-1}(S_c)$=a, such that $Prob\ (Z \leq a) = S$ for a standard normal $Z \sim N(0,1)$, and if *f(a)* stands for the density of the standard normal at value *a*, then the inverse Mills' ratio is given by

$\lambda_c = f(a)/[1- \Phi(a)] = f(a)/S_c$.

Adding this inverse Mill's ratio to model (3) provides its immigration-selection corrected version, as shown below.

$$Y_{icsgt} = \alpha + \beta LTO_c + \delta TP_{ict} + X_{it}\Gamma + \rho_g . \rho_s + \tau_t + \sigma\lambda_c + u_{icsgt} \qquad (5),$$

where σ denotes the covariance between the error term in the immigration selection equation and the error term in the health outcome equation (4). Identification of σ arises from cross-country variation in the inverse Mills ratio (λ). Put differently, the inverse Mills ratio captures an index of unobservable immigrant characteristics that influenced migration propensity and that is common to immigrants from the same country of origin.

Because σ is the covariance between the child's error term (u_i) and the parent's error term in the migration equation (m_j in Equation 4), the sign of σ provides an important insight into the relationship between unobservables that drive selection into migration and those that shape health behaviors and outcomes. For example, if σ=0, this implies that unobserved factors that make parents more likely to migrate, have no correlation with factors that make their kids more likely to engage in harmful health behaviors. On the other hand, if σ>0 (σ<0), unobserved factors that increase parents' likelihood of migrating are positively (negatively) associated with their children's engagement in harmful health behaviors.

III. Data

The data are drawn from the National Longitudinal Study of Adolescent to Adult Health (Add Health), which employed a stratified sampling method to select a random sample of U.S. schools across the country between September 1994 and April 1995, to generate a nationally representative sample of 20,745 adolescents in grades 7 through 12. The respondents were followed up since, through several waves: Wave II (1996; N=14,738), Wave III (2001-2002; N=15,197), Wave IV (2008-2009; N=15,701), Wave V (2015-2017; N=12,300), and Wave IV (2022-2025; N=11,979).

This dataset is particularly well-suited for our analysis for three main reasons. First, it provides extensive information on health behaviors during both adolescence and adulthood. Second, the survey contains information identifying the country of origin for all respondents. Third, it includes self-reported time preference and risk preference (as well as genetic

markers of risk preference) in Waves II, III, and IV. As described in the previous section, this unique feature allows us to provide insights that were not possible in prior research.

We analyze U.S. born individuals data using data from Waves II, III, and IV, because these are the waves that include information on individual time preference.[8] Respondents range from age 13 to 21 in Wave II, and from 18 to 26 in Wave III. They range from 24 to 32 in Wave IV. The dependent variables, which are also measured in each of the three waves, are indicators of health behaviors and outcomes, described below.

Outcome Variables

Cigarette is a binary variable indicating whether the respondent has ever smoked a cigarette. *Alcohol* is another binary variable indicating whether the respondent has ever had a drink of beer, wine, or liquor (not just a sip or a taste of someone else's drink) more than two or three times. If the respondent indicated that they have ever used marijuana, *Marijuana* takes the value of one, and zero otherwise. *BMI* stands for Body Mass Index (calculated as weight in kilograms divided by height in meters squared). It is not based on the respondent's self-reported height and weight. Rather, it is calculated using height and weight measured by the survey administrator. *Overweight* is a binary variable indicating whether the respondent's calculated BMI is ≥ 25.0 (for adults) or at or above the 85th percentile for their age and sex (for adolescents), based on the CDC Growth Charts for age and sex. *Obese* is another indicator for whether the respondent's calculated BMI is ≥ 30.0 (for adults) or at or above the 95th percentile for their age and sex (for adolescents), based on the CDC Growth Charts for age and sex.

If a female respondent reports ever being pregnant or a male respondent reports ever causing a pregnancy, the variable *Ever Pregnant* takes the value of one; it is zero otherwise. *Ever Unplanned Pregnancy* is a binary variable indicating that the respondent reported having any pregnancy that they "didn't want to have a child then—when thinking back to the time just before the pregnancy." This question was asked in Waves III and IV only. Furthermore, because the question is relevant only for those who experienced a pregnancy, the sample size is smaller when analyzing this outcome. *STD* is another binary variable

[8] This restriction excludes approximately 9 percent of respondents in each wave who were born outside of the U.S.

indicating a positive laboratory test result for a sexually transmitted disease. In contrast to most prior studies, the variable is not based on the respondent's self-report, but rather on a laboratory test (for chlamydia, gonorrhea, and trichomoniasis) performed on samples collected from respondents. Although this test was conducted only in Wave III and therefore it leads to a small sample size, we nevertheless add the STD variable to the analysis as an indicator of unprotected sexual activity. Table 1 presents the descriptive statistics of the outcome variables.

Long-Term Orientation of Country of Origin

We employ Hoeftede's index of long-term orientation to measure the extent to which individuals' ancestral origin has long-term orientation, which has been has used extensively in economics and other disciplines (Figlio et al. 2019)[9] The original LTO index, which ranges from 0 to 100, is re-scaled to range from 0 to 1 with higher values representing long-term orientation as a cultural attribute.

We also use an alternative measure of a country's long-term orientation, based on the language structure of the country. In some languages, the future is grammatically distinguished from the present, whereas in others it is not. Linguists describe how a language treats the future using the concept of future time reference (FTR). In languages with strong FTR, grammar requires speakers to mark future events explicitly. In contrast, languages with weak FTR do not require a grammatical distinction between present and future. These are often referred to as "futureless" languages because the same verb forms are used to describe both time frames.

As an example, Finnish lacks a dedicated future tense. Future meaning is conveyed through context or time expressions. For instance, *Tänään on aurinkoista* means "it is sunny today," while *Huomenna on aurinkoista* means "it will be sunny tomorrow." The verb *on* is simply the present tense ("is"), and the distinction between present and future arises from *Tänään* ("today") versus *Huomenna* ("tomorrow"). Similarly, the future is not marked in the verb in Thai.. *Phom kin khao* means both "I eat rice" and "I will eat rice" with *Phom* stands for "I", *kin* is "eat", and *khao* meaning "rice". There are many such languages around the

[9] Hofstede index is obtained from the website https://geerthofstede.com/researchand-vsm/dimension-data-matrix/, using the file "6 dimensions for website.xls (version 2015 12 08)". Nepal and Sri Lanka data are from "NonOfficial VSM08 scores 2014 01 04.docx".

world, including Mandarin and Cantonese (China), Japanese, Indonesian, Estonian, and various African languages.

