

The Effects of Economic Conditions on Behavior and Health

Ilaria Prometti

Ph.D. Candidate in Applied Economics and Management

Curriculum: Applied Economics

University of Pavia and University of Bergamo

Supervisor:

Gianmaria Martini – University of Bergamo

Foreign Supervisors:

Osea Giuntella – University of Pittsburgh

Alex Chan – Harvard Business School

November 2025

Index

1	General Introduction	2
2	Sounding Out Sleep: Can Audio Messages Shift Children’s Bedtime Norms?	6
	Chapter 2 – Sounding Out Sleep: Can Audio Messages Shift Children’s Bedtime Norms?	6
2.1	Introduction	10
2.2	Literature Review	12
2.2.1	Sleep as a Human Capital Investment	12
2.2.2	Racial Disparities in Sleep and Structural Determinants	13
2.2.3	Social Norms, Perceptions, and Behavioral Interventions	14
2.2.4	Source Credibility, Trust, and Cultural Tailoring in RCTs	14
2.3	Data	15
2.3.1	Data Sources	15
2.4	Experimental Design	17
2.5	Empirical Strategy	19
2.5.1	Baseline Racial Disparities in Sleep	19
2.5.2	Intergenerational Transmission of Sleep Behavior	20
2.5.3	Descriptive and Experimental Evidence	20
2.5.4	Experimental Econometric Approach	20
2.6	Results	21
2.6.1	Documenting Disparities in Children’s Sleep	21
2.6.2	Experimental Evidence - Descriptive analysis	26
2.6.3	Information Intervention and Results	28
2.7	Conclusion	38
3	The Impact of Cannabis Legalization on Sleep	61
	Chapter 3 – The Impact of Cannabis Legalization on Sleep	61
3.1	Introduction	58
3.2	Background	60
3.2.1	Cannabis Laws	63

3.3	Data	65
3.3.1	Data Sources and Sample Construction	65
3.3.2	Sample Balance and Descriptive Statistics	67
3.4	Empirical Strategy	69
3.5	Results	72
3.6	Conclusion	77
4	Early unemployment and long-term effects on health and risky health behaviors	88
Chapter 4 – Early unemployment and long-term effects on health and risky health behaviors		88
4.1	Introduction	80
4.2	Related Literature	81
4.3	Data	83
4.4	Empirical Strategy	87
4.5	Results	88
4.5.1	Smoking Behavior	88
4.5.2	Alcohol Consumption	89
4.5.3	Physical Activity	91
4.5.4	Fruit and Vegetable Intake	91
4.6	Mechanisms	93
4.6.1	Psychological Stress and Coping	93
4.6.2	Financial Constraints and Social Participation	98
4.6.3	Placebo Tests: Early-Life Conditions	102
4.6.4	Behavioral Trade-offs and Policy Implications	103
4.7	Heterogeneity and Robustness Checks	105
4.7.1	Heterogeneity by Education, Gender, and Income	105
4.7.2	Robustness Check	108
4.8	Other Long-Term Health and Labor Outcomes	111
4.8.1	Health Outcomes: Chronic Diseases	112
4.8.2	Labor-Market Outcomes: Physically Demanding Work	112
4.8.3	Integrated Pathways	112
4.9	Conclusions and Policy Implications	114

Chapter 1

General Introduction

Time is a scarce resource that individuals, as economic agents, must constantly confront, deciding how to allocate it across various activities. Like any other limited good, this allocation is shaped by individual preferences and the "bundle" of activities and goods that each person chooses to "buy" with their time.

From this perspective, the economic study of health-risk behaviors concerns how we balance the immediate attraction or benefit of an action (such as smoking a cigarette, having a drink, or working an extra hour) against the often distant and less tangible future benefits of long-term well-being. These choices, smoking, diet, physical activity, and sleep, are not merely lifestyle preferences; they constitute the raw material of human capital. Underinvesting in one's health produces repercussions that go far beyond the individual sphere, manifesting as reduced productivity, increased burdens on public coffers, a less resilient workforce, premature mortality, or a diminished quality of future life (Becker & Murphy, 1988; Grossman, 1972; Heron et al., 2019a).

If we conceive of health as a form of capital, these behaviors represent the investments necessary to preserve it. However, such investments are often hindered not only by individual preferences but also by social disparities such as poverty, information gaps, discrimination, and institutional constraints. The literature demonstrates that socioeconomic inequalities carry significant health costs.

In a scenario of limited resource allocation like time, several factors can influence individual choices and health behaviors. Among these, an element that remained at the margins of economic analysis until recently is sleep. Long considered a biological constant, sleep is today recognized as a crucial and still underexplored determinant of economic performance. Insufficient sleep is not just a personal discomfort, but a true public health crisis with concrete economic costs (Giuntella et al., 2024; Institute of Medicine, 2006). The ability to rest adequately rarely depends on "willpower" alone; rather, it is influenced by social norms, the rigidity of work schedules, and the surrounding economic context. The deep disparities in sleep duration observable today along

racial and socioeconomic lines represent a clear example of how social disadvantage can "get under the skin", translating into long-term inequalities in health and economic standing.

Alongside sleep, other key health behaviors (such as smoking, alcohol consumption, fruit and vegetable intake, and physical activity) show very similar patterns of inequality. These behaviors not only determine individual health status but also generate significant economic burdens for healthcare systems: for example, in the UK, costs attributable to smoking, excessive alcohol consumption, poor diet, and physical inactivity amount to £3.3 billion, £3.3 billion, £5.8 billion, and £0.9 billion, respectively (Candari et al., 2017; Heron et al., 2019b; Scarborough et al., 2011).

In this context, this dissertation explores the intersection of health behaviors and economic and political factors, investigating how public policies and economic shocks influence individual habits, while considering differences across population groups (heterogeneity analysis). The approach adopted is based on the idea that health-related behaviors are dynamic entities, capable of reacting and adapting to the surrounding context. To analyze this, I utilize tools from applied microeconomics: randomized experiments, public policy evaluations, and the analysis of macroeconomic dynamics.

The first part of the work examines the early stages of the life cycle. In Chapter 1, I analyze sleep as a hidden factor of inequality. Through an online experiment involving over 700 mothers, I highlight how access to information regarding children's sleep is still limited and how the mode of communication is decisive. Narrative and culturally contextualized messages generate significant changes among African American mothers, suggesting that low-cost informational "nudges" can reduce the human capital gap in the early stages of life.

Chapter 2 focuses on the regulatory context, specifically cannabis legalization in the United States and its impact on sleep. Using the staggered timing of these laws as a natural experiment, a complex picture emerges: medical cannabis appears to improve sleep for middle-aged adults, while recreational use may worsen it, especially in high-stress environments. This demonstrates that the effect of policies depends on regulatory specificities and individual factors, producing heterogeneous effects across populations.

Finally, Chapter 3 analyzes labor market entry during periods of economic crisis. Using European data from the SHARE survey and historical unemployment rates, I highlight a behavioral "scarring effect": youth unemployment not only reduces future earnings but also influences health-related behaviors, such as smoking and physical activity, with effects that persist over time. Some behaviors, such as lower alcohol consumption or higher fruit intake, show different patterns, highlighting how economic adversity can direct an individual's health trajectory. Here too, significant disparities across population groups emerge.

In summary, these chapters show that to improve public health, it is necessary to look beyond the individual dimension. It is fundamental to understand how information,

laws, and the economic context interact to shape daily choices and how these are conditioned differently across population groups. Policies that are targeted and aware of this heterogeneity may prove more effective in reducing inequalities and improving overall well-being.

References

- Becker, G. S., & Murphy, K. M. (1988). A theory of rational addiction. *Journal of Political Economy*, 96(4), 675–700.
- Candari, C. J., Cylus, J., & Nolte, E. (2017). *Assessing the economic costs of unhealthy diets and low physical activity: An evidence review and proposed framework*. European Observatory on Health Systems; Policies.
- Giuntella, O., Saccardo, S., & Sadoff, S. (2024). Sleep: Educational impact and habit formation. *Mimeo*.
- Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2), 223–255.
- Heron, L., O’Neill, C., McAneney, H., Kee, F., & Tully, M. A. (2019a). Direct healthcare costs of sedentary behaviour in the uk. *Journal of Epidemiology and Community Health*, 73(7), 625–629. <https://doi.org/10.1136/jech-2018-211758>
- Heron, L., O’Neill, C., McAneney, H., Kee, F., & Tully, M. A. (2019b). Direct healthcare costs of sedentary behaviour in the uk. *Journal of Epidemiology and Community Health*, 73(7), 625–629. <https://doi.org/10.1136/jech-2018-211758>
- Institute of Medicine. (2006). Sleep disorders and sleep deprivation: An unmet public health problem.
- Scarborough, P., Bhatnagar, P., Wickramasinghe, K. K., Allender, S., Foster, C., & Rayner, M. (2011). The economic burden of ill health due to diet, physical inactivity, smoking, alcohol and obesity in the uk: An update to 2006-07 nhs costs. *Journal of Public Health (Oxford, England)*, 33(4), 527–535. <https://doi.org/10.1093/pubmed/fdr033>

Chapter 2

Sounding Out Sleep: Can Audio Messages Shift Children's Bedtime Norms?

Ilaria Prometti^{*}
Osea Giuntella^{**}
Rania Gihleb^{***}
Wendy Troxel^{***}

We thank participants to seminars at the BEDI 2024 Local Conference and the Pitt Circadian Rhythms Research Day.

^{*} Corresponding author. Department of Economics, University of Pavia, Italy.
E-mail: ilaria.prometti01@universitadipavia.it

^{**} Department of Economics, University of Pittsburgh, USA and NBER. E-mail: osea.giuntella@pitt.edu

^{***} Department of Economics, University of Pittsburgh, USA and IZA. E-mail: osea.giuntella@pitt.edu

^{***} RAND Corporation

Abstract

Racial disparities in children’s sleep can shape health and human capital trajectories. Using U.S. time-use data and a randomized online experiment with 729 mothers, we show that Black/African-American children go to bed later and exhibit stronger parent-child bedtime correlations than White children, with socioeconomic factors only partially explaining these gaps. Our results show that Black/African-American mothers exposed to sleep-hygiene audio messages were 10% more likely to report intentions to move their children’s bedtime earlier and 16% more likely to intend to extend total sleep duration. The intervention revealed ethnic heterogeneity in behavioral engagement: newsletter subscription increased among Black/African-American mothers but decreased for White/Caucasian mothers treated. Culturally informed audio messages varied in framing and narrator ethnicity, with narrator identity having negligible effects, highlighting the importance of content over the messenger. Our findings suggest low-cost, culturally targeted interventions can reduce sleep disparities and improve child development, emphasizing both intentions and behavioral responses.

2.1 Introduction

Despite remarkable advancements in healthcare in the last period, significant racial and socioeconomic disparities persist in both access to healthcare and health outcomes in the United States and over the world. Differences in health behaviors contribute to these disparities through a wide range of conditions. The Institute of Medicine referred to sleep as a critical, yet unaddressed, public health challenge (Colten, Altevogt, et al., 2006). A growing part of research, also in economics, highlights the adverse effects of insufficient sleep on individual health, human capital accumulation, and overall productivity (Gibson & Shrader, 2018; Giuntella & Mazzonna, 2019; Giuntella et al., 2017, 2024). Indeed, sleep is increasingly recognized as one of the most prevalent risky health behaviors in our societies (Roenneberg, 2013), and a key mechanism through which minority status and socioeconomic disadvantage can affect long-term effects (Grandner et al., 2016). Trends in adolescent and child sleep are particularly concerning, in fact the evidence linking sleep patterns to academic performance, cognitive development, and subsequent labor market outcomes (Creswell et al., 2023; Giddens et al., 2022; Giuntella et al., 2024; Jagnani, 2021; Keyes et al., 2015).

The existing literature on younger age groups is limited by the paucity of data on sleep or time-use on this population. Guglielmo et al., 2018 provide a recent review of the existing work on sleep disparities among children and teenagers. In this paper, we document racial disparities in children’s sleep in the U.S. and evaluate the causal impact of culturally informed informational interventions on parental intentions and behaviors. From an economic perspective, sleep can be seen as an investment in human capital. Sufficient sleep during childhood improves learning capacity, memory consolidation, cognitive functioning, and long-term productivity. Instead, insufficient sleep during critical developmental stages can reduce educational performance, diminish health capital, and influence negatively labor market outcomes. In fact, inadequate sleep has been linked to lower academic performance, attention deficits, and potentially reduced lifetime earnings at individual level. However, sleep can have also societal effect, in fact sleep deprivation contributes to higher healthcare expenditures, increased accident rates, and reduced workforce productivity. Therefore, disparities in sleep can generate negative externalities, extending costs beyond affected individuals, and addressing them can yield substantial social returns.

One important but understudied factor influencing health behaviors is the role of social norms. Indeed, norms shape behaviors across different field such as diet, physical activity, and healthcare utilization (Bicchieri, 2023; Cialdini et al., 1990; Reid et al., 2010; Reno et al., 1993). Misperceptions of norms may exacerbate disparities, so long as individuals often conform to perceived but inaccurate behavioral standards within their communities. Furthermore, deeply rooted mistrust in medical institutions can also influence preventive behaviors (Alsan & Eichmeyer, 2024) including sleep. Misaligned norms can act as behavioral constraints, reducing effective human capital accumulation and perpetuating intergenerational inequality. Such "cultural externalities" can rep-

resent an additional mechanism through which racial and socioeconomic gaps in sleep translate into persistent disparities in education, health, and economic opportunity.

In our societies, sleep is highly private and so largely invisible, making it particularly susceptible to misperceptions of norms (Avery et al., 2022). Such misperceptions of social norms are hypothesized to drive households and individuals to suboptimal investment in sleep quality and duration, despite the proven high sleep benefit to human capital. This concept reflects broader behavioral patterns established in the health economics literature, where the existence of information frictions (Handel et al., 2019) or the documented prevalence of dominated choices in preventative care (Bhargava et al., 2017) leads to non-maximizing healthcare utilization. Therefore, understanding how perceived norms can influence sleep behavior is a critical in order to try to improve health in the population, becoming relevant for both public health policy and the study of the intergenerational transmission of economic inequality.

Using data from the American Time Use Survey (ATUS) and an online sample from Prolific, in this research we document significant racial differences in children’s sleep behaviors, with Black – African American children systematically going to bed later than White peers (Giddens et al., 2022). Indeed, in our sample, nearly 48% of Black children under 13 go to bed after 10 p.m., compared to 36% of White children, with also a higher prevalence among children of younger mothers, single mothers, and parents working night shifts. Additionally, intergenerational correlations are stronger among Black families, indicating persistent patterns across generations.

Although the study focuses on differences between ethnic groups, it is important to emphasize that belonging to a specific ethnic group does not, in itself, constitute a direct cause of differences in children’s sleep patterns. The variations observed across ethnic groups also reflect differing socioeconomic and structural conditions, such as household income, parental education levels, work schedules, family composition, and housing characteristics. These factors can influence both access to information regarding good sleep practices and the ability to implement them in daily life. When controlling for observable socioeconomic factors, a portion of the gap narrows but does not disappear completely. For this reason, in our empirical analysis, we investigate differences between White and Black/African-American mothers. However, this distinction should not be interpreted as a direct cause of differences in knowledge or behavior; rather, it serves as a useful proxy for capturing additional structural and informational factors—rooted in the social and cultural context, that are not fully observable in the data but may nonetheless influence access to information and knowledge regarding sleep practices.

To move beyond descriptive evidence and identify causal mechanisms, we implement a randomized online field experiment targeting mothers. Participants were exposed to brief, culturally informed audio messages about sleep hygiene, varying along two dimensions: the race of the narrator (White vs. Black – African American) and the framing of the message (neutral information, personal reflection, or highlighting community-specific norms). Across Black/African-American mothers, messages increased inten-

tions to advance children’s bedtimes by roughly 10–16 percentage points and intentions to extend total sleep duration by 16–22 percentage points relative to the control group. Voluntary newsletter subscription—a behavioral outcome—also rose by 12–19 percentage points. These quantitative results highlight the potential of low-cost, culturally informed interventions to shift both intentions and behavior.

Our results indicate that all messages significantly increase parents’ intentions to improve children’s sleep habits relative to a control group. While narrator identity and message framing modestly influence follow-up engagement, such as newsletter subscription, the content of the message, rather than the messenger’s identity, drives responses. These findings suggest that informed behavioral interventions can effectively promote healthier sleep practices and serve as scalable tools to reduce disparities in child development and human capital accumulation.

Understanding racial disparities in sleep is a public health concern and also essential to understand how to design effective interventions and policies. Given the well-documented impact of sleep on health, human capital, and educational outcomes, from previous studies, trying to address these disparities is crucial in order to reduce their impact to persistent racial inequalities. Social and cultural norms, along with misperceptions and mistrust, play a significant role in shaping sleep behaviors, which cannot be fully explained by socioeconomic factors alone. Communities facing structural barriers may develop misaligned norms that reinforce unhealthy behaviors, highlighting the importance of culturally informed interventions to realign norms and promote healthier sleep among minority populations.

These findings show an important effect that could be taken into account by policies, and that a low-cost public health initiatives based on informational, in some case also personalized, interventions can improve health, in our case children’s sleep, particularly in populations facing structural and informational barriers.

The paper is organized as follows. Section 2.2 reviews previous literature on racial disparities in health behaviors, particularly sleep. Section 4.3 presents the data. Section 2.4 presents the experimental design. Section 2.5 presents the empirical specification. Section 4.5 presents the main results, including descriptive and experimental evidence. Concluding remarks are in Section 2.7.

2.2 Literature Review

2.2.1 Sleep as a Human Capital Investment

Our work is situated within the growing body of economic literature that focus on health, and specifically sleep, as a critical form of human capital investment (Becker, 1964; Currie, 2009). Sleep is not merely a health behavior but a crucial input in the human capital accumulation process, particularly in critical period, as childhood and

adolescence. Adequate sleep is able to improve cognitive functioning, learning capacity, and academic performance, that could translate into higher long-term productivity and potential lifetime earnings (Giuntella et al., 2024). On the contrary, chronic sleep deprivation, especially during critical developmental stages, represents a misallocation of time, differently from what you might think. Sleep competes with other time allocations, such as work, childcare, and leisure, making it a central allocation decision in the human capital production function. This misallocation reduces both educational and health capital, generating costs that accumulate and persist into adulthood.

From a perspective of a policy maker, disparities in sleep are a growing concern due to substantial negative externalities in different fields. In fact, Hafner et al. (2017) estimate that sleep deprivation in the United States leads to an annual economic loss of up to \$411 billion, primarily due to reduced workforce productivity and increased healthcare costs (Hafner et al., 2016). Moreover, sleep inequalities (defined as persistent differences in one or more dimensions of sleep health) adversely affect disadvantaged populations, with significant impacts on public health and overall well-being (Jackson et al., 2020). These elements can also impact these disparities, such as socioeconomic status, racism, discrimination, and limited access to healthcare resources, indicating that inequalities in sleep health can perpetuate broader social and economic inequalities (Billings et al., 2021). This economic framework highlights the critical importance of analyzing sleep disparities, not only as an individual human capital issue but also as a matter with significant social and policy implications. Addressing sleep inequalities could be a good way to promote both economic efficiency and social equity.

2.2.2 Racial Disparities in Sleep and Structural Determinants

The literature has consistently documented pervasive racial and socioeconomic disparities in health behaviors (D. R. Williams & Mohammed, 2009). Sleep disparities align with this pattern, with studies consistently showing that Black–African American individuals report shorter sleep duration and poorer quality compared to White counterparts (Giddens et al., 2022; Grandner et al., 2016). These disparities are shaped by a confluence of factors. While socioeconomic variables such as income and parental education explain part of the gap, lower incomes and shift work jobs can fragment sleep cycles (Jackson et al., 2013), structural and environmental determinants are also key. Minorities are disproportionately exposed to environmental disruptors such as noise pollution, neighborhood insecurity, and housing conditions that impede restorative sleep (Troxel et al., 2018). Furthermore, stress associated with experiences of racial discrimination acts as a chronic physiological stressor, directly impacting sleep quality and duration (Yip et al., 2020). However, these structural determinants alone do not fully account for the observed disparities, suggesting that social and behavioral mechanisms may also play a decisive role in the remaining unexplained gap.

2.2.3 Social Norms, Perceptions, and Behavioral Interventions

Social norms, both descriptive (what people actually do) and injunctive (what people ought to do), are powerful regulators of individual behaviors, even in private domains such as sleep (Bicchieri, 2023; Cialdini et al., 1990). Observed differences in sleep patterns across communities may partly reflect variations in perceived norms, schedules, and expectations, which can influence household decisions about children’s bedtime. Importantly, these norms and expectations do not emerge in isolation but are often shaped by broader socio-economic and structural conditions, including work schedules, housing environments, and differential access to health-related information.

Misperceptions of norms can occur when individuals underestimate the prevalence or benefits of a behavior within their reference group. Such misperceptions may contribute to suboptimal sleep practices even when families intend to prioritize children’s rest. Behavioral economic research shows that correcting these misperceptions through low-cost informational interventions, or “nudges,” can effectively align behaviors with recommended practices, supporting better long-term outcomes (Bhargava et al., 2017; Handel et al., 2019).

In particular, the foundational works of Cialdini et al., 1990 and Cialdini et al., 1991 provide the theoretical framework for norm-based interventions, distinguishing between descriptive norms (what most people do) and injunctive norms (what one ought to do), and analyzing how these profoundly shape human behavior. More recently, research has focused on the mechanisms through which such prompts enhance decision-making processes within the healthcare sector (Bertoni et al., 2020).