Speakers of futureless languages are likely to perceive the future as closer to the present, leading them to discount future outcomes less, and to be more forward-looking. In fact, evidence indicates that these languages, where the present and future are expressed in the same way, induce long-term decision-making. For example, Chen (2013) reported findings indicating that speakers of futureless languages tend to exhibit more future-oriented behaviors. They are more likely to save and accumulate wealth by retirement, adopt healthier lifestyles. Supporting this, an analysis of savings rates across OECD countries shows that nations with languages lacking obligatory future marking save, on average, about 5 percent more of their GDP. Chen also found that speakers of futureless languages are less likely to smoke, more likely to be physically active, and less likely to be obese. In other words, they invest in their health more. Similar results are provided by a large literature in various fields (e.g. Campo et al., 2024; Chen et al., 2017; Ginsburgh and Weber, 2020; Pérez and Tavits, 2017).

It is, of course, an interesting question whether the manner in which a language expresses the future tense can shape how its speakers perceive the future and how they make decisions involving trade-offs between the present and the future. More specifically, is it the structure of a language shapes cognitive differences and perceptions of the relative importance of the present versus the future, or whether language merely reflects these underlying differences. There is, in fact, a substantial literature in linguistics and neuroscience on this topic (for a detailed discussion, see Chapter 7 of Mocan, 2006; Ayres, Katz, and Regev, 2023; Ginsburgh and Weber, 2020). However, this question is not central to our purposes. Here, we treat the way a language refers to the future as an indicator of how the future is perceived, regardless of whether the language itself influences perception or whether preexisting differences in perception led to the development of particular linguistic features.

To determine respondents' cultural backgrounds, we assign each individual to the county of origin they reported, based on the following question from Wave III: "Please describe your family origins. You may name as many as four countries, groups, or geographic areas. What are your family ancestries?" We then use the first country listed by the respondent as their primary country of ancestry.

One hundred-seventy two respondents who provided invalid answers, and 5,083 respondents who reported a continent rather than a specific country are excluded. Similarly,

5,624 respondents whose country of origin does not have a corresponding LTO value in Hofstede et al. (2010) cannot be used in the analyses. The final sample consists of 6,314 respondents in Wave II, 8,123 in Wave III, and 7,084 in Wave IV, representing 69 countries. Specific LTO values of each reported country can be found in the Appendix.

Puerto Rico has the lowest long-term orientation (LTO) score of zero, representing most short-term orientation, while South Korea has the highest score of one, representing the most long-term oriented country of origin. The sample mean of the index is 0.51 with a standard deviation of 0.24. Asian and European countries generally display higher LTO values, whereas South American and African countries tend to have lower values. Nonetheless, there exists substantial within-continent variation: the residual from regressing LTO on continent indicators ranges from -0.45 to 0.41, with a standard deviation of 0.21(86% of the original variation).

Personal time preference of the respondents is based on the following question: ″Do you agree or disagree with the statement: 'You live your life without much thought for the future.'" We construct the variable *Self-Patience*, coded as 1 if the respondent answers "disagree" or "strongly disagree" to the statement.

Other Controls and Riks Preference

The data set enables us to control for maternal and paternal education. The regressions also include country-of-origin variables that may be correlated with cultural time preference of the origin country. They are *average education of the origin country*, obtained from Barro-Lee data set, *UN index of Human Development*, and the *index of Individualism*, obtained from Hofstede, which measures the extent to which people in a society are expected to look after themselves and their immediate family only, as opposed to being integrated into strong, cohesive in-groups that provide protection in exchange for loyalty.

We employ two measures of risk. First, we use survey respondents' self-assessment, based on the question ″Do you agree or disagree with the statement: 'You like to take risks'" We construct the variable *Self-Risk*, coded as 1 if the respondent answers "disagree" or "strongly disagree" to the statement. Second, we use a polygenic score (PGS) for risk tolerance, derived from genetic data collected from consenting Add Health respondents in Wave IV (Polygenic Score Release 2—Braudt and Harris, 2020). Specifically, 96% of Wave

IV respondents provided a saliva sample, and approximately 80% of these participants (roughly 12,200 individuals) consented to long-term biospecimen archiving, making them eligible for genome-wide genotyping. After quality control procedures, genotyped data are available for 9,974 individuals.

The underlying genetic discovery evidence comes from the genome-wide association study (GWAS) of general risk tolerance reported in Karlsson Linnér et al. (2019)., which is the largest GWAS of risk preferences to date, covering more than one million individuals. Conceptually, a PGS for risk tolerance is a genome-wide summary index that aggregates the additive effects of thousands of single-nucleotide polymorphisms (SNPs) on the propensity to take risks. The score for individual *i* is computed as a weighted sum:

$$PGS_i = \sum_j \hat{\beta}_j \times SNP_{ij}$$

where SNP_{ij} is the allele frequency of the *j*-th SNP for individual *i*, and $\hat{\beta}_j$ is the estimated association between that SNP and general risk tolerance from independent GWAS summary statistics. The raw scores are subsequently standardized to mean zero and unit standard deviation within each genetic ancestry group, so that regression coefficients on the PGS have a natural standard-deviation interpretation. A more detailed explanation of the PGS is provided in the Appendix.

The use of polygenic scores (PGSs) in economics and related disciplines has expanded substantially with the availability of large-scale GWAS results and genotyped surveys. For example, Lee et al. (2018), Cheesman et al. (2025), Hollenbach (2026), and Arold et al. (forthcoming) analyze the influence of genetic endowments on educational outcomes. Barth, Papageorge, and Thom (2020) find that genes associated with educational attainment predict household wealth inequality at retirement, independent of an individual's actual education or labor income. Other studies highlight the interaction between genetics and environment: Barcellos et al. (2018) and Arold et al. (forthcoming) show that the quantity and quality of schooling can moderate genetic risks related to obesity and educational outcomes. Recent research also suggests the presence of social-genetic effects within school cohorts, indicating that peers' polygenic scores for smoking, obesity, and depression significantly influence an individual's own behavioral and health outcomes (Sotoudeh et al., 2019; Brunello et al., 2020; Jeong, 2025).