Supporting the efficacy of these tools, studies such as that by Carrieri et al., 2021 highlight how message personalization can make a difference in modifying health-related behaviors: specifically, positive framing that emphasizes protective actions increases the relevance given to health outcomes and the intention to adhere to precautionary behaviors, highlighting the role of message design and personalization in behavioral change interventions. Meanwhile, Krishnamurthy et al., 2001 confirm that even brief, targeted communications—when embedded within the appropriate care contexts—are capable of tipping the scales in everyday choices.

It is precisely this body of evidence that guides our experimental design. The objective is to determine whether targeted informational interventions can effectively improve children’s sleep routines by acting on two fronts: on the one hand, by correcting distorted perceptions of social norms; and on the other, by offering practical guidance through a simple approach firmly grounded in the principles of behavioral science.

2.2.4 Source Credibility, Trust, and Cultural Tailoring in RCTs

Institutional trust plays a critical role in shaping health behaviors. Historical and well-documented mistrust toward healthcare systems among Black–African American–

communities can influence how public health messages are received and acted upon (N. J. Williams et al., 2015). Even scientifically sound recommendations may have limited impact if the source is perceived as lacking credibility.

Evidence from prior research indicates that source characteristics, including racial or cultural concordance between communicator and recipient, can moderate the effectiveness of interventions. For example, Alsan et al. (2014) demonstrate that African American patients were more likely to follow medical guidance when the provider was African American, highlighting the importance of source credibility in influencing behavior (Alsan et al., 2019).

Building on this evidence, our study experimentally varies the race of the narrator (African-American vs. White) and the framing of audio messages about sleep hygiene. This design allows us to test whether culturally tailored messaging enhances engagement and commitment to behavior change, particularly among communities that may experience structural barriers or historical distrust. While our results show that stated intentions to improve sleep are largely similar across conditions, source and framing modestly affect follow-up engagement, such as subscribing to a sleep-hygiene newsletter, demonstrating the potential value of culturally responsive interventions.

2.3 Data

Our empirical analysis combines two complementary datasets: (i) nationally representative time-use data from the American Time Use Survey (ATUS), and (ii) novel experimental data collected through a randomized online study. Using both sources allows us to combine descriptive evidence on population-level sleep disparities with experimental evidence that isolates behavioral mechanisms. This dual approach enhances both external validity—through nationally representative descriptive patterns—and internal validity, by leveraging exogenous experimental variation in behavioral prompts related to sleep.

2.3.1 Data Sources

The American Time Use Survey (ATUS)

The ATUS, administered annually by the U.S. Bureau of Labor Statistics since 2003, provides detailed 24-hour time diaries for a nationally representative sample of U.S. residents aged 15 and older. Respondents, drawn from households that have completed the final interview of the Current Population Survey (CPS), report how they allocated their time across major activities—including work, childcare, leisure, and sleep—on the previous day.

We use data spanning 2003–2023 and restrict the sample to respondents with at least one child under age 13 who provided valid information on their child’s bedtime. To

reduce day-of-week heterogeneity, we focus on weekdays. This yields a sample of 39,573 parent–child observations with complete information on bedtime, wake-up time, and sleep duration for both parents and children.

Our main outcome variable, child bedtime, is defined as the hour (on a 24-hour scale) when the child goes to bed on the diary day. We complement this with parent bedtime and parent sleep duration as covariates in intergenerational analyses. In supplementary specifications, we replicate the analysis for adolescents aged 15–19 to assess whether racial differences persist into later developmental stages.

A key limitation of the ATUS is that children’s sleep measures are parent-reported, not directly observed. This introduces potential measurement error if parents misreport sleep schedules, particularly if such misreporting is correlated with socioeconomic or racial characteristics. We address this concern by controlling for detailed family structure, parental employment patterns (including night-shift work), and education, and by validating directionally consistent findings in experimental data.

Experimental Data

To complement the descriptive analysis, we designed and implemented an online Randomized Controlled Trial (RCT) in June–July 2024 to identify behavioral channels that may contribute to sleep disparities. The experiment was conducted on Prolific, a professional online survey platform commonly used in behavioral and social science research. Participation was restricted to residents of the United States and Canada who identified as parents. In particular, we targeted mothers of children aged 6 to 13 years, reflecting the age range most comparable to the ATUS sample used in the descriptive analysis.

The final dataset includes 729 valid observations out of 755 initial participants. The sample was stratified by race, comprising 381 Black (African-American) and 348 White (Caucasian) mothers. This sampling strategy ensures comparability with the nationally representative ATUS data while allowing for more detailed measurement of behavioral mechanisms.

Participants completed modules on parenting habits, children’s sleep routines, and behavioral responses to hypothetical interventions. The experimental design allows us to measure parental norms, perceptions of appropriate bedtime, and responses to information treatments. In particular, the RCT provides detailed, self-reported measures of both parental and child bedtime that can be linked within households, enabling direct comparison of intergenerational sleep patterns across groups.

A key advantage of this experimental data is its ability to validate and interpret the descriptive patterns observed in the ATUS within a controlled environment. By eliciting behavioral responses under randomized information conditions, the RCT isolates mechanisms—such as parental norms, expectations, and time constraints—that may drive persistent racial disparities in children’s sleep behavior. This combination of large-scale

descriptive evidence and experimentally identified mechanisms offers a comprehensive framework to understand both the extent and the origins of sleep inequality.

2.4 Experimental Design

Motivated by the descriptive evidence documenting persistent racial disparities in children’s sleep, we implemented a large-scale online Randomized Controlled Trial (RCT) in June–July 2024 to identify behavioral mechanisms underlying these differences.

While we focus on differences between White and Black/African-American families as a useful analytic proxy, it is important to emphasize that these differences partly reflect observable socio-economic and structural conditions, including household income, parental education, work schedules, and family composition. Our analyses control for these factors, which explains a portion of the gap; however, a residual difference remains. This remaining gap may reflect unobserved structural factors, that can lead to other components such as parental beliefs, perceptions of social norms, and access to sleep-related information. The RCT is therefore designed to test whether targeted informational interventions can influence children’s bedtime and sleep routines, helping to identify the role of these unobserved informational and behavioral mechanisms in explaining persistent disparities.

Participants were recruited through Prolific and completed the survey via Qualtrics, a platform widely used for online behavioral experiments. Eligibility was restricted to adults residing in the United States or Canada who were parents of at least one child aged six to thirteen years. The final analytic sample includes 729 valid observations after excluding respondents reporting multiple or ambiguous racial identities. The sample was stratified by race, resulting in 381 African-American/Black and 348 White/Caucasian mothers. This sampling strategy ensures comparability with the nationally representative ATUS sample while allowing for detailed analysis of behavioral mechanisms within families.

Participants received a guaranteed \$6.5 completion fee for the 25-minute survey and could earn up to \$15 with performance-based lottery bonuses. This compensation structure ensured engagement and high-quality responses.

The survey included detailed modules covering: (i) Demographics (age, education, income, marital status, employment, night-shift work), (ii) Parental and child sleep patterns, (iii) Beliefs about other children’s sleep, (iv) Knowledge of sleep-related risks and health conditions, and (v) Children’s bedtime routines and enforcement practices.

Participants were randomly assigned to one of six treatment conditions or a control group. Randomization was simple but ensured uniform distribution across racial groups and treatment arms. Balance checks confirm that observable characteristics—such as parental education, income, employment status, and marital status—did not differ significantly across treatment groups, supporting the internal validity of the experimental

Table 2.1: Experimental Treatment Arms

Treatment Arm	Narrator Voice	Message Framing	Description
T1	White	Neutral	Standard information on children’s sleep routines
T3	White	Disparity-focused	Highlights racial sleep gaps and benefits of earlier bedtime
T5	White	Personal narrative	Mother shares her routine and pediatrician’s advice
T2	African-American	Neutral	Standard information on children’s sleep routines
T4	African-American	Disparity-focused	Highlights racial sleep gaps and benefits of earlier bedtime
T6	African-American	Personal narrative	Mother shares her routine and pediatrician’s advice
Control	—	—	No audio message

design. A table summarizing the treatment allocation is reported below.

All the participants, both White mothers and Black and African-American mothers, are randomized to one of the treatments shown in Table 2.1. The intervention designated as “Disparities” was designed to provide specific information regarding divergences in sleep habits between Black and White children. The rationale underpinning this choice rests on two fundamental pillars.

First, the objective is to test the efficacy of messages based on disparities specifically among the group most directly affected by this issue—namely, Black and African-American parents. For this target audience, such information possesses particular relevance and salience, potentially capable of triggering a stronger response.

At the same time, extending the experiment to White parents allows us to observe an often-overlooked aspect: how individuals who are not directly affected by inequalities react to messages concerning them. This is a crucial point in public health communication, where messages designed to highlight disparities between groups are disseminated on a large scale yet are perceived in an extremely heterogeneous manner by different audience segments.

Involving White parents therefore serves to determine whether this type of communication might elicit attenuated—or, in certain instances, even counterproductive—responses when the content does not directly pertain to one’s own group. Ultimately, this methodological choice not only enables us to gather preliminary evidence on how different types of audiences process messages regarding disparities, but also offers concrete insights for designing far more targeted and effective informational interventions.

The intervention consisted of a short audio message on child sleep hygiene. The design followed a 2×3 factorial structure, manipulating two key dimensions: (i) narrator voice (African-American vs. White) and (ii) message framing (neutral informational, disparity-focused, or personal narrative). This structure allows us to test two primary behavioral mechanisms: the effectiveness of informational framing and the moderating role of cultural affinity or trust in the narrator.

All outcomes were parent-reported and measured immediately after the intervention. The main outcome variables capture parental behavioral intentions and engagement: (i) intention to advance children’s bedtime, (ii) intention to increase total sleep duration, and (iii) intention to establish a healthier bedtime routine. A behavioral engagement measure—the voluntary subscription to a sleep-hygiene newsletter—serves as an incentive-compatible indicator of post-treatment motivation. All participants were required to complete attention and manipulation checks to ensure the audio message was fully listened to before proceeding.

Treatment effects were estimated using a treatment-on-the-treated (TOT) framework, focusing on participants who fully assimilated (passing the attention checks) the intervention and complete the survey. Pre-specified heterogeneity analyses were conducted along key socioeconomic and demographic dimensions, including parental education, income, employment status, and race/ethnicity of both parent and child. Robustness checks include alternative covariate specifications, exclusion of outliers, and subgroup consistency verification.

Linking this experimental evidence to the descriptive ATUS findings enables us to move from documenting correlations to identifying mechanisms. While the ATUS analysis establishes the existence and magnitude of conditional racial gaps in children’s sleep and their inter-generational persistence, the experimental evidence isolates the causal behavioral channels—such as parental norms, expectations, and time constraints—that contribute to these disparities. These complementary approaches provide a comprehensive empirical framework for understanding sleep inequality as both a structural and behavioral phenomenon.

2.5 Empirical Strategy

2.5.1 Baseline Racial Disparities in Sleep

We begin by quantifying racial differences in children’s bedtime using the ATUS data. Specifically, we estimate the following OLS model:

$$\text{Bedtime}_{it}^{child} = \alpha + \beta_1 \text{Black}_i + \gamma X_{it} + \varepsilon_{it}, \quad (2.1)$$

where $\text{Bedtime}_{it}^{child}$ denotes the bedtime reported by the parent of child i on day t , Black_i is an indicator equal to one if the ATUS respondent identifies as Black, and X_{it} includes

parental education, income, marital status, age, number of children, employment status, night-shift work, and region fixed effects.

We interpret β_1 as the conditional racial gap in child bedtime—i.e., the average difference in bedtime between Black and White children, holding observable socioeconomic characteristics constant. Importantly, these regressions are used as descriptive statistics and are not intended to identify causal effects. A positive and statistically significant β_1 implies that, conditional on covariates, Black children tend to go to bed later than White children.

2.5.2 Intergenerational Transmission of Sleep Behavior

We next examine whether racial disparities in children’s sleep reflect differences in intergenerational behavioral transmission. We estimate:

$$\text{Bedtime}_{it}^{child} = \alpha + \rho \text{Bedtime}_{it}^{parent} + \gamma X_{it} + \varepsilon_{it}, \quad (2.2)$$

separately for Black and White households. The parameter ρ measures the intergenerational elasticity of bedtime, capturing the extent to which children’s sleep schedules mirror those of their parents. A larger ρ among Black families would suggest stronger behavioral persistence, potentially associated with socioeconomic constraints or distinct parenting practices.

2.5.3 Descriptive and Experimental Evidence

After the evidence that we observed by descriptive OLS models (Equations 2.1 and 2.2) on racial gaps and behavioral persistence, we decided to try to go more in depth in these disparities using experimental data allow us to identify the underlying causal mechanisms. Combining both sources, Atus and experimental analysis, allowed us to disentangle whether observed disparities primarily reflect structural constraints (such as income or work schedules) or modifiable behavioral norms (such as parental routines).

Descriptive, intergenerational, and experimental analysis offers us the opportunity to study sleep as both a dimension of health inequality and a form of human capital formation.

2.5.4 Experimental Econometric Approach

To estimate the causal effect of our interventions, we implement linear probability models (LPM) for each binary outcome, including both stated intentions (earlier bedtime, longer sleep, healthier routine) and behavioral engagement (newsletter subscription). The baseline specification estimates the effect of each treatment arm, including selected combinations of treatments, relative to the control group:

$$Y_i = \alpha + \beta \text{Treatment}_i + \varepsilon_i, \quad (2.3)$$

where Y_i denotes the binary outcome for participant i and Treatment_i is a dummy for assignment to a given treatment. Standard errors are robust to heteroskedasticity.

To account for participant heterogeneity and assess the differential effectiveness of treatments by ethnicity, we estimate pooled regressions including interaction terms between treatment assignment and a Black/African-American indicator:

$$Y_i = \alpha + \beta \text{Treatment}_i + \gamma \text{Black}_i + \delta (\text{Treatment}_i \times \text{Black}_i) + \varepsilon_i. \quad (2.4)$$

Here, δ captures the marginal additional effect of each treatment for Black/African-American mothers relative to White respondents. Net treatment effects for Black participants are calculated as the sum of the main treatment effect (β) and the interaction term (δ), allowing interpretation in terms of percentage-point changes relative to the control mean.

We also implement specifications controlling for parental characteristics (age, education, income, marital status, single motherhood, night-shift work) and child characteristics (age, gender, baseline sleep duration). Results remain robust to the inclusion of these covariates. Across all specifications, coefficients can be interpreted as average treatment effects on the treated, with positive values indicating higher likelihood of the outcome relative to the control group.

2.6 Results

2.6.1 Documenting Disparities in Children’s Sleep

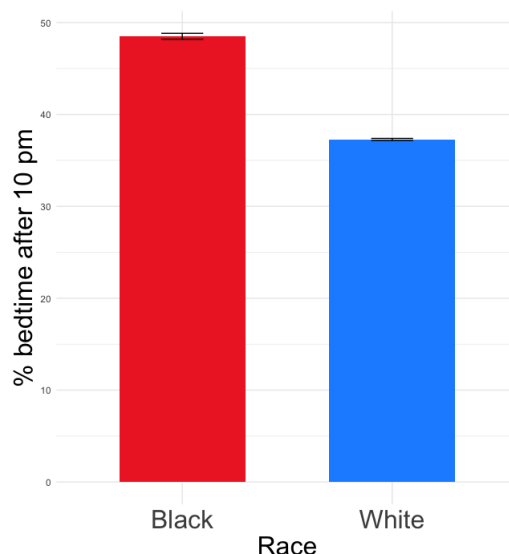
We begin by documenting racial disparities in children’s bedtime behavior using ATUS data (2003–2023), restricted to households with at least one child under age 13. Our main outcome is a binary indicator equal to 1 if the parent’s child reports a bedtime after 10:00 p.m. (i.e., bedtime > 10pm).

Raw Gap and Socioeconomic Gradients

Figure 2.1 presents the share of children awake at 10pm by race. Approximately 48% of Black/African-American children go to bed after 10pm, compared to 37% among White children. This difference is statistically significant, revealing a substantial racial disparity in children’s sleep schedules.

The disparity is embedded in strong socioeconomic gradients. Figure A.1 documents a strong and monotonic negative gradient between bedtime and socioeconomic status. The share of children awake at 10pm is around 45% among households in the bottom income quartile, compared to roughly 30% in the top quartile. A similar pattern emerges from parental education with nearly 45% of children whose parents did not complete

Figure 2.1: Bedtime by Race: % of Children with Bedtime Later than 10pm



Note: Data are drawn from the 2003–2023 American Time Use Survey (ATUS). The sample is restricted to households with at least one child under age 13.

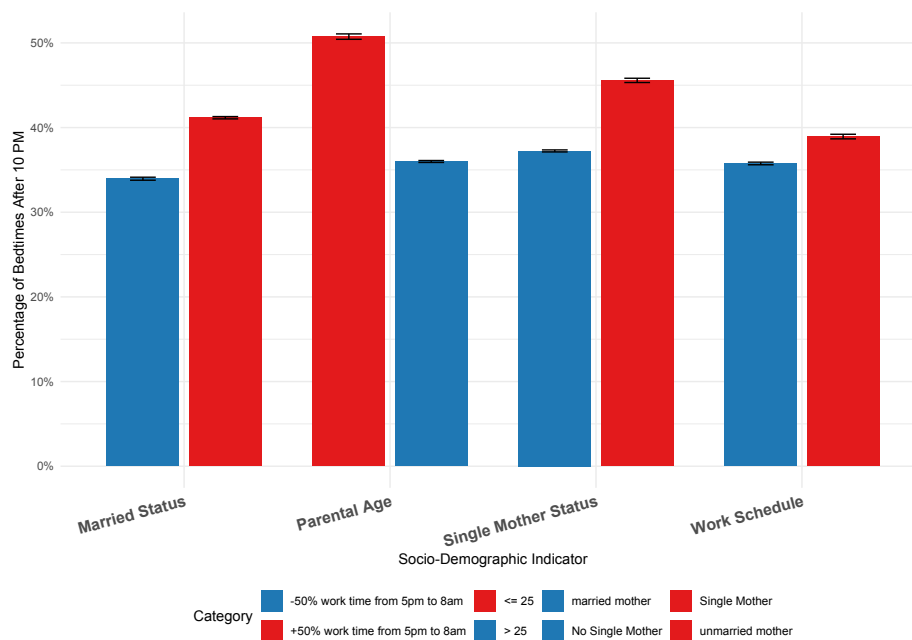
high school remain awake at 10pm and the only 10% among children of college-educated parents.

As shown in Figure 2.2, also family structure and parental characteristics matter. The 45% of children of single mothers are awake at 10pm, compared to 37% among children of other parents. Children of unmarried mothers exhibit similar patterns. Additionally, parental age and work schedules play a role: about 50% of children with parents under age 25 are awake at 10pm, in contrast with 35% among those with older parents. Likewise, children of parents working primarily night shifts (more than 50% of their work between 5pm and 8am) are considerably more likely to have late bedtimes than those whose parents work mostly standard hours.

On the other hand, we can see that Black/African-American children are disproportionately represented among families with lower income, lower parental education, single or unmarried mothers, and parents working night shifts. Figure A.2 illustrates that the share of African-American parents is substantially higher at the bottom of the income distribution. In our sample, 22% of African-American parents hold a college degree, compared to 37% among White parents. Similarly, in Figure 2.3, 40% of African-American mothers are single, versus only 15% of White mothers; and only 18% of African-American mothers are married, compared to 38% of White mothers. African-American parents are also, on average, younger and more likely to work night shifts.

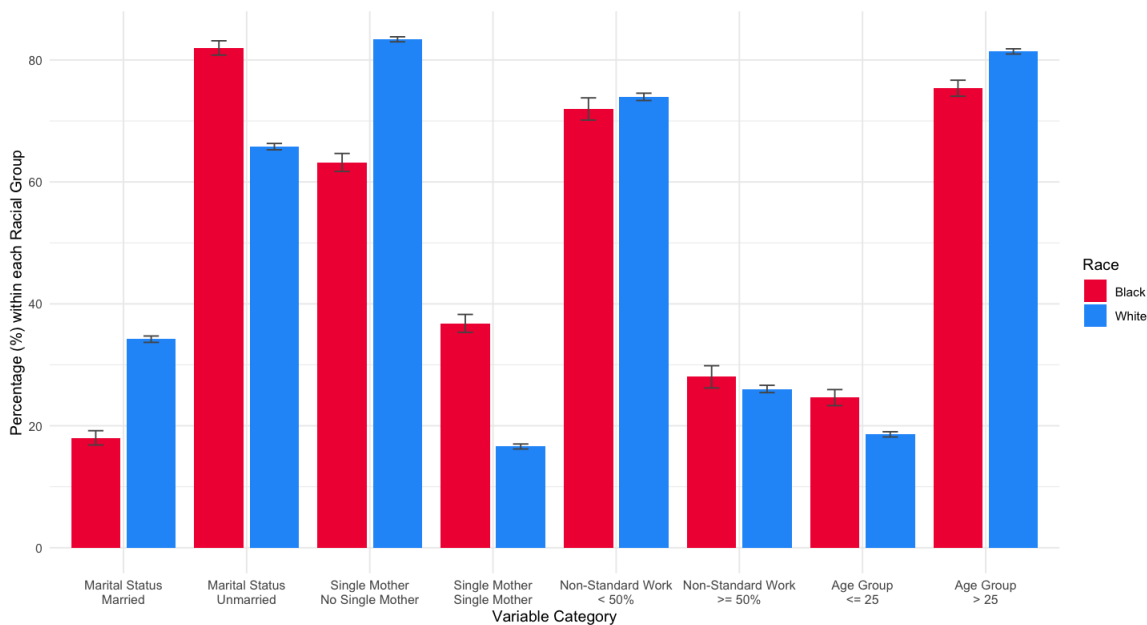
To provide a detailed descriptive account of racial disparities in children’s bedtime and to quantify the extent to which observable characteristics explain the gap, we estimate the baseline OLS model in Equation (2.1). The estimated coefficients and the sequential

Figure 2.2: Percentage of Children's Bedtime After 10 PM (22:00) by Parent Characteristics



Note: Data are drawn from the 2003–2023 American Time Use Survey (ATUS). The sample is restricted to households with at least one child under age 13.

Figure 2.3: Socio-Demographic Determinants of Bedtime by Race



Note: Data are drawn from the 2003–2023 American Time Use Survey (ATUS). The sample is restricted to households with at least one child under age 13.

inclusion of controls are reported in Table 2.2.

Table 2.2 Column (1) reports the unconditional racial gap: Black/African-American children are 11 percentage points more likely to be awake at 10pm than White children. After controlling for parental sociodemographic characteristics (column 2), the gap declines to 9 percentage points. Adding maternal characteristics (column 3) has little effect. When controlling for whether the responding parent goes to bed after the sample median (column 4), the coefficient declines to 7.3 percentage points. Finally, adjusting for parental night-shift work (column 5) reduces the estimated racial gap to 7.2 percentage points.

Table 2.2: Racial gap in % of children going to bed after 10pm

	(1)	(2)	(3)	(4)	(5)
Black	0.112*** -0.007	0.092*** -0.007	0.088*** -0.008	0.073*** -0.007	0.072*** -0.007
Sociodemographic chars.		x	x	x	x
Mother chars.			x	x	x
Parental late bedtime				x	x
Parental night shift					x
Mean Dep.Var.	0.389	0.389	0.389	0.389	0.389
Std. Dev.	0.487	0.487	0.487	0.487	0.487
Observations	35,973	35,973	35,973	35,973	35,973

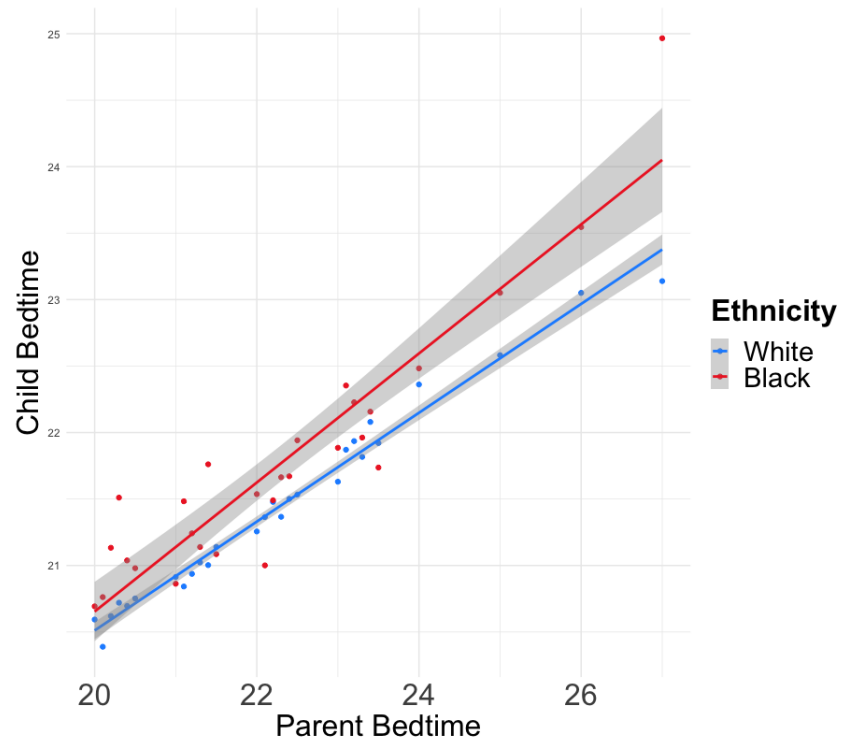
Notes: Data are drawn from the ATUS survey 2003-2022. We restricted the sample to ATUS-respondents with children under the age of 13. Robust standard errors are reported in parenthesis.

Although these observable characteristics explain part of the difference, a substantial portion of the racial disparity in children’s bedtime remains unexplained. This residual gap may reflect unobserved structural, institutional, or socioeconomic factors that systematically disadvantage Black/African-American families—such as unequal access to stable work schedules, neighborhood safety, or housing conditions—that are not fully captured by individual-level covariates.

Intergenerational Correlation

Figure 2.4 plots the intergenerational correlation, from Equation (2.2), children whose parents go to bed later are more likely to do so themselves. The interaction term ρ_2 is positive and statistically significant, indicating a stronger parent–child bedtime correlation in Black/African-American families than the white ones. Even conditional on parental bedtime, Black/African-American children exhibit later bedtimes relative to White children, and the racial gap tends to widen as parental bedtime becomes later—consistent with persistent normative or contextual constraints that reinforce late sleep schedules.

Figure 2.4: Intergenerational Correlation in Bedtime: Parent vs. Child Bedtime



Note: Data are drawn from the 2003–2023 ATUS. The sample includes respondents with children under age 13. Time intervals refer to clock time as follows: 20 indicates 8:00 p.m., 22 indicates 10:00 p.m., 24 indicates 12:00 a.m., and 24 indicates 2:00 a.m..

2.6.2 Experimental Evidence - Descriptive analysis

We complement the descriptive ATUS evidence with an online experiment conducted on Prolific in May 2024. The sample includes 729 mothers (381 Black/African-American, 348 White) with at least one child aged 6–13. The experiment tests whether targeted informational messages and narrator identity influence parental beliefs, intentions, and a concrete behavioral marker (newsletter subscription).

Descriptive Statistics

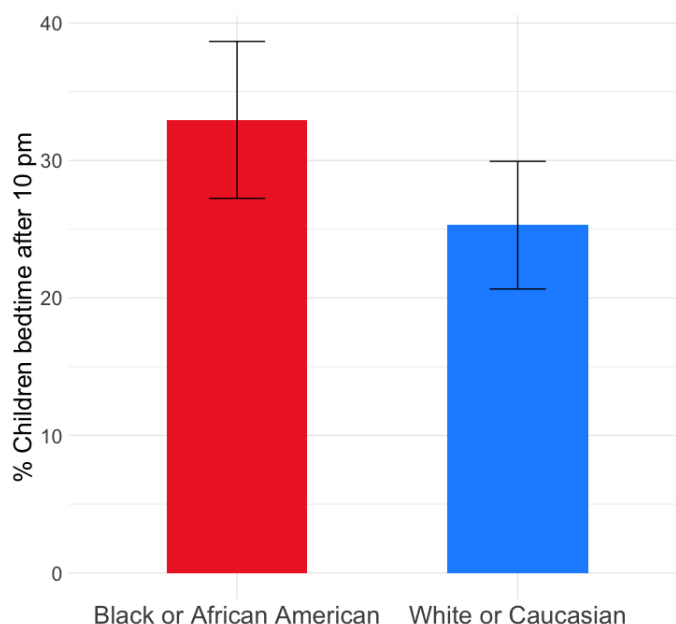
Figure 2.5 presents the distribution of children’s bedtimes by maternal ethnicity in the Prolific sample. Consistent with ATUS evidence, 34% of Black/African-American children report bedtimes after 10 p.m., compared with 25% of White children. Figure 2.1 from ATUS shows that 48% of Black/African-American children go to bed after 10 p.m., compared with 37% of White children. Although the levels observed in our online sample differ from those in ATUS, the racial gap is remarkably stable across the two datasets (11% in the ATUS dataset and 9% in our Prolific sample).

Socioeconomic correlates documented in ATUS are closely reflected in the online sample. Figure A.3 shows that, along both income and education gradients, children from less advantaged households tend to go to bed later, while Figure A.4 indicates that late bedtimes (after 10 p.m.) are also more prevalent among children of single mothers, unmarried mothers, and mothers working night shifts.

Black/African-American children remain disproportionately represented in families with lower income, single-parent households, unmarried mothers, and parents working night shifts (Figures A.5 and A.6). From Figure A.5, we also observe that the education distribution is more heavily concentrated in the “some college” category among Black/African-American mothers, which is consistent with ATUS patterns showing a higher prevalence of Black/African-American parents in intermediate education categories.

The intergenerational correlation between parental and child bedtimes is again stronger among Black/African-American families than among White families (see Figure A.7 in the Appendix).

Figure 2.5: Online Survey – Bedtime by Ethnicity: % Children with Bedtime Later than 10pm

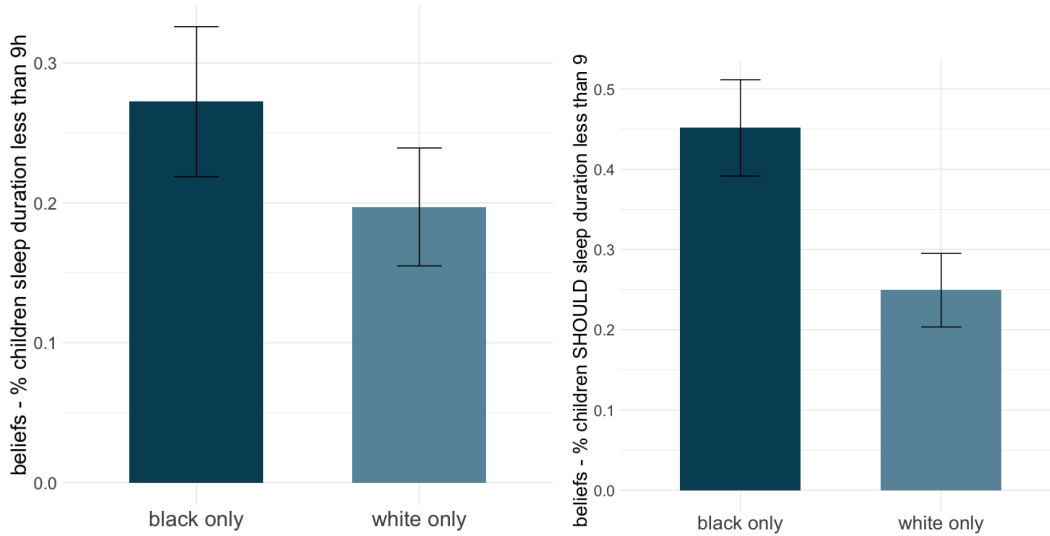


Note: Data are drawn from the Online Survey conducted on Prolific (May 2024). The sample is restricted to parents with at least one child aged 6–13.

Beliefs Results

The survey also elicits parental beliefs and norms about children’s sleep. Only 35% of Black/African-American mothers believe that other children sleep more than nine hours (descriptive norms), compared to 44% of White mothers. For injunctive norms, 53% of Black/African-American mothers believe children *should* sleep more than nine hours, compared to 75% of White mothers. These persistent racial disparities in perceived and prescriptive norms motivate our information intervention, and are visually represented in Figure 2.6 in the Appendix.

Figure 2.6: Online Survey - Mothers beliefs on other children, descriptive norms vs. injunctive norms



Note: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed.

2.6.3 Information Intervention and Results

To establish a standard reference point prior to analyzing heterogeneous effects, 2.3 presents the Average Treatment Effect (ATE) for the full sample, encompassing both Black/African-American and White mothers. The coefficient for the Treatment variable represents the average effect of the informational intervention on the treated group relative to the control group, without distinguishing between racial subgroups.

As shown, the intervention increases—on average—the probability that parents intend to advance their child’s bedtime by 7.8 percentage points, and the probability of increasing total sleep duration by 15.2 percentage points. Conversely, the effects on intentions to improve the pre-sleep routine and on voluntary newsletter subscription appear negligible.

This aggregated estimate serves as a starting point for the subsequent heterogeneity analyses, in which we will explore differences across racial subgroups and across different types of informational messages.

We now turn to the analysis for the Black/African-American mothers subgroup to assess treatment effects within this specific population.

Appendix B shows all survey information and forms. T1–T2 provide CDC-based sleep recommendations; T3–T4 emphasize racial disparities in bedtime patterns; T5–T6 provide first-person narrative accounts in the mother’s own voice, describing her experience. Participants were randomized to one of six treatment arms or a control

Table 2.3: Parental Intentions - All Population

	<i>Dependent variable:</i>			
	Bed Earlier	Sleep Longer	Healthy Routine	Newsletter
	(1)	(2)	(3)	(4)
Treatment	0.078* (0.044)	0.152*** (0.039)	-0.044 (0.041)	-0.0001 (0.048)
Mean dep. var	0.681	0.76	0.758	0.428
SD dep. var	0.467	0.428	0.428	0.495
Observations	739	739	738	738
R ²	0.040	0.040	0.062	0.036
Adjusted R ²	0.027	0.027	0.049	0.023

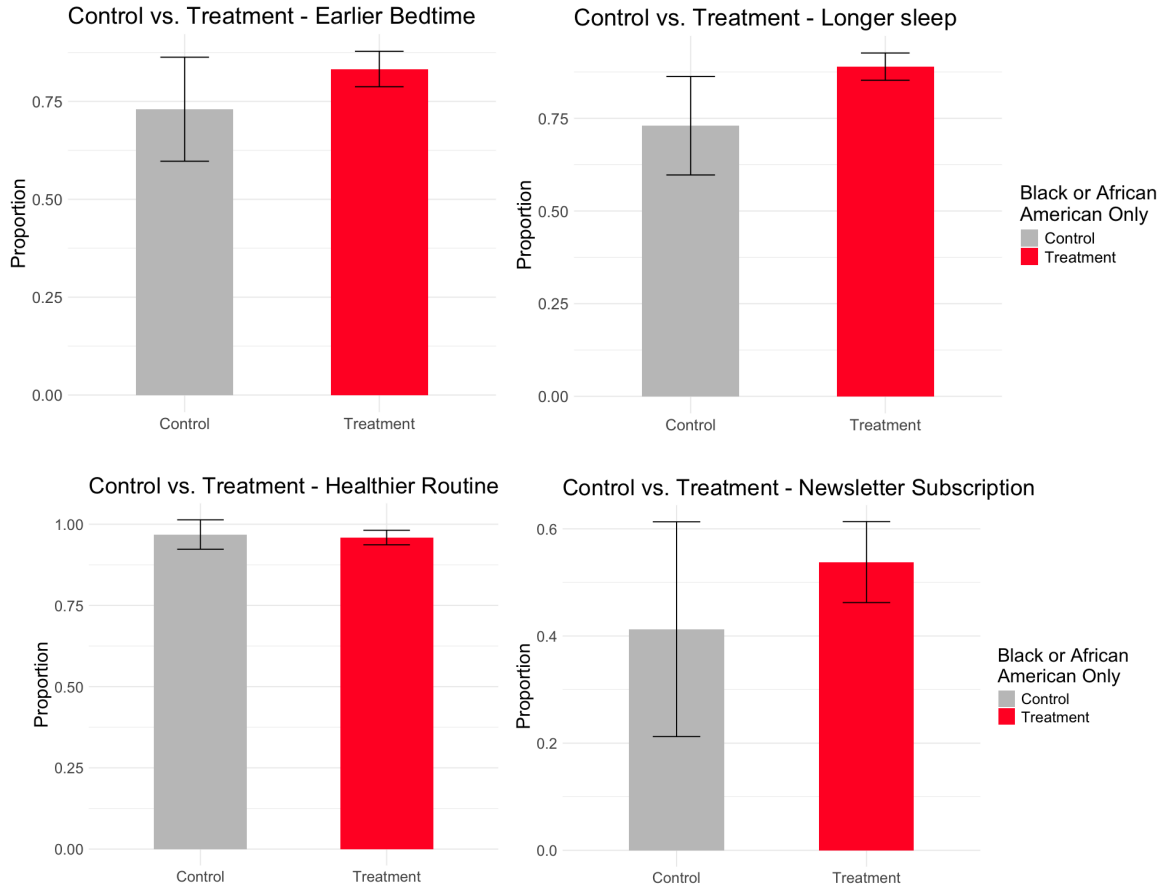
Notes: The table reports estimated differences between the treatment group and the control group for the entire experimental sample, including both Black/African-American and White mothers, using data from the Prolific sample. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* captures parents’ intention to move their child’s bedtime earlier; *Longer Sleep* indicates intentions to increase total sleep duration; *Healthier Routine* reflects intentions to implement or improve a healthy pre-bedtime routine. The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

group (Table 2.1). Treatments vary on two dimensions: narrator identity (White vs. Black/African-American) and message framing (neutral informational, disparity-focused, personal reflection). The main outcomes are coded as binary indicators, where a value of 1 corresponds to respondents who answered “probably yes” or “definitely yes,” and 0 corresponds to “probably no,” “definitely no,” or “might or might not,” in the following intention measures. *Earlier Bedtime* captures parents’ stated intention to move their child’s bedtime earlier; *Longer Sleep* reflects intentions to extend total sleep duration; *Healthier Routine* measures willingness to create or improve a healthy pre-bedtime routine. A revealed-preference behavioral measure is voluntary subscription to a sleep-hygiene *newsletter*; for this outcome, a value of 1 indicates voluntary subscription to the sleep-hygiene newsletter, while 0 denotes refusal to subscribe.

For the following analysis we focus exclusively on Black/African-American mothers, in order to assess the effectiveness of the intervention within this population.

Effect of Treatment versus Control. Table A.1 and Figure 2.7 reports the average treatment effects comparing all treatment arms pooled together versus the control group. We find that the intervention affects several outcomes in a statistically meaningful way. Parents in the treatment group are 10 percentage points more likely to report an intention to advance their child’s bedtime and 16 percentage points more likely to report an intention to increase sleep duration. We observe no detectable impact on intentions to improve bedtime routines. However, the revealed-preference measure shows a 12.5-percentage-point increase in newsletter subscription among treated participants, indicating that the intervention meaningfully shifts at least some real behavioral commitments.

Figure 2.7: Online Experiment (prolific sample) - Any Treatments vs. Control



Notes: Data are drawn from the Prolific sample. We restricted the sample analyzed to the only Black or African American Mothers. The table reports estimated differences between the treatment group and the control group, using data from the Prolific sample. Dependent variables are coded as binary indicators: a value of 1 corresponds to respondents answering “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* indicates parents’ intention to move their child’s bedtime earlier; *Longer Sleep* reflects intentions to increase total sleep duration; *Healthier Routine* captures intentions to create or improve a healthy pre-bedtime routine; and the newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter.

Effects of Treatment Types versus Control: Neutral, Disparities, and Personal Framing. Table A.2 reports the treatment effects on parents’ stated intentions for four sleep-related outcomes among Black/African-American respondents, while Figure 2.8 visualizes the same estimates with 95% confidence intervals. All coefficients represent differences relative to the control group mean reported at the bottom of the table.

The Neutral Treatment generates modest but directionally positive changes in parents’ stated intentions. The treatment significantly increases intentions to extend children’s

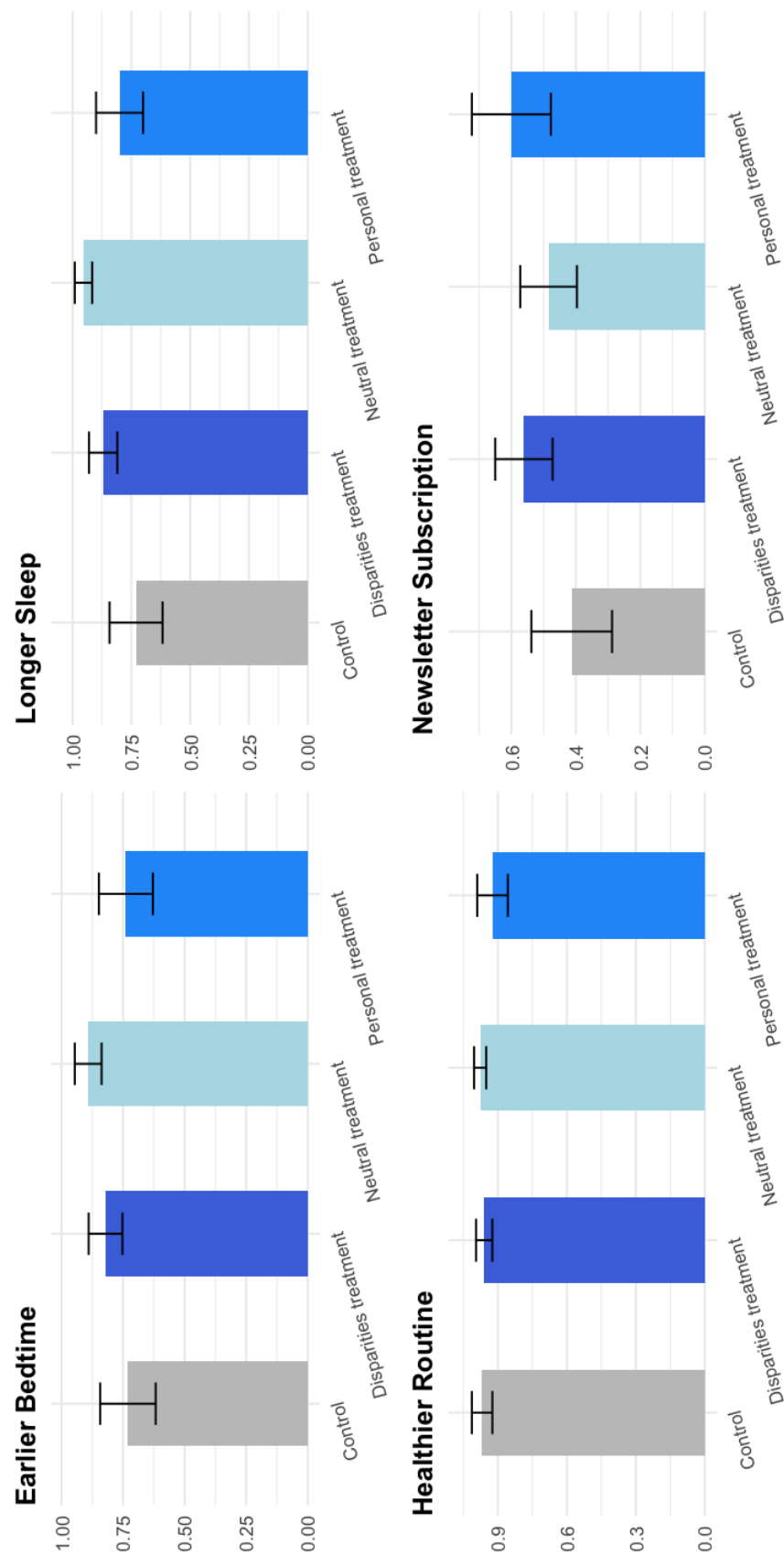
total sleep duration by 0.140 ($p < 0.01$), or about 16% of the baseline level, and produces a similarly sized increase in voluntary newsletter subscription (0.148; $p < 0.10$). No meaningful effects emerge for the intention to establish a healthier bedtime routine or to move the child's bedtime earlier (for this last outcome, the estimated magnitude is positive but not statistically significant).