Table 2 presents descriptive statistics for the control variables, along with two alternative key explanatory variables: the index of long-term orientation (LTO) and a dichotomous indicator for languages with weak future-time reference (Weak FTR, or

"*Futureless*"). When we use the futureless-language indicator as the explanatory variable, observations from certain countries must be excluded because multiple languages with different future-time reference properties are spoken in those countries. For example, in Switzerland, German, French, Italian, and Romansh are spoken; while German is a weak-FTR language, French is not.

IV. Results

Table 3 presents the main results. Each column corresponds to a specific outcome. Standard errors are clustered at the country-of-origin level; alternative clustering schemes (e.g., at the school level) yield similar results. Each regression in Panel A includes age, sex, mother's education, father's education, and school-by-grade and survey-wave fixed effects. Panel A shows that the coefficient on LTO is negative and statistically significant across all nine outcomes analyzed. The coefficient in column 1 implies that individuals from short-term–oriented countries of origin (such as Colombia or the Dominican Republic, with LTO scores around 0.13) are approximately 6 percentage points more likely to have ever tried cigarettes—about a 6.5 percent increase—relative to individuals from long-term–oriented countries such as Japan (LTO ≈ 0.88). Similarly, holding other factors constant, individuals whose country of ancestry exhibits greater long-term orientation are less likely to try alcohol and marijuana. Long-term orientation also leads to lower BMI and a reduced likelihood of being overweight or obese. Individuals from more long-term–oriented cultures are less likely to have ever been pregnant (or to have caused a pregnancy, for males) and less likely to have experienced an unplanned pregnancy. They are also less likely to have a sexually transmitted disease. It is worth noting that while the pregnancy-related variables are self-reported, the other outcomes in the physical health and sexual health categories are based on objective measures, including recorded height and weight and laboratory tests (in the case of sexually transmitted diseases).

Panel B presents results from models that include the additional variables discussed in the Conceptual Framework section. More specifically, regressions in Panel B include the same variables in Panel A, but further control for country-of-origin characteristics, including average education, the Individualism Index, and the UN Human Development Index. These variables are included to ensure that the long-term orientation (LTO) index is not simply capturing other country-of-origin characteristics. In fact, LTO and individualism are

positively correlated: more individualistic countries tend to be more long-term oriented. Similarly, long-term orientation is correlated with country-level education and with the Human Development Index. Appendix Figure B1illustrates these relationships among the origin countries.

Regressions reported in Panel B also include survey respondents' individual time preference, attitudes towards risk and their PGS score that measures the genetic proclivity towards risk-taking (PGS score). Also included is the inverse Mills ratio (IMR), which accounts for the correlation between the error term and unobserved parental characteristics that influence the decision to migrate to the United States.

The results in Panel B indicate that adding these additional controls does not alter the inference, with the exception of unplanned pregnancy and sexually transmitted diseases, for which the coefficient on LTO becomes statistically insignificant. Notably, long-term orientation is the only country-of-origin characteristic that consistently predicts health behaviors and outcomes; average education, the Human Development Index, and the Individualism Index are not statistically significant.

The coefficient of self-reported patience is negative across all specifications, but statistically significant only for substance use outcomes (cigarette, alcohol, and marijuana use). Individuals who report being patient are 3.8 percentage points (4.6 percent) less likely to have ever smoked, 1.4 percentage points (1.5 percent) less likely to have tried alcohol, and 6.8 percentage points (11 percent) less likely to have used marijuana. The opposite pattern emerges for individual risk attitudes: those who are more willing to take risks are more likely to engage in smoking, drinking alcohol, and marijuana use, with estimated effects that are approximately two times larger for smoking, 3.7 times larger for alcohol use, and 1.5 times larger for marijuana use relative to the effects of patience. The PGS, an index of genetic propensity for risk-taking, has an independent effect. Individuals with higher PGS scores are more likely to have ever tried marijuana and to have experienced a pregnancy or an unplanned pregnancy.

One interesting result is that individuals' propensity for risk-taking has a negative effect on BMI and the probability of being overweight. The limited literature on the relationship between risk attitudes and body weight has produced mixed findings: while some studies report a positive association between risk-taking propensity and body mass, others find the opposite. The negative effect of risk-taking on BMI may operate through its

influence on other behaviors. An example is shown in column (1), where risk-taking has a positive effect on smoking, which acts as an appetite suppressant.[10]

Panel B also reports the estimated coefficient on the inverse Mills ratio (IMR), which is consistently negative across outcomes, although not statistically significant in all cases. The negative sign suggests that unobserved parental characteristics that increase the propensity to migrate to the United States are negatively correlated with the unobserved determinants of their children's harmful health behaviors.

Table 4 presents the same models as does Table 3 with one difference: The index of cultural long-term orientation (LTO) is replaced by an alternative indicator of cultural patience: whether the language of the country or origin is futureless. The results are consistent with those reported in Table 3. Individuals with ancestral roots from countries where the language does not differentiate between the present and the future are less likely to smoke, use alcohol or marijuana. They have lower BMI and are less likely to be overweight or obese. They are also less likely to have experienced an unplanned pregnancy. The impact of individual time preference, risk attitude and the Inverse Mill's ratio are also consistent between Tables 3 and 4.

The regressions reported in Tables 3 and 4 use all three waves of the panel. In contrast, Table 5 presents results obtained by estimating the models separately for each survey wave. As individuals age across waves, their behaviors—as well as their risk and time preferences (which are measured in each wave)—may change. Table 5 therefore examines the sensitivity of the estimated effects of cultural time preference to this life-cycle variation.