The Personal Treatment, which presents the information in a more individualized narrative form from a mother's perspective, yields the largest and most consistent effects. Intentions to move bedtime earlier rise by 0.161 ($p < 0.01$), equivalent to nearly 20% of the control group mean. The effect on intentions to increase overall sleep duration is even larger, 0.223 ($p < 0.01$), or 26% of the baseline level, representing the strongest response across outcomes. Effects on healthier bedtime routines remain negligible, while newsletter subscription increases modestly but not significantly.

In contrast, the Disparities Treatment, which emphasizes racial disparities in children's sleep patterns, produces a more selective pattern of responses. It does not meaningfully affect intentions to move bedtime earlier, increase sleep duration, or improve bedtime routines. However, it substantially increases newsletter subscription by 0.187 ($p < 0.05$), corresponding to 36% of the control group mean. This points to a greater effectiveness of the disparity-focused messages in stimulating information-seeking behavior than in changing stated intentions.

The evidence presented in Table A.2 and illustrated in Figure 2.8 indicates the personalized framing generates the strongest shifts in reported parenting intentions regarding children's sleep, whereas disparity-focused messaging primarily increases engagement with additional informational resources.

Figure 2.8: Online Experiment (prolific sample) - Any Treatments vs. Control



Notes: Data are drawn from the Prolific sample. We restricted the sample analyzed to the only Black or African American Mothers.

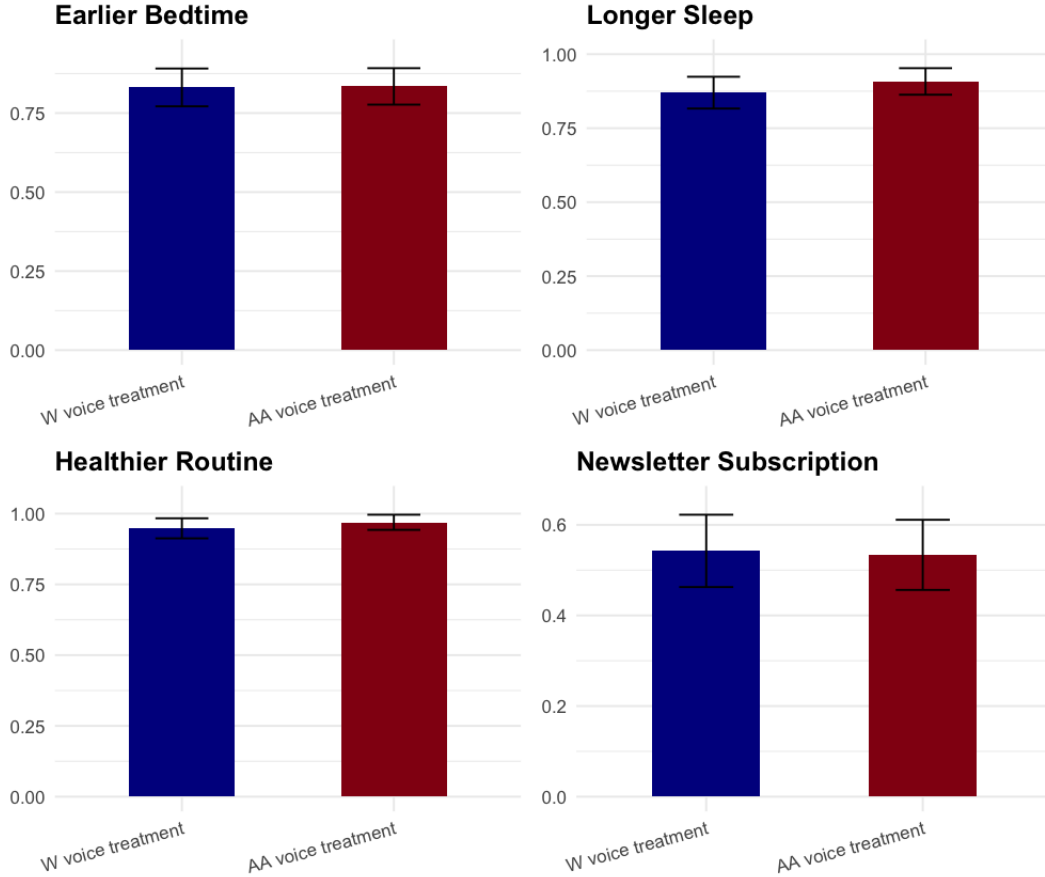
Effects of Narrator Ethnic Accent versus Control. Table A.3 reports treatment effects separately for messages delivered with a White-accented voice and an African-American-accented voice, each relative to the control group, while Figure 2.9 provides a graphical representation of the same estimates. Both voice treatments generate positive and statistically significant effects on several outcomes for the subgroup of Black and African-American mothers. Exposure to the White-accented voice increases the likelihood of intending to move a child’s bedtime earlier by 0.101 ($p < 0.10$) and significantly raises intentions to increase total sleep duration by 0.140 ($p < 0.01$), corresponding to about 16% of the mean. Newsletter subscription also rises by 0.130 ($p < 0.10$) with the White-accented voice, which corresponds to an increase of approximately 25% relative to the control group mean, while no effect is detected for intentions to improve bedtime routines.

The African-American-accented voice produces a very similar pattern of effects. Intentions to advance bedtime increase by 0.104 ($p < 0.10$), corresponding to about 13% of the control group mean, and intentions to extend sleep duration rise by 0.178 ($p < 0.01$), which represents an increase of approximately 21% relative to baseline and is slightly larger than the effect observed for the White-accented voice. Effects on healthier routines remain close to zero, with no significant effect.

To isolate whether the ethnic accent itself generates differential responses, Table A.4 directly compares the African-American-accented voice to the White-accented voice, excluding the control group. None of the estimated differences are statistically significant across any outcome. The point estimates are small in magnitude and close to zero for all four measures, including earlier bedtime, longer sleep, healthier routines, and newsletter subscription. One possible explanation for these null differences is that, when the informational content is identical, ethnic vocal cues may simply not be salient enough to shape parental responses, suggesting that respondents primarily respond to the substance of the message rather than to the narrator’s accent. Alternatively, the lack of differential effects may reflect the novelty of the information and the scarce availability of easily accessible, credible sleep-related resources in this environment, which may dominate any framing effects associated with the speaker’s identity.

The values observed from Tables A.3 and A.4, as well as from Figure 2.9, suggests that the presence of an audio message itself drives the behavioral response, while the ethnic accent of the narrator does not generate additional differential effects. Both White- and African-American-accented voices are similarly effective in increasing intentions to improve children’s sleep duration and, to a lesser extent, bedtime timing, but neither affects intentions to improve bedtime routines.

Figure 2.9: Online Experiment (prolific sample) - White accent vs African-American accent



Notes: Data are drawn from the Prolific sample. We restricted the sample analyzed to the only Black or African American Mothers.

Heterogeneity on different voice accent. Patterns have been documented in prior studies emphasizing the role of messenger identity and institutional trust in shaping behavioral responses, particularly among historically underrepresented groups (Alsan et al., 2019; DellaVigna and Linos, 2022). These studies typically find that culturally concordant messengers or trusted sources can meaningfully influence health-related behaviors. In contrast, in our experiment, we find no statistically significant differences in outcomes driven solely by the ethnic accent of the narrator, suggesting that the audio dimension per se does not independently shape parental responses.

These suggest that the audio dimension per se does not independently shape parental responses. As discussed above, this null result is likely consistent with a broader and pervasive scarcity of accessible, credible information on children’s sleep that affects parents across all ethnic groups, and is particularly pronounced among Black/African-American mothers (Yu et al., 2025). In this context, respondents may primarily react to

the novelty and informational content of the message itself, rather than to the identity of the messenger.

More broadly, limited dissemination and difficult access to pediatric sleep information could characterize the information environment faced by many parents, regardless of ethnicity. However, structural and socioeconomic barriers to information acquisition (such as time constraints, work schedules, healthcare access, and institutional trust) may be more binding for Black/African-American families, as suggested by the population characteristics documented earlier in the paper and by additional unobserved constraints. These frictions may attenuate potential differential effects of culturally targeted delivery channels, even when messenger identity varies.

All Treatments Effects vs Control Group. Tables A.5 and A.6 report treatment effects on parental intentions controlling for parental characteristics (education, income, marital status, single motherhood, age, and night-shift work) and child characteristics (age, gender, and baseline sleep duration). The patterns are highly stable across specifications. Also here, as in the previous analysis, we focus only on Black and African-American mothers.

For intentions to adopt an earlier bedtime (Panel A), both neutral framings generate positive and statistically significant effects, between 12 and 19 percentage points across specifications (with a higher effect for the African-American-accented voice). The personal White-framed treatment is also positive and statistically significant once controls are included, while the personal African-American-framed treatment is positive but not statistically significant. The disparities-framed treatments yield coefficients close to zero and are never statistically significant.

Panel B shows strong and robust effects on intentions to increase total sleep duration. Both neutral treatments produce large and precisely estimated effects (approximately 20–25 percentage points). Both personal framings also significantly increase intentions, with magnitudes between 13 and 17 percentage points. In contrast, the disparities framings remain positive but statistically insignificant.

Panel C indicates no statistically significant effects of any treatment on intentions to improve bedtime routines, with all coefficients close to zero (except for the disparity-framed treatment with an African-American-accented voice, which shows a negative effect of 6 percentage points on willingness to improve the child’s bedtime routine). Panel D shows that behavioral engagement, measured by newsletter subscription, responds only to the personal African-American-accented framing and to White-accented disparity framing, which increase take-up by approximately 18–21 percentage points. The remaining treatments are not statistically significant.

Overall, the analyses in this section indicate that the disparity framing has no statistically significant effect on the main outcomes of interest, except for the outcome subscription to the sleep-hygiene newsletter, and specifically only for the White-accented

voice among the Black and African-American population treated relative to the control group.

Ethnic Heterogeneity in Treatment Effects and Behavioral Engagement.

Table A.7 presents pooled regressions including both White and Black/African-American respondents and allowing for differential treatment effects through interaction terms. The main indicator for Black or African-American respondents is positive and marginally significant only for intentions to advance bedtime (0.133, $p < 0.10$), corresponding to a 16% increase relative to the sample mean (0.82). The coefficient is not statistically different from zero for longer sleep, healthier routines, and newsletter subscription.

Regarding the main treatment effects, neutral (White-accented voice) and personal (both accents) framings significantly increase intentions to extend sleep duration for the White mothers sample. For example, the neutral White-accented treatment raises the probability of intending to increase sleep duration by 0.158 ($p < 0.05$), corresponding to an 18% increase relative to the mean (0.86), while the personal White-accented treatment increases this outcome by 0.180 ($p < 0.01$), equal to a 21% increase. In contrast, for newsletter subscription, the main effects of several treatments are negative and statistically significant for White respondents, most notably for the neutral White framing (-0.206 , $p < 0.05$) and the personal African-American framing (-0.227 , $p < 0.05$), implying reductions of about 40–44% relative to the mean subscription rate (0.52).

The negative effects found in the group of white mothers (Table A.7) appear counterintuitive at first glance and require further reflection. Several psychological mechanisms may lie behind these responses. One hypothesis is that some mothers perceived the advice as irrelevant to their reality or, conversely, excessively directive, leading to a sort of rejection of its content. Alternatively, the results could reflect what is known in communication psychology as the "boomerang effect": a well-documented phenomenon in which a message, if perceived as morally judgmental or intrusive, ends up having the opposite effect than intended, decreasing the intention to change behavior (Brehm, 1966; Cialdini, 2001). It cannot be ruled out that part of this negative response stems from a general disinterest in the topic discussed.

At present, the data available to us do not allow us to determine which of these factors is predominant. Future research will shed light on these issues, perhaps through qualitative surveys, message perception tests, or targeted behavioral experiments, to decipher the psychological processes that influence parents' reactions to this type of educational intervention.

The interaction terms capture the marginal additional effect of each treatment for Black/African-American mothers relative to the baseline (White) treatment effects. In our case, these interaction terms reveal substantial heterogeneity by ethnicity, especially for the behavioral outcome. For newsletter subscription, the interaction effects for Black mothers are large and positive for multiple framings, including the neutral White treat-

ment (0.317, $p < 0.05$), the disparities White treatment (0.219, $p < 0.10$), the disparities African-American treatment (0.412, $p < 0.01$), and the personal White treatment (0.334, $p < 0.05$). When combined with the corresponding main treatment coefficients, these imply positive net treatment effects for Black/African-American mothers, in stark contrast to the negative or muted effects observed for White respondents: respectively, neutral White-accent framing net effect of 0.111, corresponding to a 21% increase relative to the mean subscription rate (0.52); disparities White (0.090, +17%), disparities African-American (0.402, +77%), and personal White (0.221, +42%).¹

These findings are consistent with a potential broader lack of clear and accessible information in the population about recommended sleep durations for children, which could also differ between the two groups. We observed that all the treatments are effective in our population, especially among Black and African-American mothers. The behavioral engagement outcome (newsletter take-up) is strongly and positively differentiated for Black/African-American mothers compared to White mothers, revealing opposite behavior between these two groups and ethnic heterogeneity.

2.7 Conclusion

Our study documents sizable and persistent racial disparities in children’s sleep patterns in the United States and examines whether low-cost informational interventions can help reduce these gaps. Using nationally representative time-use data (ATUS) and a controlled online experiment on Prolific (May 2024, $n = 729$ mothers), we provide both descriptive and causal evidence on the determinants of children’s sleep behavior, and document several key findings.

Our descriptive analysis shows that significant racial gaps exist in children’s bedtimes. Black/African-American children are more likely to go to bed after 10:00 PM—48% in ATUS and 34% in the Prolific sample—compared with 37% and 25% of White children, respectively. While socioeconomic and parental characteristics explain part of the gap, a residual disparity remains, highlighting joint role of structural and socio-cultural factors. Intergenerational correlations in bedtime are stronger in Black/African-American families, and perceived injunctive norms for sleep duration are lower, suggesting the persistence of socially transmitted behaviors.

It is important to emphasize, in this section as well, that the residual disparities persisting after controlling for observable socioeconomic and family factors suggest that unobserved constraints—such as limited access to reliable information or the development of inaccurate beliefs regarding sleep—may continue to shape children’s sleep patterns across different groups.

¹The differences between White and Black/African-American groups are remarkable. Black mothers show increases of approximately 40–80% (61%, 42%, 79%, 64%, respectively, for each treatment) above the mean, relative to White mothers.

Moreover, it should be noted that an increase in sleep duration inevitably reduces the time available for children’s other daily activities, such as play, study, or sports. However, unlike in adults, this reallocation does not depend on the child’s autonomous choices but is, to a large extent, determined by family routines and institutional constraints. This implies that, although the time devoted to other activities may decrease, the observed effect on sleep routines primarily reflects sleep itself, with less confounding due to time reallocation. In the economic literature on sleep, it has been highlighted that the time budget constraint complicates the causal identification of the effect of sleep duration on economic outcomes, as an additional hour of sleep reduces other activities (Bertoni et al., 2025).

The experimental evidence complements these patterns by identifying a causal role for information. Pooling all treatment arms, Black/African-American mothers exposed to audio messages were 10 percentage points more likely to report intentions to advance their child’s bedtime and 16 percentage points more likely to report intentions to extend total sleep duration relative to the control group (excluding white mothers). The intervention also translates into a concrete behavioral response: voluntary newsletter subscription rose by 12.5 percentage points (excluding white mothers).

The ethnicity of the narrator (White vs. African-American accent) has little to no additional effect on parental intentions or behavioral engagement, suggesting that the informational content itself drives responses rather than vocal cues. This finding is consistent with a context in which credible information on children’s sleep is scarce and highly valued across groups. The same also applies to message framing; we do not observe a substantial difference overall between the different message framings.

Heterogeneity analyses reveal that while stated intentions were broadly similar across ethnic groups, revealed behavioral engagement differs sharply. Black/African-American mothers exhibited substantially higher newsletter take-up across multiple treatments (net increases ranging from 17% to 77% relative to baseline), whereas White mothers often showed muted or even negative responses. This contrast suggests important differences in baseline access to, and demand for, credible sleep-related information across groups.

Our findings underscore that sleep disparities among children are shaped by both structural inequalities and behavioral norms. Targeted, personalized informational interventions represent promising yet cautious avenue to shift parental intentions and behaviors, particularly in populations facing structural and informational barriers. At the same time, the heterogeneous responses across groups suggest that uniform policy tools may generate uneven effects.

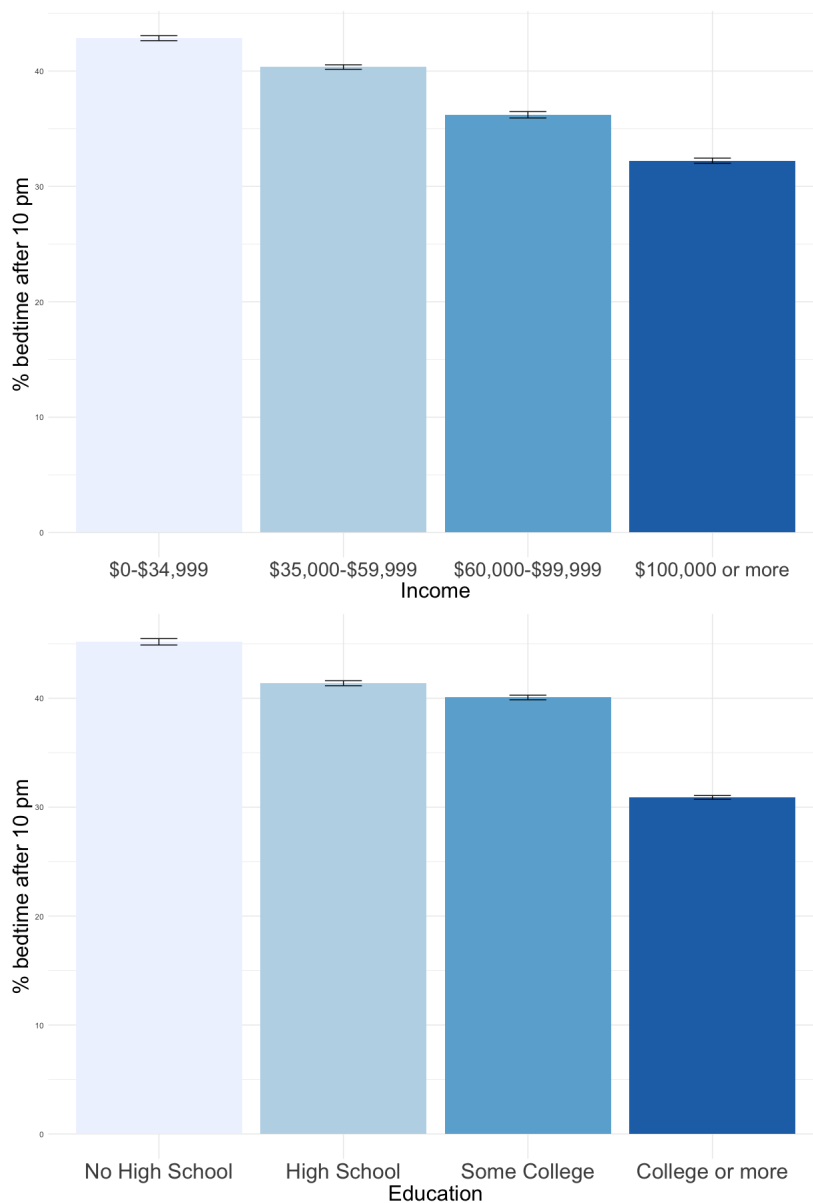
For policymakers and public health prospective, our findings could suggest that low-cost, personalized informational interventions to improve children’s sleep, particularly in populations facing structural barriers, thereby potentially reducing early-life health disparities and supporting cognitive and developmental outcomes.