Panels A–C report the coefficients on LTO, while Panels D–F report the coefficients on the futureless-language indicator. In all cases, the effect of cultural time preference remains statistically significant. For substance use (cigarettes, alcohol, and marijuana), however, the magnitude of the effect declines as respondents age. For example, the coefficient on LTO in column (1) is −0.11 in Wave I (when respondents are in high school), −0.06 in Wave II, and −0.047 in Wave III. Because the proportion of individuals who have

[10] For example, Chou et al. (2004) show that higher cigarette prices lead to higher body weight. At the same time, columns (2) and (3) show that individuals who are more willing to take risks are more likely to consume alcohol and use marijuana—behaviors that may increase caloric intake. Nevertheless, risk attitudes likely influence other behaviors, such as exercise, which may be the mechanism that explains the negative effect of risk-taking on BMI.

ever smoked increases across waves, the effect of LTO in percentage terms declines even more sharply. The same pattern holds for alcohol and marijuana use.

This pattern is also observed when using the futureless-language indicator as the measure of cultural time preference. Put differently, Table 5 shows that the influence of ancestral time preference on smoking, alcohol, and marijuana use diminishes with age. In contrast, the effects on BMI and the probability of being overweight or obese remain stable over the duration of the panel.

VI. Extensions and Robustness

We performed a number of extensions and robustness analyses. Although these analyses have been completed, we did not have sufficient time to present them fully. Below, we summarize these additional exercises and their results.

1. Because we analyze nine health behaviors and outcomes, we addressed the issue of multiple hypothesis testing. Specifically, we grouped the outcomes into three categories (as reported in the tables): (i) substance use (smoking, alcohol, marijuana); (ii) physical fitness (BMI, obesity, overweight); and (iii) sexual health (ever having experienced a pregnancy, unplanned pregnancy, and having an STD). We conducted multiple hypothesis testing within each group. The results indicate that statistical significance is retained in almost all cases. In summary, adjusting for multiple hypotheses does not alter our conclusions.
2. We re-estimated the models after excluding individuals whose parents migrated from Mexico. We then further excluded respondents with ancestral ties to Central American countries, and finally those from South America. The purpose of these exercises was to assess the sensitivity of the results to the exclusion of second-generation immigrants whose parents may have faced lower migration costs due to geographic proximity. The results remains the same.

   In addition, we refined the Heckman selection term (Inverse Mills ratio) by incorporating the distance between the United States and each country of origin. Although this refinement reduced the statistical significance of the estimated coefficient on the Inverse Mills ratio—which captures the correlation between migration-selection unobservables and the error term in the outcome equations—it had no impact on the results.

3. Although not central to the paper, we also investigated the time consistency of self-reported risk and time-preference attitudes. Recall that respondents reported their risk and time preferences in each survey wave. We therefore tested—and rejected—the hypothesis that these responses are random. Put differently, there is strong persistence in revealed risk and time preferences across waves.
   Table 6 presents the descriptive statistics that form the basis for this analysis. It reports the transitions in revealed risk and time-preference attitudes across the three survey waves.
4. We conducted several sensitivity analyses, including adding additional controls related to the households in which respondents were raised, whcih did not alter the results. We also estimated the models separately by gender. The results for men remained unchanged. The female sample yielded similar inferences when Long-Term Orientation (LTO) was used as the key explanatory variable. When we used Futureless Language instead of Long-Term Orientation, the statistical significance of the Futureless Language coefficient declined in the models of physical fitness and sexual health, but not in those for smoking, marijuana use, and alcohol consumption.

VII. Conclusion

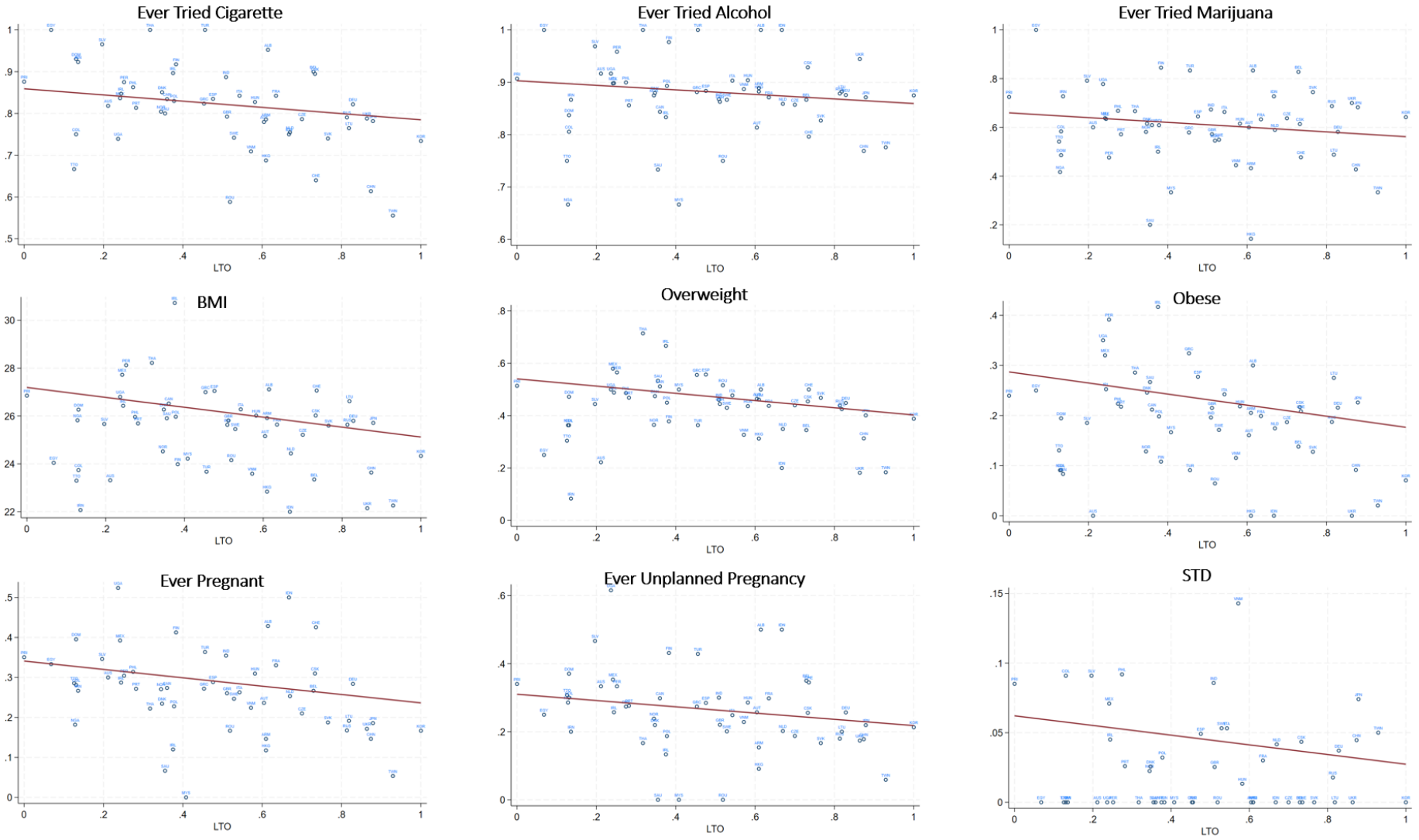
This paper provides evidence that culturally transmitted time preferences play an important role in shaping health behaviors. Using a panel of U.S.-born second-generation immigrants, we show that long-term orientation—measured at the country-of-origin level—has a significant effect on a wide range of outcomes, including substance use (smoking, alcohol consumption, marijuana use), physical fitness (BMI, overweight, obesity), and sexual health behaviors (ever having been pregnant, unplanned pregnancy, sexually transmitted disease). These findings are robust across alternative measures of cultural time preference, including one based on linguistic structure.