Our experimental sample is drawn from Prolific and, despite being stratified by race, is likely to select individuals with greater digital literacy and a greater propensity to seek information than the general low-income population. This characteristic may explain why the percentage of children who go to bed after 10 pm is approximately 10% lower than in the ATUS population. While this may limit the generalizability of the findings, it is plausible that a targeted intervention on populations with lower digital literacy, lower propensity to seek information, or less knowledge about sleep habits could generate even larger effects. Our findings are indicative of the potential impact of targeted educational policies and the lack of information in this area. Future studies could extend the experiment to more representative samples of the overall population or to specific subgroups with less access to information to confirm the external validity of the findings.

In addition, for the experimental part of this study, the primary outcome analyzed concerns parents' intentions to improve their children's sleep habits, rather than the concrete actions actually taken. It is therefore possible that actual behaviors differ from stated intentions. This choice represents a first practical step in evaluating the impact of educational messages, but at the same time highlights a limitation of the study. Future research could consider conducting field experiments in which it is possible to directly observe participants' actual behavior to verify the translation of intentions into concrete actions.

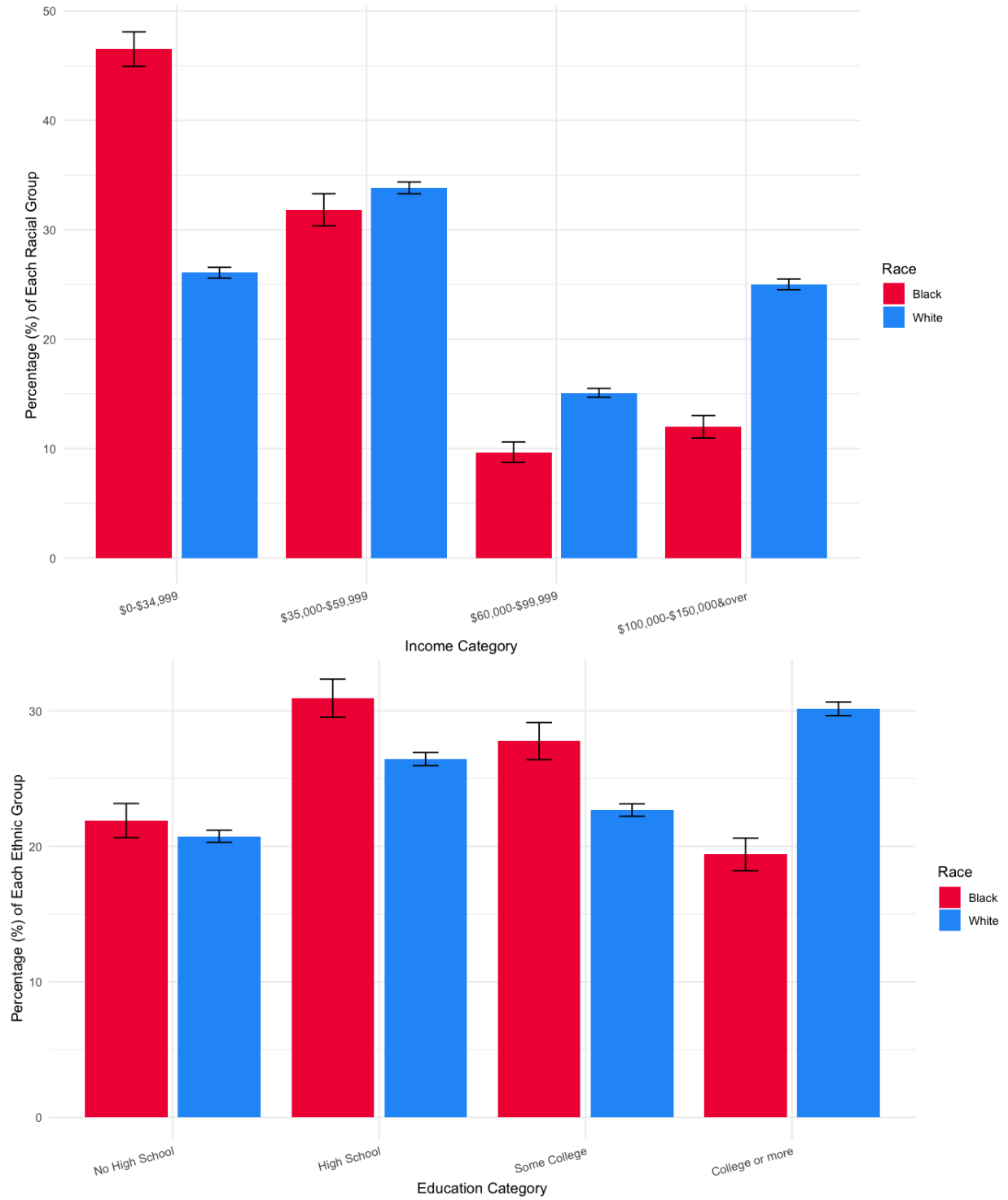
Appendix A. Figures and tables

Figure A.1: Bedtime by Income and Education, % with children bedtime later than 10pm



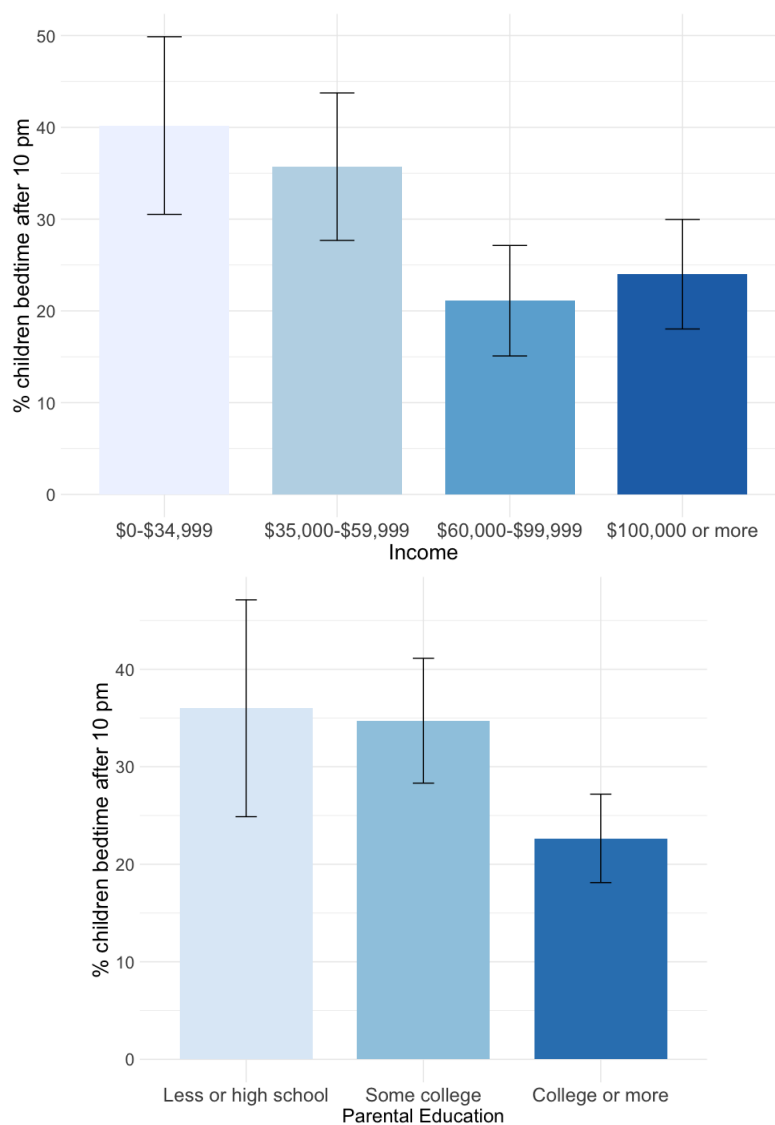
Notes: Data are drawn from the ATUS survey 2003-2023. We restricted the sample to ATUS-respondents with children under the age of 13. All reported confidence intervals correspond to the 95% level.

Figure A.2: Income and Education by White and Black



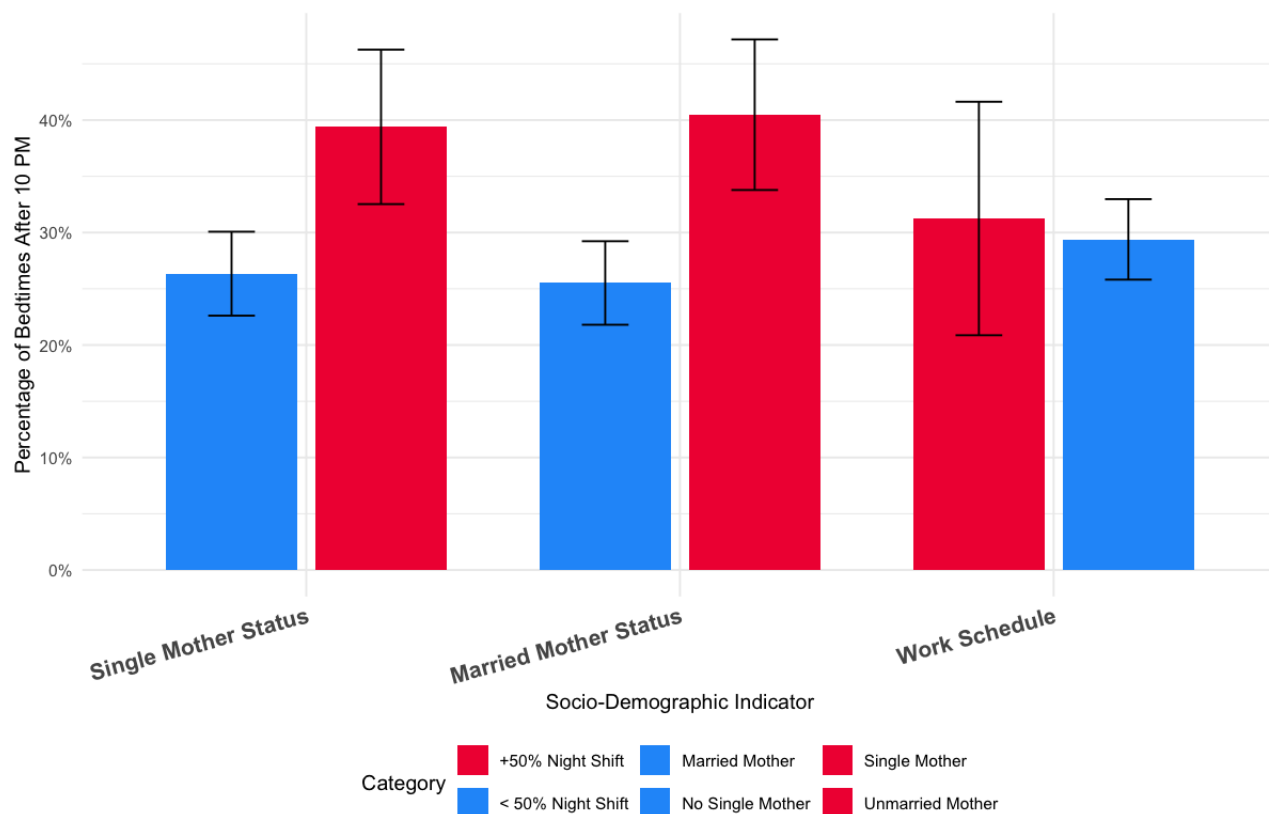
Notes: Data are drawn from the ATUS survey 2003-2023. We restricted the sample to ATUS-respondents with children under the age of 13. All reported confidence intervals correspond to the 95% level.

Figure A.3: Online Survey - Bedtime by Income and Education, % children with bedtime later than 10pm



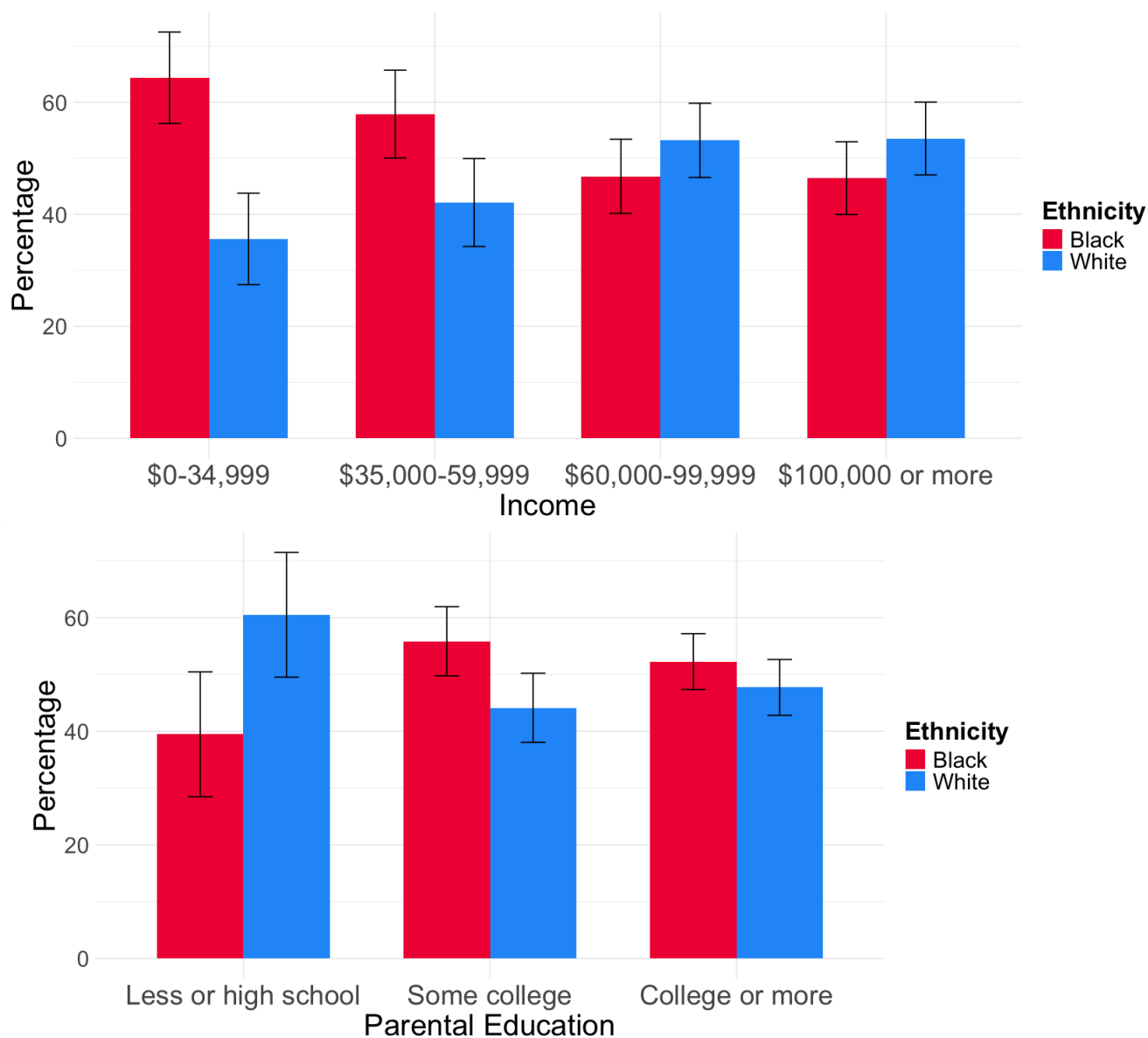
Notes: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. All reported confidence intervals correspond to the 95% level.

Figure A.4: Online Survey - Bedtime by Parental Characteristics, % with children bedtime later than 10pm



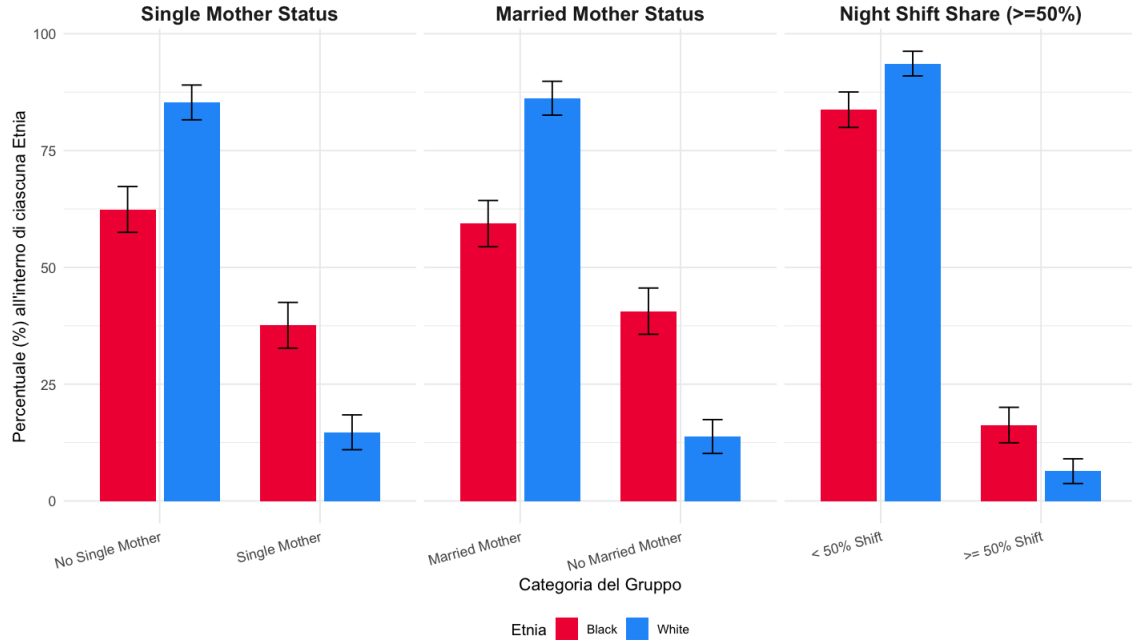
Notes: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. All reported confidence intervals correspond to the 95% level.

Figure A.5: Online Survey - Income and Parental Education by White and Black



Notes: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. All reported confidence intervals correspond to the 95% level.

Figure A.6: Online Survey - Racial Differences in Socio-Demographic Determinants of Bedtime by Race



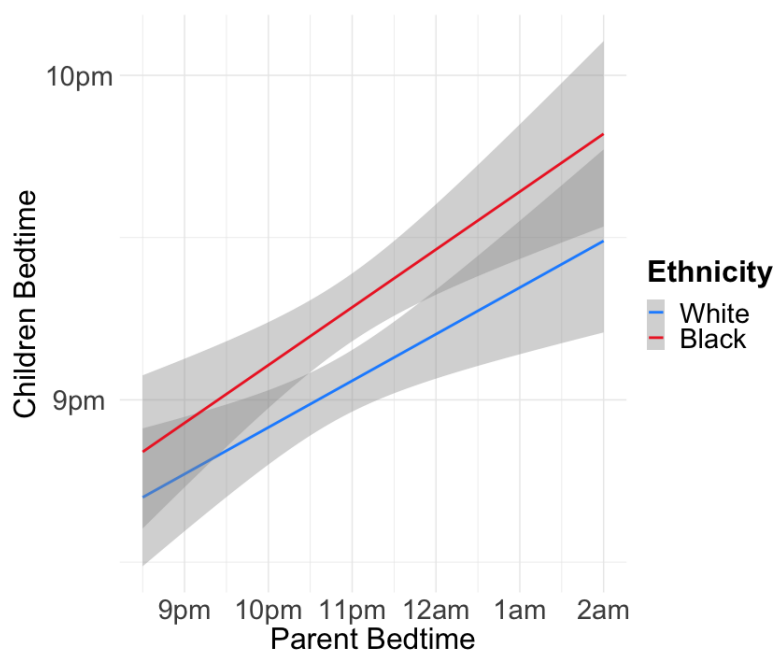
Notes: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed.

Table A.1: Treatment vs Control

	<i>Dependent variable:</i>			
	Earlier Bedtime	Longer Sleep	Healthier Routine	Newsletter
Treatment Group (vs. Control)	0.103* (0.053)	0.159*** (0.047)	-0.009 (0.027)	0.125* (0.069)
DV Mean	0.816	0.863	0.961	0.517
Observations	380	380	380	379
R ²	0.010	0.030	0.0003	0.009

Notes: The table reports estimated differences between the treatment group and the control group for the Black/African-American mothers only, using data from the Prolific sample. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* captures parents’ intention to move their child’s bedtime earlier; *Longer Sleep* indicates intentions to increase total sleep duration; *Healthier Routine* reflects intentions to implement or improve a healthy pre-bedtime routine. The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Figure A.7: Online Survey - Intergenerational Correlations in Bedtime: Parental and Children Bedtime



Notes: Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. All reported confidence intervals correspond to the 95% level.

Table A.2: Control vs Different Type of Treatments: Neutral, Disparities, and Personal

	<i>Dependent variable:</i>			
	Earlier Bedtime	Longer Sleep	Healthier Routine	Newsletter Subscription
	(1)	(2)	(3)	(4)
Neutral Treatment	0.091 (0.060)	0.140*** (0.052)	−0.009 (0.030)	0.148* (0.077)
Personal Treatment	0.161*** (0.059)	0.223*** (0.052)	0.008 (0.030)	0.072 (0.077)
Disparities Treatment	0.008 (0.068)	0.070 (0.059)	−0.045 (0.034)	0.187** (0.088)
DV Mean	0.816	0.863	0.961	0.517
Observations	380	380	380	379
R ²	0.028	0.054	0.009	0.016

Notes: The table reports estimated differences between the treatment group and the control group for the Black/African-American mothers only, using data from the Prolific sample. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* captures parents’ intention to move their child’s bedtime earlier; *Longer Sleep* indicates intentions to increase total sleep duration; *Healthier Routine* reflects intentions to implement or improve a healthy pre-bedtime routine. The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Different Ethnic Voice Audio vs Control

	<i>Dependent variable:</i>			
	Earlier Bedtime	Longer Sleep	Healthier Routine	Newsletter Subscription
	(1)	(2)	(3)	(4)
W voice treatment	0.101* (0.058)	0.140*** (0.051)	-0.020 (0.029)	0.130* (0.075)
AA voice treatment	0.104* (0.057)	0.178*** (0.050)	0.001 (0.029)	0.121 (0.074)
DV Mean	0.816	0.863	0.961	0.517
Observations	380	380	380	379
R ²	0.010	0.032	0.003	0.009

Notes: The table reports estimated differences between the treatment group and the control group for the Black/African-American mothers only, using data from the Prolific sample. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* captures parents’ intention to move their child’s bedtime earlier; *Longer Sleep* indicates intentions to increase total sleep duration; *Healthier Routine* reflects intentions to implement or improve a healthy pre-bedtime routine. The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Different Ethnic Voice Audio

	<i>Dependent variable:</i>			
	Earlier Bedtime	Longer Sleep	Healthier Routine	Newsletter Subscription
	(1)	(2)	(3)	(4)
AA voice treatment	0.003 (0.042)	0.038 (0.035)	0.021 (0.022)	-0.009 (0.056)
DV Mean	0.833	0.890	0.959	0.538
Observations	317	317	317	316
R ²	0.00002	0.004	0.003	0.0001

Notes: The table reports estimated differences between the treatment group for the Black/African-American mothers only. In this case we compare only voice audio without control group. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” *Earlier Bedtime* captures parents’ intention to move their child’s bedtime earlier; *Longer Sleep* indicates intentions to increase total sleep duration; *Healthier Routine* reflects intentions to implement or improve a healthy pre-bedtime routine. The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Results Panel A and Panel B

	<i>Dependent variable:</i>					
	PANEL A: INTENTION EARLIER BEDTIME			PANEL B: INTENTION LONGER SLEEP		
	(1)	(2)	(3)	(4)	(5)	(6)
T1 - neutral w	0.129* (0.068)	0.132* (0.068)	0.121* (0.069)	0.207*** (0.060)	0.206*** (0.060)	0.198*** (0.061)
T2 - neutral aa	0.193*** (0.068)	0.198*** (0.068)	0.188*** (0.068)	0.239*** (0.060)	0.247*** (0.060)	0.237*** (0.060)
T5 - personal w	0.127* (0.071)	0.181** (0.071)	0.180** (0.072)	0.127** (0.062)	0.151** (0.063)	0.151** (0.063)
T6 - personal aa	0.061 (0.068)	0.084 (0.067)	0.079 (0.068)	0.150** (0.059)	0.171*** (0.059)	0.165*** (0.060)
T3 - disparities w	0.005 (0.082)	0.010 (0.081)	0.014 (0.081)	0.035 (0.072)	0.039 (0.071)	0.039 (0.072)
T4 - disparities aa	0.012 (0.084)	0.027 (0.084)	0.019 (0.084)	0.109 (0.074)	0.116 (0.074)	0.106 (0.075)
Model	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Parental Characteristics		v	v		v	v
Children Characteristics			v			v
Mean dep.var	0.82	0.82	0.82	0.86	0.86	0.86
SD dep.var	0.39	0.39	0.39	0.34	0.34	0.34
Observations	380	374	371	380	374	371

Notes: The table reports estimated differences between all specific treatment groups and the control group for the Black/African-American mothers only. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.6: Results Panel C and Panel D

	<i>Dependent variable:</i>					
	PANEL C: INTENTION HEALTHIER ROUTINE	PANEL D: INTENTION NEWSLETTER				
	(1)	(2)	(3)	(4)	(5)	(6)
T1 - neutral w	0.0005 (0.035)	-0.001 (0.032)	-0.006 (0.032)	0.111 (0.089)	0.121 (0.090)	0.093 (0.091)
T2 - neutral aa	0.016 (0.034)	0.019 (0.031)	0.013 (0.032)	0.033 (0.088)	0.029 (0.088)	0.022 (0.089)
T5 - personal w	-0.040 (0.036)	-0.0001 (0.033)	-0.002 (0.033)	0.105 (0.092)	0.123 (0.094)	0.119 (0.094)
T6 - personal aa	0.017 (0.034)	0.037 (0.031)	0.032 (0.031)	0.184** (0.088)	0.191** (0.088)	0.188** (0.089)
T3 - disparities w	-0.027 (0.041)	-0.028 (0.038)	-0.029 (0.038)	0.205* (0.106)	0.195* (0.106)	0.197* (0.106)
T4 - disparities aa	-0.065 (0.043)	-0.062 (0.039)	-0.066* (0.039)	0.168 (0.110)	0.169 (0.110)	0.173 (0.111)
Model	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Parental Characteristics		v	v		v	v
Children Characteristics			v			v
Mean dep.var	0.96	0.96	0.96	0.52	0.52	0.52
SD dep.var	0.19	0.19	0.19	0.5	0.5	0.5
Observations	380	374	371	379	373	370

Notes: The table reports estimated differences between all specific treatment groups and the control group for the Black/African-American mothers only. Dependent variables are coded as binary indicators: 1 corresponds to “probably yes” or “definitely yes,” while 0 corresponds to “probably no,” “definitely no,” or “might or might not.” The newsletter variable equals 1 when participants voluntarily subscribe to the sleep-hygiene newsletter. Data are drawn from the Online Survey on Prolific 2024. Only parents with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.7: All Output - Interaction terms Black/African-American and Treatments

	<i>Dependent variable:</i>			
	Earlier Bedtime	Longer Sleep	Healthier Routine	Newsletter
	(1)	(2)	(3)	(4)
Black or African American	0.133* (0.078)	0.101 (0.070)	0.001 (0.034)	-0.039 (0.087)
T1 - neutral w	-0.056 (0.079)	0.158** (0.071)	-0.001 (0.034)	-0.206** (0.087)
T2 - neutral aa	0.020 (0.079)	0.071 (0.071)	0.016 (0.034)	-0.085 (0.088)
T5 - personal w	0.080 (0.077)	0.180*** (0.069)	0.032 (0.033)	-0.113 (0.085)
T6 - personal aa	0.058 (0.080)	0.147** (0.071)	-0.037 (0.035)	-0.227** (0.089)
T3 - disparities w	-0.081 (0.096)	0.048 (0.086)	-0.000 (0.042)	-0.129 (0.107)
T4 - disparities aa	0.109 (0.094)	0.136 (0.083)	-0.056 (0.040)	-0.010 (0.103)
p_black_only:Treatment 1	0.185* (0.111)	0.049 (0.099)	0.001 (0.048)	0.317** (0.123)
p_black_only:Treatment 2	0.173 (0.111)	0.168* (0.099)	0.001 (0.048)	0.118 (0.123)
p_black_only:Treatment 3	0.047 (0.111)	-0.053 (0.099)	-0.072 (0.048)	0.219* (0.123)
p_black_only:Treatment 4	0.002 (0.111)	0.004 (0.099)	0.054 (0.048)	0.412*** (0.123)
p_black_only:Treatment 5	0.086 (0.134)	-0.014 (0.120)	-0.027 (0.058)	0.334** (0.148)
p_black_only:Treatment 6	-0.097 (0.134)	-0.027 (0.120)	-0.009 (0.058)	0.178 (0.148)
mean dep.var	0.82	0.86	0.96	0.52
sd dep.var	0.39	0.34	0.19	0.5
Observations	754	754	754	753

Notes: The table reports estimates between all specific treatment and the control group and intersection variables. Dependent variables are binary indicators as before. Data are Online Survey on Prolific 2024. Both Black/African-American and White mothers with at least one child between the ages of 6 and 13 were interviewed. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix B: Information intervention

The first set of messages (T1 and T2) provided general sleep recommendations, emphasizing the risks of insufficient sleep and the benefits of proper sleep routines, based on CDC guidelines.

Specifically:

"The percentage of children (up to 13 years old) going to bed before 10 pm among participants in the American Time Use Survey was 63%. The remaining 37% instead goes to bed after 10 pm, risking to sleep less than the recommended hours. Children who do not get enough sleep are more likely to have attention and behavior problems, which can contribute to poor academic performance. There is extensive literature indicating that good academic performance translates into higher future earnings. The CDC recommends the following sleep routine for children: Children should sleep for a certain number of hours per day depending on their age group. For example, children 1 to 2 years old should sleep 11 to 14 hours, and children 6 to 12 years old should sleep 9 to 12 hours. Children should follow the same steps every night before going to bed, such as brushing their teeth, reading a story, or listening to soothing music. Children should have a consistent bedtime and wake-up time every day, even on weekends and holidays."

A second set of messages (T3 and T4) highlighted racial disparities in bedtime behaviors, presenting data showing that Black children were more likely to go to bed later than White children.

Specifically:

"The percentage of children (up to 13 years old) who go to bed before and after 10 pm among participants in the American Time Use Survey was different between Black and White participants. Among white children, 36% go to bed after 10 PM, while among black children 47%, risking not to get the recommended number of hours of sleep. Children who do not get enough sleep are more likely to have attention and behavior problems, which can contribute to poor academic performance. There is extensive literature indicating that good academic performance translates into higher future earnings. The CDC recommends the following sleep routine for children: Children should sleep for a certain number of hours per day depending on their age group. For example, children 1 to 2 years old should sleep 11 to 14 hours, and children 6 to 12 years old should sleep 9 to 12 hours. Children should follow the same steps every night before going to bed, such as brushing their teeth, reading a story, or listening to soothing music. Children should have a consistent bedtime and wake-up time every day, even on weekends and holidays."

Finally, a third set of messages (T5 and T6) used a personal reflection style, where a narrator described their own experience of enforcing bedtime routines and the positive outcomes associated with sufficient sleep. This variation allowed us to examine the relative influence of neutral versus personal storytelling, as well as the impact of explicitly addressing racial disparities in sleep patterns.

Specifically:

"Every night, I make sure my kids stick to their bedtime routine, which includes brushing their teeth, reading a story, and cuddling before they fall asleep. On average, they sleep about 10 hours, as recommended by our pediatrician for children aged 6-13. I've noticed that when they get enough sleep, they're in a better mood, behave well, and perform much better at school."

The following Figures provide some evidence about the survey and how this is design. FigureA.8 shows an example of Treatment, in this case we are in Treatment 1 neutral and with white voice accent. After the treatment there is always an attention checks, that varies from the treatment, as the one that is shown in Figure A.9. Our results are the same with or without the participants that fail the attention checks because the number of them is really low.

Figure A.9: Online Survey - Attention Checks



Based on the audio, what is the share of children going to bed after 10pm?

☐ 20.5%

☐ 36.7%

☐ 80%

☐ 5%

Notes: Online Survey on Prolific 2024. Example of an attention checks.

Figure A.8: Online Survey - Treatment Interface



▶ 0:00 / 1:00 — 🔊 ⋮

Please listen carefully to the following audio. You will then be asked to answer questions related to the information provided.

If your answer is correct you will enter a lottery which may add **\$5** to your final pay.

Notes: Online Survey on Prolific 2024. Example of a treatment.

The next Figure (A.10) shows the questions that are asked to participants in order to collect the measure of our outcomes.

Figure A.10: Questions - Main Outcomes Checks

Do you intend to help your children go to bed earlier each night?

Definitely yes ☐	Probably yes ☐	Might or might not ☐	Probably not ☐	Definitely not ☐
--	--	--	--	--

Do you intend to help your children sleep longer per night?

Definitely yes ☐	Probably yes ☐	Might or might not ☐	Probably not ☐	Definitely not ☐
--	--	--	--	--

Do you intend to help your children create a healthy routine
before sleep?

Definitely yes ☐	Probably yes ☐	Might or might not ☐	Probably not ☐	Definitely not ☐
--	--	--	--	--

SleepFoundation.org provides resources to get the sleep you
need and deserve. Their mission is to create a healthy, well-
restored world.

Would you like to receive their newsletter?

☐ Yes (You will get the newsletter in your Prolific mailbox)
☐ No

Notes: Online Survey on Prolific 2024. Example of questions for our main questions.

References

- Alsan, M., & Eichmeyer, S. (2024). Experimental evidence on the effectiveness of non-experts for improving vaccine demand. *American Economic Journal: Economic Policy*, 16(1), 394–414.
- Alsan, M., Garrick, O., & Graziani, G. (2019). Does diversity matter for health? experimental evidence from oakland. *American Economic Review*, 109(12), 4071–4111. <https://doi.org/10.1257/aer.20181446>
- Avery, M., Giuntella, O., & Jiao, P. (2022). Why don't we sleep enough? a field experiment among college students. *Review of Economics and Statistics*, 1–45.
- Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.
- Bertoni, M., Corazzini, L., & Robone, S. (2020). Nudging healthcare: A review of behavioral interventions for improving healthcare decisions. *Health Economics*, 29(10), 1235–1255.
- Bertoni, M., Meli, F., & Rocco, L. (2025). *Rest assured: The effects of sleep on labor productivity* (Discussion Paper No. 17618). IZA Institute of Labor Economics. <https://docs.iza.org/dp17618.pdf>
- Bhargava, S., Loewenstein, G., & Sydnor, J. (2017). Choose to lose: Health plan choices from a menu with dominated options. *The Quarterly Journal of Economics*, 132(3), 1319–1372.
- Bicchieri, C. (2023). Norm nudging and twisting preferences. *Behavioural Public Policy*, 7(4), 914–923.
- Billings, M. E., Cohen, R. T., Baldwin, C. M., Johnson, D. A., Palen, B. N., Parthasarathy, S., Patel, S. R., Russell, M., Tapia, I. E., Williamson, A. A., & Sharma, S. (2021). Disparities in sleep health and potential intervention models: A focused review. *Chest*, 159(3), 1232–1240. <https://doi.org/10.1016/j.chest.2020.09.249>
- Brehm, J. W. (1966). *A theory of psychological reactance*. Academic Press.
- Carrieri, V., De Paola, M., & Gioia, F. (2021). Targeted behavioral interventions in health: Evidence from personalized informational messages. *Journal of Economic Behavior & Organization*, 188, 615–632.
- Cialdini, R. B. (2001). *Influence: Science and practice* (4th). Allyn & Bacon.
- Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: When norms do and do not affect behavior. *Personality and Social Psychology Bulletin*, 17(6), 687–698.
- Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of personality and social psychology*, 58(6), 1015.
- Colten, H. R., Altevogt, B. M., et al. (2006). Committee on sleep medicine and research. *Sleep disorders and sleep deprivation: an unmet public health problem*.
- Creswell, J. D., Tumminia, M. J., Price, S., Sefidgar, Y., Cohen, S., Ren, Y., Brown, J., Dey, A. K., Dutcher, J. M., Villalba, D., et al. (2023). Nightly sleep dura-

- tion predicts grade point average in the first year of college. *Proceedings of the National Academy of Sciences*, 120(8), e2209123120.
- Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of Economic Literature*, 47(1), 87–122. <https://doi.org/10.1257/jel.47.1.87>
- DellaVigna, S., & Linos, E. (2022). Rcts to scale: Comprehensive evidence from two nudge units. *Econometrica*, 90(1), 81–116. <https://doi.org/10.3982/ECTA18709>
- Gibson, M., & Shrader, J. (2018). Time use and labor productivity: The returns to sleep. *Review of Economics and Statistics*, 100(5), 783–798.
- Giddens, N. T., Juneau, P., Manza, P., Wiers, C. E., & Volkow, N. D. (2022). Disparities in sleep duration among american children: Effects of race and ethnicity, income, age, and sex. *Proceedings of the National Academy of Sciences*, 119(30), e2120009119.
- Giuntella, O., Han, W., & Mazzonna, F. (2017). Circadian rhythms, sleep, and cognitive skills: Evidence from an unsleeping giant. *Demography*, 54(5), 1715–1742.
- Giuntella, O., & Mazzonna, F. (2019). Sunset time and the economic effects of social jetlag: Evidence from US time zone borders. *Journal of Health Economics*, 65, 210–226.
- Giuntella, O., Saccardo, S., & Sadoff, S. (2024). Sleep: Educational impact and habit formation. *Mimeo*.
- Grandner, M. A., Williams, N. J., Knutson, K. L., Roberts, D., & Jean-Louis, G. (2016). Sleep disparity, race/ethnicity, and socioeconomic position. *Sleep medicine*, 18, 7–18.
- Guglielmo, D., Gazmararian, J. A., Chung, J., Rogers, A. E., & Hale, L. (2018). Racial/ethnic sleep disparities in us school-aged children and adolescents: A review of the literature. *Sleep health*, 4(1), 68–80.
- Hafner, M., Stepanek, M., Taylor, J., Troxel, W. M., & Van Stolk, C. (2016, November). *Why sleep matters — the economic costs of insufficient sleep: A cross-country comparative analysis* (Research Report No. RR-1791) (Accessed: 2025-10-15). RAND Corporation. https://www.rand.org/pubs/research_reports/RR1791.html
- Handel, B. R., Kolstad, J. T., & Spinnewijn, J. (2019). Information frictions and adverse selection: Policy interventions in health insurance markets. *The Review of Economics and Statistics*, 101(2), 326–340. https://doi.org/10.1162/rest_a_00773
- Jackson, C. L., Redline, S., Kawachi, I., Williams, M. A., & Hu, F. B. (2013). Racial disparities in short sleep duration by occupation and industry. *American journal of epidemiology*, 178(9), 1442–1451.
- Jackson, C. L., Walker, J. R., Brown, M. K., Das, R., & Jones, N. L. (2020). A workshop report on the causes and consequences of sleep health disparities. *Sleep*, 43(8), zsaa037. <https://doi.org/10.1093/sleep/zsaa037>
- Jagnani, M. (2021). Children’s sleep and human capital production. *The Review of Economics and Statistics*, *Forthcoming*.

- Keyes, K. M., Maslowsky, J., Hamilton, A., & Schulenberg, J. (2015). The great sleep recession: Changes in sleep duration among us adolescents, 1991–2012. *Pediatrics*, *135*(3), 460–468.
- Krishnamurthy, P., Carter, R., & Blair, R. (2001). The effect of brief targeted messages on health-related behaviors. *Journal of Health Economics*, *20*(5), 675–695.
- Reid, A. E., Cialdini, R. B., & Aiken, L. S. (2010). Social norms and health behavior. *Handbook of behavioral medicine: Methods and applications*, 263–274.
- Reno, R. R., Cialdini, R. B., & Kallgren, C. A. (1993). The transsituational influence of social norms. *Journal of personality and social psychology*, *64*(1), 104.
- Roenneberg, T. (2013). The human sleep project. *Nature*, *498*(7455), 427–428.
- Troxel, W. M., DeSantis, A., Richardson, A. S., Beckman, R., Ghosh-Dastidar, B., Nugroho, A., Hale, L., Buysse, D. J., Buman, M. P., & Dubowitz, T. (2018). Neighborhood disadvantage is associated with actigraphy-assessed sleep continuity and short sleep duration. *Sleep*, *41*(10), zsy140.
- Williams, D. R., & Mohammed, S. A. (2009). Discrimination and racial disparities in health: Evidence and needed research. *Journal of behavioral medicine*, *32*, 20–47.
- Williams, N. J., Grandner, M. A., Snipes, S. A., Rogers, A., Williams, O., Airhihenbuwa, C., & Jean-Louis, G. (2015). Racial/ethnic disparities in sleep health and health care: Importance of the sociocultural context. *Sleep health*, *1*(1), 28–35.
- Yip, T., Cheon, Y. M., Wang, Y., Cham, H., Tryon, W., & El-Sheikh, M. (2020). Racial disparities in sleep: Associations with discrimination among ethnic/racial minority adolescents. *Child Development*, *91*(3), 914–931.
- Yu, Y., Altares, A., Leib, A., Bellows, L. L., Berry, C., Graham, D. J., & Mueller, M. P. (2025). Sociodemographic disparities in health literacy among american adults: A national survey study. *Preventive Medicine Reports*, *57*, 103179. <https://doi.org/10.1016/j.pmedr.2025.103179>

Chapter 3

The Impact of Cannabis Legalization on Sleep

Ilaria Prometti^{*}
Coleman Drake^{**}
Osea Giuntella^{***}

^{*} Corresponding author. Department of Economics, University of Pavia, Italy. E-mail: ilaria.prometti01@universitadipavia.it

^{**} Department of Health Policy and Management, University of Pittsburgh School of Public Health, USA. E-mail: cdrake@pitt.edu

^{***} Department of Economics, University of Pittsburgh, USA. E-mail: osea.giuntella@pitt.edu

Abstract

This paper provides the first causal evidence on how medical and recreational cannabis legalization (MCL and RCL) affect adult sleep duration in the United States. Exploiting the staggered adoption of cannabis policies across states from 2003 to 2023, we estimate effects using a two-way fixed effects Difference-in-Differences framework with a robust event-study approach to account for heterogeneous treatment effects. We find that MCL increases the probability of sleeping at least seven hours per night by 2.5 percentage points in the probability of sleeping at least seven hours (2-3% relative) among adults aged 45–60. In contrast, RCL reduces adequate sleep by 2–4 percentage points in the probability of reporting at least seven hours of sleep ($\approx 5\%$ relative) among adults aged 30–44. These results highlight that cannabis policy effects are strongly heterogeneous by policy type, age, and occupational context, implying that medical—but not recreational—legalization can improve sleep duration for specific working-age populations. The findings carry important implications for public health, labor productivity, and cannabis regulation.