The panel nature of the data allows us to follow individuals over time and to incorporate repeated measures of their own time preferences. While individual-level patience matters, the results indicate that culturally inherited long-term orientation exerts an independent influence on behavior. In addition, by controlling for both self-reported and biological (gene-based) measures of risk aversion, we isolate the effect of time preference from risk-taking tendencies.

We address several potential sources of bias. High school fixed effects mitigate concerns about neighborhood and school selection, while controls for origin-country characteristics ensure that ancestral long-term orientation is not capturing other correlated attributes. Furthermore, a Heckman-type correction for parental selection into migration suggests that unobserved parental traits that promote migration are negatively correlated with unobserved predispositions toward harmful health behaviors among their children.

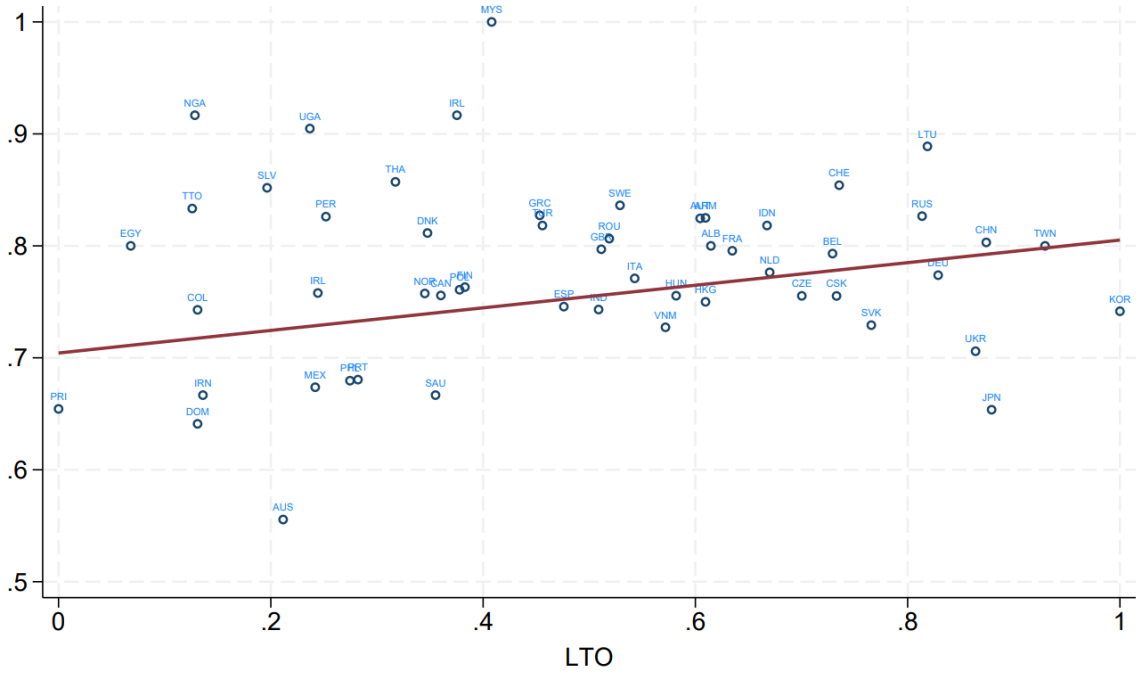
Overall, the results highlight the importance of cultural transmission as a mechanism underlying intergenerational persistence in behaviors and outcomes. They contribute not only to the literature on the determinants of health behaviors, but also to the broader literature on the root causes of intergenerational persistence in outcomes.

Figure 1. Long-Term Orientation and Health



Notes: Outcome variables and LTO are aggregated at the origin-country level.

Figure 2. Long-Term Orientation and Self-Patience



Notes: Self-Patience and LTO are aggregated at the origin-country level.

Table 1

Summary Statistics of the Outcome Variables

Variable	N	Wave	Mean	SD
Ever Tried Cigarette	22,514	II, III, IV	0.8213	0.3831
Ever Tried Alcohol	22,911	II, III, IV	0.8807	0.3242
Ever Used Marijuana	19,786	II, III, IV	0.6091	0.4880
BMI	20,523	II, III, IV	26.1212	6.6489
Overweight	20,523	II, III, IV	0.4693	0.4991
Obese	20,523	II, III, IV	0.2299	0.4208
Ever Pregnant	21,448	II, III, IV	0.2868	0.4523
Ever Unplanned Pregnancy	13,611	III, IV	0.2619	0.4397
STD (Chlamydia, Gonorrhea, or Trichomoniasis)	6,449	III	0.0440	0.2052

Notes: The table presents summary statistics for the pooled sample from Waves II, III, and IV of the Add Health survey. The sample size (N) varies for each variable due to item non-response and because some measures were collected only in specific waves. All variables, with the exception of the continuous BMI measure, are binary.

Table 2

Summary Statistics of Control Variables

Variable	N	Mean	SD
Age in Years	21,051	22.8027	5.1083
Female	23,829	0.5205	0.4996
Residential Mother: College or Higher	23,829	0.2714	0.4447
Residential Father: College or Higher	23,829	0.2669	0.4423
Self-Patience	21,027	0.7569	0.4290
Self-Risk	21,036	0.5077	0.5000
Origin Country Long-Term Orientation	23,829	0.5147	0.2435
Origin Country Futureless Language	22,443	0.3287	0.4698
Origin Country Individualism	23,103	0.6158	0.1916
Origin Country Educational Attainment in Years	23,445	11.0818	1.5551
Origin Country Human Development Index	23,406	0.8275	0.0875
Polygenic Score for Risk Tolerance	12,738	-0.0280	1.0005

Notes: The table presents summary statistics for the pooled sample from Waves II, III, and IV of the Add Health survey. The sample size (N) varies for each variable due to item non-response and because some measures were collected only in specific waves. Self-Patience is a binary measure of self-reported time preference, coded as 1 if the respondent answers 'disagree' or 'strongly disagree' to the statement: 'You live your life without much thought for the future.' Self-Risk is a binary measure of self-reported risk preference, coded as 1 if the respondent answers 'disagree' or 'strongly disagree' to the statement: ‘You like to take risks.' Origin Country Long-Term Orientation measures the extent to which a culture emphasizes long-term orientation (see Appendix A for more details), and Individualism captures the degree to which individuals view themselves as independent rather than as members of larger interdependent groups. Origin Country Futureless Language captures whether the language spoken in the origin country has a weak future-time reference based on Chen (2013). Origin Country Educational Attainment in Years is calculated for the total population in 1950–2010 using data from Barro and Lee (2013). Origin Country Human Development Index is a composite index of life expectancy, education, and per capita income indicators for the year 2000, calculated by the United Nations. Polygenic Score for Risk is derived from genetic data collected from consenting Add Health respondents in Wave IV and captures genetic predisposition toward risk-taking.

Table 3. Long-Term Orientation and Health

	Substance Use			Physical Fitness			Sexual Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ever Tried Cigarette	Ever Tried Alcohol	Ever Used Marijuana	BMI	Overweight	Obese	Ever Pregnant	Ever Unplanned Pregnancy	STD
Panel A. Parsimonious Model									
LTO	-0.0707**	-0.0475**	-0.0691**	-0.8478***	-0.0585***	-0.0389**	-0.0795***	-0.0440**	-0.0270***
	(0.0349)	(0.0193)	(0.0282)	(0.3094)	(0.0202)	(0.0194)	(0.0249)	(0.0220)	(0.0088)
N	20,515	20,783	19,197	20,523	20,523	20,523	19,683	13,611	6,449
Panel B. Full Model									
LTO	-0.0738***	-0.0567***	-0.0807***	-1.3008***	-0.0871***	-0.0469*	-0.0337**	-0.0207	0.0033
	(0.0210)	(0.0076)	(0.0274)	(0.3432)	(0.0241)	(0.0251)	(0.0154)	(0.0160)	(0.0150)
Self-Patience	-0.0384***	-0.0144*	-0.0680***	-0.0891	0.0015	-0.0127	0.0009	-0.0226	-0.0138
	(0.0077)	(0.0082)	(0.0106)	(0.1636)	(0.0073)	(0.0088)	(0.0105)	(0.0144)	(0.0082)
Barro-Edu	0.0019	-0.0003	-0.0025	0.2153	0.0100	0.0066	-0.0156*	-0.0253***	-0.0054
	(0.0062)	(0.0033)	(0.0123)	(0.1799)	(0.0111)	(0.0115)	(0.0083)	(0.0085)	(0.0047)
HDI	0.0952	0.0992	0.2798	-1.0272	0.1251	-0.0310	0.0409	0.3671***	-0.0538
	(0.1696)	(0.0847)	(0.2106)	(2.9189)	(0.1938)	(0.1630)	(0.1471)	(0.1334)	(0.1009)
IDV	0.0064	-0.0279	-0.0141	-0.1771	-0.1066	0.0183	0.0738	0.0123	0.0280
	(0.0440)	(0.0259)	(0.0787)	(1.2432)	(0.0853)	(0.0772)	(0.0474)	(0.0643)	(0.0366)
Self-Risk	0.0805***	0.0530***	0.1034***	-0.2199*	-0.0153**	-0.0141	-0.0143	0.0233*	0.0061
	(0.0095)	(0.0061)	(0.0096)	(0.1297)	(0.0072)	(0.0093)	(0.0099)	(0.0132)	(0.0095)
PGS	0.0063	0.0028	0.0233***	0.0906	0.0058	0.0075	0.0171***	0.0155***	0.0045
	(0.0045)	(0.0051)	(0.0066)	(0.1006)	(0.0058)	(0.0063)	(0.0035)	(0.0051)	(0.0036)
IMR	-0.0753**	-0.0281**	-0.0541	-0.7581	-0.0230	-0.0605**	-0.0675***	-0.0563**	-0.0337**
	(0.0321)	(0.0117)	(0.0374)	(0.5036)	(0.0434)	(0.0277)	(0.0213)	(0.0264)	(0.0138)
N	11,127	11,267	10,490	11,147	11,147	11,147	10,761	7,590	3,444

Notes: The table reports OLS estimates of the effect of Long-Term Orientation (LTO) on health behaviors and outcomes. All specifications include controls for age, sex, mother's education, father's education, and fixed effects for school, grade, school-by-grade interaction, and wave. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Futureless Language and Health