3.1 Introduction

Sleep is a fundamental input into health, productivity, and well-being, yet its determinants are highly heterogeneous across the life cycle and across working conditions (Cappuccio et al., 2011; Costa-Font et al., 2024; Gibson & Shrader, 2018; Giuntella & Mazzonna, 2019; Giuntella et al., 2024). A large medical and economic literature shows that sleep is tightly linked to physical pain, cumulative fatigue, and psychological stress—factors that vary sharply with age and with the physical and mental demands of work (Finan et al., 2013; Fletcher et al., 2011; Karasek, 1990).

Sleep disorders are often treated with both medical and non-medical interventions, but access to these treatments is highly uneven across the population. One example is non-pharmacological therapies, such as cognitive-behavioral therapy (CBT), which are recommended as first-line treatment for insomnia and sleep disorders. However, these treatments are often inaccessible to the population due to limited supply. Consequently, many patients who do not have access to this type of treatment resort to pharmacological treatments, such as benzodiazepines. These can be effective against sleep disorders but also have significant side effects. A recent study by (Carrieri et al., 2020) highlights how cannabis is sometimes used as an alternative to benzodiazepines, suggesting its potential role as a "second-best" medical treatment for sleep problems.

In line with the work (Carrieri et al., 2020), one possible interpretation of sleep changes following cannabis legalization is linked to the so-called self-medication hypothesis. Some literature suggests that individuals may use cannabis as a form of self-medication to manage symptoms such as chronic pain, anxiety, or sleep disturbances. In this context, increased legal availability of the substance may facilitate such behaviors, reducing barriers to access and encouraging the use of cannabis as a potential substitute for other treatments or coping strategies. Consequently, legalization could influence sleep-related outcomes through this behavioral channel.

In fact, in this context with taking into account also widespread physical pain and fatigue, cannabis use (often motivated by its perceived analgesic and sleep-promoting properties (Boehnke et al., 2016; Walsh et al., 2013)) has expanded rapidly following state-level medical and recreational legalization. Clinical evidence suggests that cannabinoids can modestly improve sleep quality in specific patient populations, particularly among individuals with chronic pain, but these effects appear short-run and tightly tied to medical contexts (AminiLari et al., 2022). Much less is known about how broad, policy-driven access to cannabis affects sleep in the general population and—critically—whether such effects differ systematically by age. These dimensions are likely central to the sleep–cannabis nexus because the underlying drivers of sleep—pain, fatigue, and stress—exhibit sharp gradients across the working life cycle and across occupations (Mazzonna & Peracchi, 2017). As well as the automedication behaviour. Understanding these heterogeneous responses is therefore essential for assessing both the health consequences and the distributional implications of cannabis legalization.

As explain in (Babson et al., 2017), cannabis is a heterogeneous substance, whose main components, 9-tetrahydrocannabinol (THC) and cannabidiol (CBD), can have opposing effects on sleep: THC, responsible for the psychoactive effects, can increase arousal and alter sleep patterns, while CBD tends to promote relaxation and sedation. Consequently, the expected effect of cannabis use on sleep is theoretically ambiguous. Medical cannabis generally has a different composition from recreational cannabis. Indeed, medical cannabis is characterized by more standardized and controlled compositions, often featuring a higher presence of CBD and more moderate levels of THC. This is to maximize therapeutic effects and limit psychoactive effects. On the other hand, recreational cannabis usually has higher levels of THC and more variation in the THC to CBD ratios since the main aim is to induce a psychoactive effect rather than therapeutic one. Furthermore, medical cannabis and recreational cannabis also differ in terms of market availability. In most states, medical cannabis still requires a prescription, while recreational cannabis is freely available to adults. Consequently, access to recreational cannabis is easier, while access to medical cannabis is more limited. This difference in marketing is also closely linked to the possibility of self-medication and could lead to inappropriate use or suboptimal combinations of medical and recreational products, increasing variability and uncertainty about the overall effects of cannabis on sleep quality and duration in the population. Therefore, the effects of cannabis legalization on sleep may be ambiguous.

In line with this, recent studies show that cannabis users often use it to relieve chronic pain, anxiety, PTSD, or sleep disturbances, and a significant portion of adults over 50 report using it specifically to improve sleep (Bonn-Miller et al., 2014; Gavin, 2024). However, actual effects vary depending on the compound, dose, and duration of use, with THC potentially reducing sleep latency in the short term but worsening REM sleep with intense or chronic use, and CBD having dose-dependent effects (Babson et al., 2017).

In ordert to understand better the effect of the cannabis legalizazion on sleep, this study uses the American Time Use Survey (ATUS) and the State Policy & Politics Database (SPPD). The ATUS is a nationally representative dataset from 2003 to 2023, which records detailed daily activities of individuals in US including sleep. The ATUS allows us to analyze differences in sleep duration across age groups and states. The SPPD is a databased provide by Syracuse University that collects different policy informazion for the US, including the legalizazion of both medical and recreatuonal cannabis.

Over the past two decades, the U.S. regulatory landscape surrounding cannabis has undergone a rapid and profound transformation. States have progressively adopted medical cannabis legalization (MCL) and, more recently, recreational cannabis legalization (RCL), with substantial variation in timing between 2003 and 2023 . This staggered policy adoption has generated a growing economic literature documenting the effects of cannabis legalization on health outcomes (Pacula & Smart, 2017; Powell et al., 2018). In particular, MCL has been linked to reductions in the use of prescrip-

tion drugs, including opioids (Raman and Bradford, 2022; Raman et al., 2023). While previous studies have documented the link between cannabis use and sleep outcomes (Ried et al., 2023a, Wang et al., 2025), in this paper, we exploit the staggered implementation of medical and recreational cannabis legalization laws to study their effects on adult sleep duration. Our central contribution is to uncover strong heterogeneity in these effects by age.

While previous studies have documented links between cannabis use and sleep outcomes, Xu and Sturman, 2025 focus on mental health outcomes related to cannabis policies. Our study builds on their work by specifically analyzing adult sleep duration, distinguishing between medical and recreational cannabis legalization, and examining heterogeneous effects by age. This allows us to identify how different groups respond to policy changes, which is the main contribution of our chapter.

Exploiting the temporal and spatial variation in the adoption of MCL and RCL across states, we find evidence of substantial heterogeneity in the effects of cannabis legalization across policy type and age groups. Medical legalization significantly increases the probability of sleeping at least seven hours per night by 2.5 percentage points (a 4.2 percent relative increase) among adults aged 45–60. In contrast, recreational legalization reduces adequate sleep by 2–3 percentage points in the probability of reporting at least seven hours of sleep (approximately 5 percent in relative terms) among adults aged 30–44 and 45–60.

These findings provide the first causal evidence in this domain and highlight that the response to cannabis legalization is intrinsically linked to demographic and occupational characteristics. While medical legalization appears to improve sleep duration for specific working-age populations, recreational legalization entails a non-negligible risk of sleep reduction.

The remainder of the paper is organized as follows. Section 3.2 reviews the related literature and discusses the institutional background of cannabis policies. Section 4.3 describes data used. Section 3.4 describes the data and the empirical strategy. Section 4.5 presents the causal estimates, with a focus on heterogeneous effects by age. Section 3.6 concludes by discussing implications for public health and optimal cannabis regulation.

3.2 Background

Sleep is a fundamental determinant of physical and mental health. A large body of evidence shows that insufficient sleep impairs cognitive functioning (Alhola & Polo-Kantola, 2007; CDC, 2011; Gibson & Shrader, 2018; Giuntella et al., 2017; Giuntella et al., 2024) and increases the risk of numerous physical and mental health conditions, including cardiovascular disease, obesity, and depression (Cappuccio et al., 2011; Giuntella & Mazzonna, 2019; Grandner et al., 2010; Knutson & Van Cauter, 2008; Patel &

Hu, 2008; van Cauter et al., 2007). Despite its recognized importance, sleep deprivation remains widespread in the population. Recent CDC data indicate that the share of adults sleeping fewer than seven hours per night ranges from 30% in Vermont to 46% in Hawaii (CDC - Centers for Disease Control and Prevention, 2024b), and more than 70% of U.S. high school students and a majority of undergraduate students fail to achieve sufficient sleep (Avery et al., 2025; CDC - Centers for Disease Control and Prevention, 2024c). An estimated 50 to 70 million U.S. adults suffer from chronic sleep disorders or persistent sleep deprivation (Colten & Altevogt, 2006; National Academies of Sciences, Engineering, and Medicine, 2017). Consistent with this prevalence, Chong et al. (2013) document that about 4% of adults used prescription sleep aids in 2005–2010, with use rising sharply with age and being higher among women, the more educated, and non-Hispanic white adults, highlighting the substantial burden of sleep problems, particularly in mid and later life.

Against this backdrop of pervasive sleep disturbances, it is hardly surprising that demand for both pharmaceutical and non-pharmaceutical sleep aids has expanded rapidly. Survey evidence suggests that up to two-thirds of U.S. adults experience occasional difficulty sleeping, fueling a growing consumer market for alternative remedies Gavin, 2024. In this context, cannabis-derived products have attracted increasing attention, with consumers turning not only to tetrahydrocannabinol (THC) and cannabidiol (CBD), but also to lesser-studied cannabinoids such as cannabinol (CBN), which is widely marketed as a “natural” sleep aid. Yet, despite this surge in popular interest, the scientific evidence on the sleep-promoting effects of cannabinoids remains limited and mixed.

According to Bonn-Miller et al. (2014), most cannabis users report using it to manage chronic pain, anxiety, post-traumatic stress disorder (PTSD), or sleep disturbances. The University of Michigan’s 2024 National Poll on Healthy Aging found that, among adults aged 50 and older, 21% had used cannabis in the past year, and 68% of these users reported using it to improve sleep (Gavin, 2024). However, the effects of cannabis on sleep are complex and vary depending on the compound and duration of use. Babson et al. (2017) reviewed the literature up to 2014 and concluded that, while 9-tetrahydrocannabinol (THC) can reduce sleep latency in the short term, chronic or heavy use can reduce REM sleep and worsen overall sleep quality. In contrast, cannabidiol (CBD) exhibits dose-dependent effects: low doses tend to promote wakefulness, while higher doses can induce sedation and improve sleep quality.

One mechanism that has been a major focus of recent research is the so-called self-medication hypothesis. Essentially, the underlying idea is that people are starting to use cannabis as a kind of “do-it-yourself tool” to manage complex symptoms (think chronic pain, anxiety, or sleep disorders) that often aren’t addressed satisfactorily by traditional medical treatments. Several studies suggest that cannabis could become a true substitute for conventional medications, especially when regulatory reforms break down barriers to access. From this perspective, legalization ultimately impacts sleep through a change in habits: the substance becomes a readily available alternative to

traditional sleeping pills or standard therapeutic protocols.

This interpretation is supported by a growing body of research documenting clear substitution effects. The work of Bradford and Bradford, 2016 and Bradford and Bradford, 2017, for example, clearly demonstrates how medical cannabis laws go hand in hand with a decline in prescription drug use; Along the same lines, Bachhuber et al., 2014 even notes a decrease in opioid overdose mortality following the adoption of these regulations. Recent evidence also highlights that these self-medication behaviors are influenced by local policy and economic context, with cannabis increasingly substituting for traditional pharmacological treatments when availability improves (Darden and Papageorge, 2024). Also looking at the European experience, Carrieri et al., 2020 observes that the emergence of "cannabis light" in Italy has eroded market share from several traditional drugs, including anxiolytics and sedatives. Overall, these data paint a clear picture: many patients now see cannabis as a concrete alternative to traditional pharmacopoeia for regulating their psychophysical balance and, consequently, the quality of their sleep.

Wang et al. (2025) conducted a randomized, double-blind, placebo-controlled crossover trial using a cannabidiol-terpene formulation in adults with insomnia and found improvements in subjective sleep quality and reductions in sleep-onset latency, without major adverse effects or next-day impairment. These results suggest that CBD-dominant formulations combined with specific terpenes may generate short-term improvements in clinical insomnia, complementing earlier evidence on THC's role in reducing sleep latency (Babson et al., 2017). However, the small sample size and focus on a clinical population limit the external validity of these findings for population-level sleep behavior.

The efficacy of cannabinoids for sleep improvement is classified as moderate, yet remains notably narrow in scope (Whiting et al. (2015); National Academies of Sciences, Engineering, and Medicine (2017)). Both reports emphasize that these benefits have been observed primarily in clinical populations where sleep disturbances are secondary to conditions such as chronic pain or multiple sclerosis. Due to the small sample sizes of the studies and the lack of data on primary insomnia, there is insufficient evidence to generalize these findings to sleep behaviors in the broader, non-clinical population.

More recent work has explored the direct association between cannabis access laws and sleep outcomes at the population level, producing mixed results. Xu and Sturman (2025) find that the legalization of recreational cannabis is associated with small decreases in average sleep duration and delayed sleep timing, suggesting that the increased availability for recreational use may not translate into better sleep health. Conversely, some studies included in the review by Amaral and et al. (2023) and the randomized trial by Ried et al. (2023b) report that medical cannabis can improve self-reported sleep quality and sleep duration among patients with chronic insomnia or pain-related disorders, particularly in the short term. However, Amaral and et al. (2023) concludes that there is a lack of robust evidence to support its general use due to inconsistent

findings.

Importantly, the effects of cannabis on sleep appear highly heterogeneous across populations and depend on the purpose and context of use. Medical users, who are typically older and motivated by therapeutic goals (e.g., pain management, insomnia), tend to experience more consistent sleep benefits than recreational users, whose consumption often occurs later in the evening and may disrupt sleep timing (Walker et al., 2024). These findings align with the epidemiological evidence that cannabis use among adults aged 45–65 has risen markedly in recent years, largely for medical purposes (Walker et al., 2024).

Sleep is often closely related to behaviors and physical and mental health conditions. Stress, anxiety, and depression are among the most commonly reported factors for insomnia and poor sleep, particularly among working-age adults. Clinical guidelines generally recommend non-pharmacological interventions as the first-line treatment for chronic insomnia. One particularly recommended treatment is cognitive behavioral therapy for insomnia (CBT-I), which has been shown to produce lasting improvements in sleep quality and duration. However, despite its documented efficacy, access to CBT-I remains limited in many settings due to a lack of qualified providers, long wait times, and limited insurance coverage. Precisely for these reasons, patients who have difficulty accessing non-pharmacological therapies often turn to pharmacological treatments. Among these, benzodiazepines and related sedative-hypnotic drugs are widely prescribed and are known to be effective in reducing sleep onset latency and improving short-term sleep outcomes. However, these medications also carry significant risks, including dependence, tolerance, daytime sedation, and cognitive impairment, particularly among older adults. Due to these side effects and concerns about long-term use, patients and physicians are increasingly seeking alternative or complementary treatments. In this context, cannabis products may be perceived as a substitute or “second choice” for individuals who face barriers to non-pharmacological therapies or wish to avoid the adverse effects associated with traditional sleep medications. Data from the health economics literature suggest that cannabis legalization may indeed lead to a substitution for conventional medications (Bradford and Bradford, 2016, 2017 and (Raman & Bradford, 2022). For example, Carrieri et al., 2020 shows that increased access to medical cannabis is associated with a reduction in the use of certain prescription drugs, consistent with the idea that individuals may turn to cannabis as an alternative treatment for various health conditions. This substitution mechanism provides a key rationale for examining whether changes in cannabis availability also affect sleep outcomes at the population level.

3.2.1 Cannabis Laws

Since the first legalization of medical cannabis in 1996, the legal landscape in the United States has evolved rapidly. As of February 2024, medical cannabis is legal in 47 states, the District of Columbia, and three territories, while 24 states allow recreational use

(CDC - Centers for Disease Control and Prevention, 2024a). Medical and recreational cannabis are regulated in very different ways. Under medical cannabis laws, access is usually limited to state-licensed dispensaries and requires approval from a physician, who confirms that the patient has a qualifying medical condition. Some of the qualifying conditions include those for which research suggests cannabis may offer therapeutic benefits—most notably chronic pain, nausea and vomiting related to chemotherapy, and muscle spasticity associated with multiple sclerosis—as summarized in the 2017 report by the National Academies of Sciences, Engineering, and Medicine (NASEM National Academies of Sciences, Engineering, and Medicine, 2017). In contrast, when cannabis is legalized for recreational (adult-use) purposes, legal access is extended to all adults aged 21 and over, with no requirement to demonstrate medical need or provide a reason for use. Although cannabis remains illegal at the federal level, this policy heterogeneity provides a valuable quasi-experimental context to study its public health effects. Crucially, a robust body of work in health economics and public policy has established that cannabis legalization, particularly for medical purposes (MCL), triggers significant substitution effects in the prescription drug market. For instance, Bradford and Bradford (2016) provided early evidence that MCLs led to a reduction in the overall use of prescription drugs for Medicare Part D patients. Subsequent studies have confirmed and expanded these results, showing that legal cannabis access reduces the use of prescription pain medications among commercially insured patients (Lozano-Rojas et al., 2022) and opioids in general (Drake et al., 2021; Raman & Bradford, 2022; Raman et al., 2023). This evidence establishes a clear mechanism through which increased cannabis availability can influence the use of other substances and medications, suggesting that similar substitution effects may extend to sleep medications. This is also in line with evidence that cannabis use has increased after legalization in the older population (Hollingsworth et al., 2022), especially among those who suffer from chronic diseases (Han and Palamar, 2020).

Beyond pharmaceutical substitution, researchers have also investigated whether cannabis legalization influences the consumption of other substances, such as tobacco and e-cigarettes. Findings here are mixed, with some studies suggesting that Medical Marijuana Laws (MMLs) may be associated with an increase in adult tobacco cigarette consumption (Choi et al., 2019), potentially complicating public health efforts. Conversely, other work finds that Recreational Marijuana Laws (RMLs) are associated with a reduction in adult cigarette smoking and e-cigarette use, suggesting a substitution effect (Dave et al., 2023). This is also supported by Anderson and Rees, 2023 recent review. By synthesizing decades of research, they show that many of the alarmist predictions regarding legalization have simply not materialized in the data. In fact, the literature on youth use often shows null or even negative associations between Recreational Marijuana Laws (RMLs) and cannabis consumption among high school students (Anderson et al., 2021), though findings vary by specific policy and outcome measure (Anderson et al., 2020). These studies highlight that legalization is a multifaceted policy intervention with heterogeneous effects that extend beyond the direct medical goal,

providing a crucial context for analyzing health-related outcomes like sleep.

Building on this body of work, the present study contributes new causal evidence by examining how the legalization of medical and recreational cannabis affects the likelihood of sleeping seven or more hours per night across U.S. states between 2003 and 2023, with a focus on age-specific effects.

3.3 Data

Our analysis combines individual-level sleep data with state-level cannabis legalization information to evaluate the effects of medical and recreational cannabis on population sleep patterns. We focus on the period 2003–2023 across all 51 U.S. states. The unit of observation is the individual respondent in each ATUS survey wave, while cannabis policies vary at the state-year level. Because ATUS is a repeated cross-section, our dataset constitutes a pseudo-panel in which independent cross-sections are observed for each year from 2003 to 2023, allowing us to track population-level behavioral changes over time.

3.3.1 Data Sources and Sample Construction

Sleep outcomes are drawn from the *American Time Use Survey* (ATUS), which records detailed time use for roughly 20,000 respondents per year aged 15 and older, resulting in 245,139 observations over the study period. Respondents report all activities during the previous day in ten-minute intervals, allowing us to construct individual sleep measures. ATUS also provides a rich set of sociodemographic characteristics, including age, gender, education, ethnicity, and employment. Given the strong variation in sleep patterns across the life course, we stratify the population into five age groups: 15–20, 21–34, 35–44, 45–60, and 61–80 years. It is worth noting time-use data tend to overestimate sleep duration (Avery et al., 2025; Lauderdale et al., 2008).

In some states and for certain years, ATUS observations for the youngest cohorts (specifically, ages 15–20 and 21–29) are quite limited. This paucity of data could reduce the statistical power of the estimates for these groups; consequently, any null findings could be due to the small sample size rather than a true absence of effects. For transparency, we have reported the number of observations by state and year in the Appendix A.3, Table A.3.1, and treatment by year in the Appendix, Tables A.3.2, documenting the heterogeneity of the sample. We therefore recommend interpreting the results for these age groups with due caution. Despite these limitations, we preferred not to combine the 15–20 and 21–29 age groups in the main analysis, as their daily routines and sleep habits are profoundly different. However, for completeness, we also present the pooled results in the event-study analyses, which confirm the absence of significant effects for these cohorts.

We exclude respondents with missing diary information—including those with missing diary days—so that all observations included in the analysis have complete time-use diaries.

To avoid distortions related to the COVID-19 pandemic and to substantial differences between weekday and weekend time use, we exclude all ATUS observations from 2020 and restrict our sample to weekday diary days only.

Cannabis legalization data come from the *State Policy & Politics Database* (SPPD), which compiles annual state-level policy and political information across multiple domains relevant to population health. The SPPD provides annual data from 1980 to 2023, covering labor and economic regulations, social safety net policies, behavior-related policies (e.g., tobacco taxation, opioid prescribing restrictions), and measures of political ideology. From this database, we extract dichotomous indicators for the legality of medical and recreational cannabis in each state-year. Table 3.1 shows the adoption date in SPPD for each state in our analysis.