	Substance Use			Physical Fitness			Sexual Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ever Tried Cigarette	Ever Tried Alcohol	Ever Used Marijuana	BMI	Overweight	Obese	Ever Pregnant	Ever Unplanned Pregnancy	STD
Panel A. Parsimonious Model									
Futureless Language	-0.0207	-0.0149*	-0.0270*	-0.4173**	-0.0295**	-0.0188*	-0.0163*	-0.0041	-0.0049
	(0.0180)	(0.0080)	(0.0139)	(0.1799)	(0.0119)	(0.0103)	(0.0082)	(0.0082)	(0.0051)
N	19,367	19,625	18,130	19,365	19,365	19,365	18,598	12,865	6,087
Panel B. Full Model									
Futureless Language	-0.0457***	-0.0296***	-0.0618***	-0.6207***	-0.0472***	-0.0304**	-0.0115	-0.0160*	0.0022
	(0.0130)	(0.0067)	(0.0143)	(0.1992)	(0.0152)	(0.0119)	(0.0078)	(0.0082)	(0.0084)
Self-Patience	-0.0371***	-0.0121	-0.0675***	-0.0588	0.0042	-0.0113	0.0006	-0.0260*	-0.0160*
	(0.0078)	(0.0082)	(0.0109)	(0.1599)	(0.0069)	(0.0083)	(0.0108)	(0.0146)	(0.0086)
Barro-Edu	-0.0054	-0.0033	-0.0066	0.1232	0.0058	0.0031	-0.0187**	-0.0252***	-0.0070
	(0.0067)	(0.0039)	(0.0105)	(0.1559)	(0.0099)	(0.0102)	(0.0083)	(0.0074)	(0.0052)
HDI	0.4510**	0.2569***	0.6165**	1.7380	0.3001	0.1382	0.1475	0.5095***	-0.0084
	(0.1838)	(0.0944)	(0.2582)	(3.6590)	(0.2570)	(0.2064)	(0.1753)	(0.1519)	(0.1266)
IDV	-0.0061	-0.0409	-0.0789	-0.4187	-0.1278	0.0040	0.0847	-0.0254	0.0250
	(0.0506)	(0.0269)	(0.0861)	(1.2656)	(0.0967)	(0.0748)	(0.0506)	(0.0653)	(0.0404)
Self-Risk	0.0833***	0.0554***	0.1091***	-0.2206*	-0.0130*	-0.0131	-0.0109	0.0269**	0.0035
	(0.0088)	(0.0061)	(0.0086)	(0.1284)	(0.0069)	(0.0091)	(0.0095)	(0.0126)	(0.0095)
PGS	0.0062	0.0034	0.0218***	0.0471	0.0017	0.0050	0.0168***	0.0150***	0.0061*
	(0.0047)	(0.0052)	(0.0071)	(0.1093)	(0.0057)	(0.0068)	(0.0037)	(0.0055)	(0.0036)
IMR	-0.1246***	-0.0514***	-0.0761*	-1.4073**	-0.0564	-0.0903***	-0.0983***	-0.0623**	-0.0455***
	(0.0287)	(0.0140)	(0.0393)	(0.5717)	(0.0530)	(0.0318)	(0.0252)	(0.0304)	(0.0166)
N	10,742	10,878	10,127	10,760	10,760	10,760	10,391	7,325	3,328

Notes: The table reports OLS estimates of the effect of speaking futureless languages on health behaviors and outcomes. All specifications include controls for age, sex, mother's education, father's education, and fixed effects for school, grade, school-by-grade interaction, and wave. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Results by Wave

	Substance Use			Physical Fitness			Sexual Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ever Tried Cigarette	Ever Tried Alcohol	Ever Used Marijuana	BMI	Overweight	Obese	Ever Pregnant	Ever Unplanned Pregnancy	STD
Panel A. Full Model; LTO; Wave 2									
LTO	-0.1132***	-0.0867***	-0.0269	-1.0225***	-0.0539*	-0.0408**	0.0163		
	(0.0274)	(0.0233)	(0.0350)	(0.2757)	(0.0269)	(0.0195)	(0.0199)		
N	3,208	3,206	3,090	3,171	3,171	3,171	3,171		
Panel B. Full Model; LTO; Wave 3									
LTO	-0.0609**	-0.0678***	-0.1129***	-1.1275***	-0.1088***	-0.0601**	0.0386	0.0112	0.0033
	(0.0268)	(0.0100)	(0.0285)	(0.3187)	(0.0291)	(0.0257)	(0.0282)	(0.0206)	(0.0150)
N	3,952	4,014	3,626	3,926	3,926	3,926	3,514	3,514	3,444
Panel C. Full Model; LTO; Wave 4									
LTO	-0.0472**	-0.0167*	-0.0876***	-1.5629***	-0.0890***	-0.0357	-0.1318***	-0.0432**	
	(0.0199)	(0.0088)	(0.0287)	(0.5022)	(0.0320)	(0.0415)	(0.0250)	(0.0198)	
N	3,967	4,047	3,774	4,050	4,050	4,050	4,076	4,076	
Panel D. Full Model; Futureless Language; Wave 2									
Futureless Language	-0.0575***	-0.0487***	-0.0640***	-0.5533**	-0.0291	-0.0345***	0.0080		
	(0.0191)	(0.0166)	(0.0234)	(0.2180)	(0.0195)	(0.0094)	(0.0136)		
N	3,100	3,099	2,983	3,063	3,063	3,063	3,066		
Panel E. Full Model; Futureless Language; Wave 3									
Futureless Language	-0.0464***	-0.0341***	-0.0645***	-0.5379**	-0.0532***	-0.0257	0.0220	0.0021	0.0022
	(0.0167)	(0.0080)	(0.0167)	(0.2309)	(0.0195)	(0.0166)	(0.0151)	(0.0074)	(0.0084)
N	3,814	3,874	3,503	3,790	3,790	3,790	3,393	3,393	3,328
Panel F. Full Model; Futureless Language; Wave 4									
Futureless Language	-0.0331***	-0.0063	-0.0532***	-0.7434***	-0.0575***	-0.0325*	-0.0556***	-0.0307**	
	(0.0119)	(0.0064)	(0.0177)	(0.2540)	(0.0204)	(0.0169)	(0.0167)	(0.0119)	
N	3,828	3,905	3,641	3,907	3,907	3,907	3,932	3,932	

Notes: The table reports OLS estimates of the effect on health behaviors and outcomes for each wave. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Transition of Preference Measures Across Waves

Panel A. Self-Patience

	Wave 4 – Wave 3			
Wave 3 - Wave 2	-1	0	1	Total
-1	0	136	390	526
0	260	3,070	375	3,705
1	212	1,008	0	1,220
Total	472	4,214	765	5,451

Panel B. Self-Risk

	Wave 4 – Wave 3			
Wave 3 - Wave 2	-1	0	1	Total
-1	0	792	240	1,032
0	1,024	2,332	157	3,513
1	551	360	0	911
Total	1,575	3,484	397	5,456

Notes: Each cell reports the number of observations with the corresponding combination of within-wave changes in the preference measure. Values of -1, 0, and 1 indicate a decrease, no change, and an increase across consecutive waves, respectively.

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Appendix A Country of Origin and LTO

We identify the country of origin using the Wave III survey question, which asks: "Please describe your family origins. You may name as many as four countries, groups, or geographic areas. What are your family ancestries?" We use the first country listed, assuming that respondents report their most influential ancestry first. Responses are excluded if they are invalid (e.g., "don't know") or list a continent rather than a specific country (e.g., "America", "Africa").

Although the survey asks individual countries, the Add Health data team recoded these identifiers for countries with fewer than ten respondents. In such cases, countries were grouped according to the Geographic Subject Headings classification used in Ovid Medline. For these grouped categories, we assign the mean Long-Term Orientation (LTO) value of the constituent countries for which LTO data are available. For instance, Argentina, Chile, and Uruguay (combined frequency $n = 9$) are grouped. The assigned LTO score is 25.86, the average of Argentina (20.40), Chile (30.98), and Uruguay (26.20). In cases where some countries within a group lack an LTO value, the mean is calculated using only those with available data. For example, Algeria, Libya, Morocco, and Tunisia (combined frequency $n = 3$) are grouped. The assigned LTO score is 20.03, the average of Algeria (25.94) and Morocco (14.11), as LTO values for Libya and Tunisia are unavailable.

Table A1 provides a comprehensive list of the specific countries, their frequencies in our U.S.-born sample, and their assigned LTO values (rounded to two decimal places). It includes 69 country groups and 8,123 respondents in Wave III.

Table A1. Country of Origin: Frequencies and LTO Scores

Ancestry Response	Frequency	Assigned LTO	Source Countries (LTO)
Albania	7	61.46	
Algeria, Libya, Morocco, and Tunisia	1	20.03	Algeria (25.94), Morocco (14.11)
Antigua and Barbuda, Aruba, Cayman Islands, Dominica, Grenada, Guad eloupe, Montserrat, Netherlands Antilles, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenad ines, and Virgin Islands of the United States	6	13.10	
Argentina, Chile, and Uruguay	9	25.86	Argentina (20.40), Chile (30.98), Uruguay (26.20)
Armenia	15	60.96	
Australia	4	21.16	
Austria	20	60.45	
Bahrain, Iraq, Jordan, Kuwait, Palestine, Oman, Qatar, United Arab Emirates, Yemen, and Burma	9	20.53	Iraq (24.94), Jordan (16.12)
Bangladesh, Nepal, Pakistan, and Sri Lanka	9	47.24	Bangladesh (47.10), Pakistan (49.87), Nepal (43.00), Sri Lanka (49.00)
Belgium and Luxembourg	10	72.92	Belgium (81.86), Luxembourg (63.98)
Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Senegal, Sierra Leone, and Togo	10	17.04	Burkina Faso (27.46), Ghana (3.53), Mali (20.15)
Brazil, Bolivia, and Paraguay	4	43.83	Brazil (43.83)
Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Sudan , Tanzania, Angola, Botswana, Lesotho, Malawi, Mozambique, Namibia, South Africa, Swaziland, Zambia, and Zimbabwe	6	26.40	Rwanda (18.39), Tanzania (34.01), South Africa (34.00), Zambia (30.23), Zimbabwe (15.37)
Canada	65	36.02	
China	151	87.41	
Colombia	13	13.10	
Czech Republic	39	70.03	
Czechoslovakia	54	73.30	Czech Republic (70.03), Slovak Republic (76.37)
Denmark	46	34.76	
Dominican Republic	17	13.10	
Egypt	2	6.80	

Ancestry Response	Frequency	Assigned LTO	Source Countries (LTO)
El Salvador	11	19.65	
England	617	51.13	
Estonia, Latvia, and Bulgaria	8	73.30	Estonia (82.12), Latvia (68.77), Bulgaria (69.02)
Figi, Guam, New Zealand, and Tonga	60	32.75	
Finland	29	38.29	
France	296	63.48	
Germany	1886	82.87	
Great Britain	10	51.13	
Greece	43	45.34	
Guyana, Suriname, and Venezuela	5	15.62	
Hong Kong	6	60.96	
Hungary	86	58.19	
Iceland, Azores, Bermuda, and Falkland Islands	33	27.96	
India	42	50.88	
Indonesia and Singapore	4	66.75	Indonesia (61.96), Singapore (71.54)
Iran	6	13.60	
Ireland and Northern Ireland	1128	24.43	
Israel	11	37.53	
Italy and Malta	649	54.28	Italy (61.46), Malta (47.10)
Japan	74	87.91	
Lithuania	17	81.86	
Malaysia	2	40.81	
Mexico	893	24.18	
Netherlands	56	67.00	
Nigeria	4	12.85	
North and South Korea	37	100.00	
Norway	114	34.51	
Peru	8	25.19	
Philippines	237	27.46	
Poland	264	37.78	
Portugal	94	28.21	
Puerto Rico	120	0.00	
Romania	12	51.89	

Ancestry Response	Frequency	Assigned LTO	Source Countries (LTO)
Russia	75	81.36	
Saudi Arabia	6	35.52	
Scotland	253	51.13	
Slovakia	18	76.57	
Spain	155	47.61	
Sweden	109	52.90	
Switzerland	18	73.55	
Taiwan	22	92.95	
Thailand	3	31.74	
Trinidad and Tobago	9	12.59	
Turkey and Cyprus	4	45.59	
Uganda	8	23.68	
Ukraine	13	86.40	
Vietnam	23	57.18	
Wales	48	51.13	

Notes: The 'Ancestry Response' and 'Frequency' are from U.S.-born respondents in the Wave III Add Health survey. Grouped categories were provided by Add Health (based on Ovid Medline Geographic Subject Headings) to ensure a minimum of 10 respondents per category in the raw data. The 'Assigned LTO' is the individual LTO score for single countries or the mean LTO score of the listed 'Source Countries' for grouped categories.