Because cannabis policies are measured annually, we map policy status to ATUS respondents using the survey year of the interview, which corresponds to the calendar year of the diary day, ensuring consistent alignment between annual policies and individual sleep reports.

By merging ATUS and SPPD, we construct a panel linking individual sleep reports to state-level policy context. Our final sample includes 235,978 observations. By 2023, 38 states had legalized cannabis in some form (37 medical, 23 recreational), while 12 states had not legalized either form.

The study period begins in 2003 because the American Time Use Survey (ATUS) was first fielded in that year, and earlier time-use microdata are not available. Several states—including California (1996), Oregon (1998), Washington (1998), Alaska (1998), Maine (1999), and Hawaii (2000)—legalized medical cannabis prior to 2003. For these early-adopting states, 2003 therefore serves as the baseline year, corresponding to the first year of ATUS observation.

Our dependent variable is a binary indicator equal to 1 if an individual reports sleeping seven or more hours on the previous day and 0 otherwise. This is the recommended sleep duration for the adult population (Cappuccio et al., 2011; Hirshkowitz et al., 2015; Panel: et al., 2015). We construct sleep duration by summing all ATUS activities coded as “sleeping” that occur between 8:00 PM of the previous evening and 8:00 AM of the diary day. We first compute total minutes and then convert them into total hours.

Table 3.1: Year of Enactment of Medical and Recreational Cannabis Laws by U.S. State

state	Adoption MCL Year	Adoption RCL Year	state	Adoption MCL Year	Adoption RCL Year
AK	1998	2015	MT	2004	2021
AL	2021	.	NC	.	.
AR	2016	.	ND	2016	.
AZ	2011	2020	NE	2024	.
CA	1996	2016	NH	2013	.
CO	2001	2012	NJ	2010	2021
CT	2012	2021	NM	2007	2021
DC	2010	2014	NV	2001	2017
DE	2011	2023	NY	2014	2021
FL	2016	.	OH	2016	2023
GA	.	.	OK	2018	.
HI	2000	.	OR	1998	2015
IA	.	.	PA	2016	.
ID	.	.	RI	2006	2022
IL	2013	2020	SC	.	.
IN	.	.	SD	2020	.
KS	.	.	TN	.	.
KY	2023	.	TX	.	.
LA	2016	.	UT	2018	.
MA	2013	2016	VA	2020	2021
MD	2014	2023	VT	2004	2018
ME	1999	2018	WA	1998	2012
MI	2008	2018	WI	.	.
MN	2014	2023	WV	2016	.
MO	2020	2022	WY	.	.
MS	2022	.			

Note: The table reports the year of enactment of medical (MCL) and recreational (RCL) cannabis laws in the United States. The main data are drawn from the State Policy & Politics Database (SPPD), Version 1.3.1, 2025, developed by the Center for Aging and Policy Studies (NIA P30AG066583). For the District of Columbia (DC), information was added manually based on local legislation available at washingtondccannabis.org. Years prior to 2003 have been set to 2003 as a baseline, since the SPPD dataset provides complete coverage starting from that year.

3.3.2 Sample Balance and Descriptive Statistics

To ensure comparability, we examine pre- and post-legalization characteristics for both medical and recreational cannabis. Tables 3.2 and 3.3 present key demographic and sleep variables, showing no significant differences between treatment and control states before legalization. These statistics provide reassurance that treatment and control groups are broadly comparable and support the validity of subsequent causal analyses. To assess pre-treatment balance and ensure comparability between treated and control units, we defined a law-specific cutoff year that separates the pre-intervention and post-intervention periods. Specifically, we use 2012 as the cutoff for Medical Marijuana Laws and 2019 as the cutoff for Recreational Marijuana Laws. These cutoff years correspond to the timing of policy adoption and allow us to identify treatment and comparison groups in the pre-policy period.

Descriptive statistics—including means, standard deviations, and the 10th, 50th, and 90th percentiles of sleep duration—are reported in Table 3.4. The table also documents heterogeneity by age group, highlighting within-age-group variation in sleep duration that underpins our identification strategy

Table 3.2: Balance Table Medical Cannabis: Treatment Vs. Control Group

Variable Name	Mean Treated	Sd Treated	Mean Control	Sd Control
Sleep $\geq$ 7 Hours	0.817	0.386	0.802	0.399
Age (Years)	47.511	17.765	48.278	17.942
Education (Years)	13.901	3.241	13.728	3.046
Family Income (Categorical)	11.143	3.975	10.635	4.052
Female (Share)	0.545	0.498	0.560	0.496
Black (Share)	0.074	0.262	0.152	0.359
Asian (Share)	0.065	0.247	0.025	0.156
Hispanic (Share)	0.202	0.401	0.107	0.309
Other Race (Share)	0.026	0.159	0.015	0.122

Notes: Data from the ATUS survey and SPPD (2003-2023). The sample is split pre intervention by control and treated groups. The variables sleep, female, White, Black, Hispanic, Asian, other ethnicity, employed are dummies variables. The variable is age continuous, as education that is express by year of education. The variables income is a categorical variable with 16 levels (Level 11 express \$40,000 to \$49,999). To assess pre-treatment balance and ensure comparability between treated and control units, we defined a law-specific cutoff year that separates the pre-intervention and post-intervention periods. Specifically, we use 2012 as the cutoff for Medical Marijuana Laws (MEDMAR) and 2019 as the cutoff for Recreational Marijuana Laws (RECMAR). These cutoff years correspond to the timing of policy adoption on average and allow us to identify treatment and comparison groups in the pre-policy period.

Table 3.3: Balance Table Recreational Cannabis: Treatment Vs. Control Group

Variable Name	Mean Treated	Sd Treated	Mean Control	Sd Control
Sleep ≥ 7 Hours	0.820	0.384	0.802	0.399
Age (Years)	47.319	17.739	48.292	17.938
Education (Years)	13.944	3.275	13.725	3.045
Family Income (Categorical)	11.204	3.966	10.645	4.050
Female (Share)	0.546	0.498	0.559	0.497
Black (Share)	0.073	0.260	0.147	0.355
Asian (Share)	0.065	0.246	0.027	0.163
Hispanic (Share)	0.191	0.393	0.115	0.319
Other Race (Share)	0.021	0.145	0.017	0.130

Notes: Data from the ATUS survey and SPED (2003-2023). The sample is split pre intervention by control and treated groups. The variables sleep, female, White, Black, Hispanic, Asian, other ethnicity, employed are dummies variables. The variable is age continuous, as education that is express by year of education. The variables income is a categorical variable with 16 levels (Level 11 express \$40,000 to \$49,999). To assess pre-treatment balance and ensure comparability between treated and control units, we defined a law-specific cutoff year that separates the pre-intervention and post-intervention periods. Specifically, we use 2012 as the cutoff for Medical Marijuana Laws (MEDMAR) and 2019 as the cutoff for Recreational Marijuana Laws (RECMAR). These cutoff years correspond to the timing of policy adoption on average and allow us to identify treatment and comparison groups in the pre-policy period.

Table 3.4: Aggregate Descriptive Statistics on Sleep by Age Group

Age Group	Mean (μ)	Dev. Std. (σ)	p10	Median(p50)	p90
15-20	0.8615	0.3454	0	1	1
21-30	0.8159	0.3875	0	1	1
31-44	0.7773	0.4161	0	1	1
45-60	0.7626	0.4255	0	1	1
60+	0.8612	0.3457	0	1	1
All Pop	0.8060	0.3954	0	1	1

Notes: This table reports summary statistics of sleep variable showing the difference between the age groups. The sleep variable is a dummy variable indicates if the individual sleep more than 7 hours per night (1 = more than 7 hours and 0 = less then 7 hours).

3.4 Empirical Strategy

To estimate the causal impact of medical and recreational cannabis legalization on population sleep outcomes, we exploit the staggered adoption of these policies across U.S. states over time. Identification relies on the assumption that, conditional on

state and year fixed effects and individual-level covariates, sleep outcomes in states that legalize cannabis would have followed the same trends as in states that do not, absent legalization. This corresponds to a cohort-specific parallel-trends assumption (Callaway & Sant’Anna, 2021; Sun & Abraham, 2021). The empirical strategy follows a structured approach based on Two-Way Fixed Effects, event-study methods, and estimators designed for staggered treatment adoption.

In practice, we estimate the following model:

$$sleep_{ist} = \gamma_1 MedicalCannabis_{st} + \gamma_2 RecreationalCannabis_{st} + X'_{ist}\beta + \delta_s + \lambda_t + \varepsilon_{ist}, \quad (3.1)$$

where $sleep_{ist}$ denotes the sleep outcome of individual i in state s and year t ; $MedicalCannabis_{st}$ and $RecreationalCannabis_{st}$ are dichotomous indicators for legalization. The vector X_{ist} includes individual-level characteristics such as gender, race/ethnicity, educational attainment, employment status, age, diary day of the week, and family income quartiles. All specifications include state fixed effects δ_s and year fixed effects λ_t , with standard errors clustered at the state level. Importantly, when estimating the effect of medical cannabis legalization, recreational legalization is included as a control variable, and vice versa. This ensures that each policy’s estimated effect is not confounded by the other.

In our regressions, we chose to include indicators for medical and recreational cannabis laws simultaneously. This specification is not random: the goal is to isolate the impact of medical legalization and, separately, capture the incremental effect resulting from the transition to recreational legalization. Indeed, in the US, recreational laws have almost always been introduced in contexts where medical programs had already been in place for some time. Consequently, omitting the medical cannabis variable when assessing the impact of recreational legalization would risk generating a specification error, incorrectly attributing part of the effects attributable to the previous medical reform to the recreational legalization regime. By including both indicators in the same model, we allow the recreational legalization coefficient to measure the additional impact of open access compared to a baseline scenario in which cannabis is already available for therapeutic purposes.

To analyze dynamic treatment effects and assess the validity of the parallel-trends assumption, we estimate an event-study model:

$$sleep_{ist} = \delta_s + \lambda_t + \sum_{k=-5, k \neq -1}^{+5} \beta_k D_{st}^k + X'_{ist}\gamma + \varepsilon_{ist}, \quad (3.2)$$

where D_{st}^k is an indicator for event time k relative to legalization ($k = -5, \dots, +5$), omitting $k = -1$ as the reference period. Following the literature, early-adopting

states (CA, OR, WA, AK, ME, HI) are treated as already legalized in 2003 to ensure comparability in relative timing.

The coefficients β_k allow us to evaluate pre-treatment dynamics ($k < 0$), which provide evidence on parallel trends, and to trace the evolution of post-treatment effects ($k > 0$).

However, TWFE and conventional event-study specifications may produce biased estimates under staggered treatment adoption because later-treated states may serve as inappropriate controls for earlier-treated states (Callaway & Sant’Anna, 2021; Goodman-Bacon, 2021). To address this, we implement the estimator of Sun and Abraham (2021), which constructs cohort-specific event-time indicators and avoids contamination from differential timing.

The corresponding specification is:

$$sleep_{ist} = \delta_s + \lambda_t + \sum_{k=-5, k \neq -1}^{+5, k \neq -1} \beta_k^* D_{st,k}^* + X'_{ist} \gamma + \varepsilon_{ist}, \quad (3.3)$$

where $D_{st,k}^*$ denotes cohort-specific event-time indicators. This estimator identifies dynamic treatment effects separately for each cohort and then aggregates them to obtain overall post-legalization effects. Covariates and clustering are handled as in Equation (3.1).

Because the Sun & Abraham estimator is designed to evaluate the dynamic effects of a single treatment with staggered adoption, we estimate the event-study specifications separately for medical and recreational cannabis legalization, always inserting the other legalization as a control variable. This approach allows us to trace the dynamic effects associated with each policy regime without conflating differences in timing and mechanisms across the two policy changes.

In the Sun & Abraham specification, the control group consists of ”later-treated” states (units that will adopt the policy in the future but have not yet done so) rather than never-treated states. This choice follows the standard implementation of the estimator, which allows the control to be defined as either never-treated or last-treated. Using later-treated states as controls, identification is based on a comparison between treated cohorts and states that, at the time of policy adoption, were not yet treated but shared similar characteristics. States that never adopt the policy are therefore excluded, explaining the smaller number of clusters in the Sun & Abraham estimates compared to the TWFE estimates. To address potential concerns related to the relatively small number of clusters, we perform inference using the Wild Cluster Bootstrap procedure. This method provides more reliable p-values when the number of clusters is limited and errors are clustered at the state level. Appendix B. 3, Tables B.3.1 and B.3.2, reports the results of the wild bootstrap analysis. These results confirm that the main estimated patterns remain consistent.

3.5 Results

Event-study analyses illustrate the dynamic effects of cannabis legalization on sleep. Figures 3.1–3.2 report TWFE dynamics, while Figures 3.3–3.4 report Sun–Abraham estimates. Pre-treatment coefficients are approximately flat across all groups, supporting the parallel-trends assumption. Post-treatment effects of medical cannabis are predominantly positive, with the largest increases concentrated among adults aged 45–60 and occurring within the first three years after legalization. In contrast, recreational cannabis effects are consistently negative for the 30–44 cohort.

In the Sun–Abraham model, a negative and statistically significant effect of recreational cannabis also appears for adults aged 45–60 at some horizons; however, the aggregated dynamic effect is not statistically significant (Figure 3.4), suggesting caution in interpretation.

The event studies point to a beneficial and economically meaningful impact of medical cannabis legalization for adults aged 45–60, and a negative effect of recreational cannabis concentrated among adults aged 30–44.

We don’t find results on the younger cohorts, but as discussed in the 4.3 section, the age groups 15–20 and 21–29, may suffer by a lack of power due to the small sample size for these groups. The results for these cohorts must be interpreted with caution, and any null effects for these groups may reflect low statistical power rather than the absence of true effects.

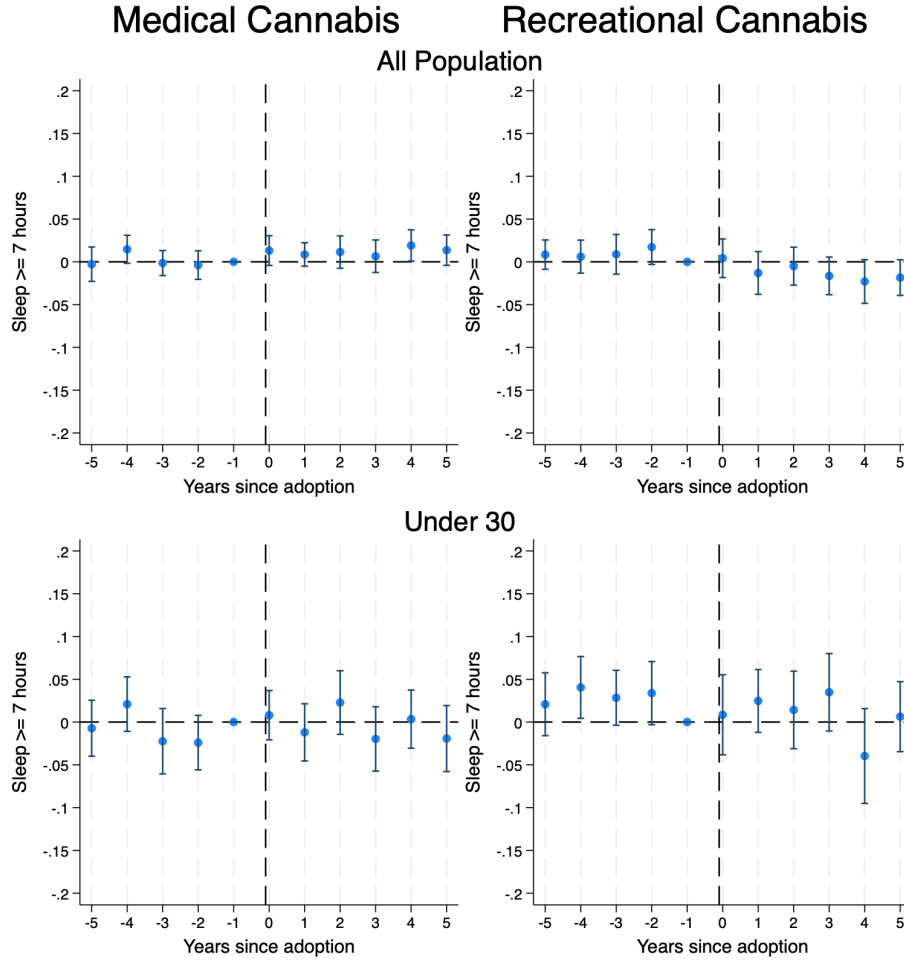


Figure 3.1: Regression Results Dynamic TWFE by age Groups: all population and Under 30

To gauge the magnitude of the policy effects, we report TWFE and Sun–Abraham estimates in Table 3.5. Panel A presents TWFE estimates of the effects of medical and recreational cannabis legalization on the probability of sleeping at least seven hours per night, while Panels B and C (Tables 3.6 and 3.7) report the corresponding Sun–Abraham estimates for medical and recreational cannabis, respectively. All models include state and year fixed effects, state-specific linear trends, and a full set of demographic controls.

All models include state and year fixed effects, state-specific linear trends, and a full set of demographic controls. In the full population, we find no robust evidence of significant effects. The TWFE estimate for medical cannabis legalization is marginally significant (0.011, $p < 0.10$), corresponding to a 1.36% increase relative to the baseline mean of 0.806. However, the Sun–Abraham estimate for medical cannabis is much smaller (0.0039), statistically insignificant, and implies only a 0.49% increase, indicating limited

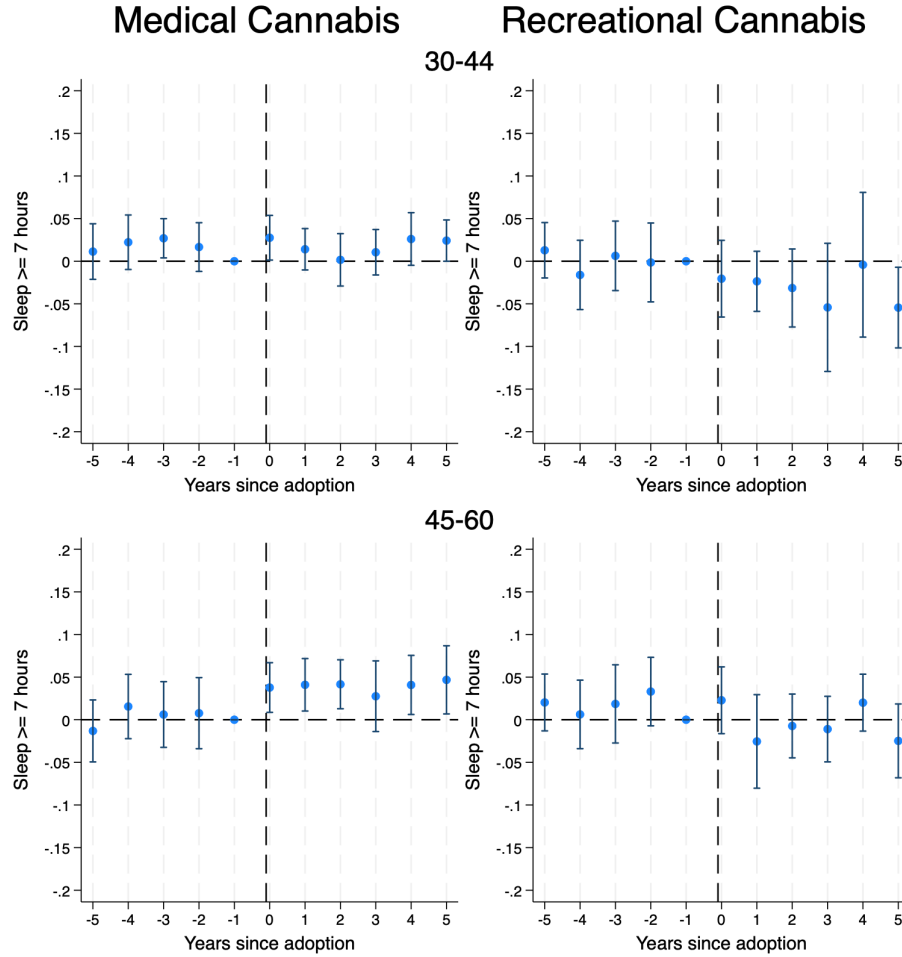


Figure 3.2: Regression Results Dynamic TWFE by age Groups: 30-44 and 45-60

robustness (entire population). Recreational cannabis legalization on full population has a negative but statistically insignificant effect in both specifications (-0.008 under TWFE; -0.010 under Sun-Abraham).

Age-disaggregated results reveal substantial heterogeneity. For ages 15–20 and 21–29 (Columns 2–3), neither policy has statistically significant effects. However, is important to highlight that these are the groups that could suffer from power issue, therefore the results should be interpreted with caution.

Among adults aged 30–44 (Column 4), recreational cannabis legalization significantly reduces sleep in the TWFE model (-0.020 , $p < 0.10$), a 2.57% decline relative to the mean of 0.778; the Sun-Abraham estimate is larger (-0.039 , $p < 0.10$), implying a 5.0% decline. Medical cannabis has no detectable effect for this group.

For adults aged 45–60 (Column 5), medical cannabis legalization shows the most consistent positive impact: TWFE estimates an increase of 0.025 ($p < 0.05$), a 3.28% rise

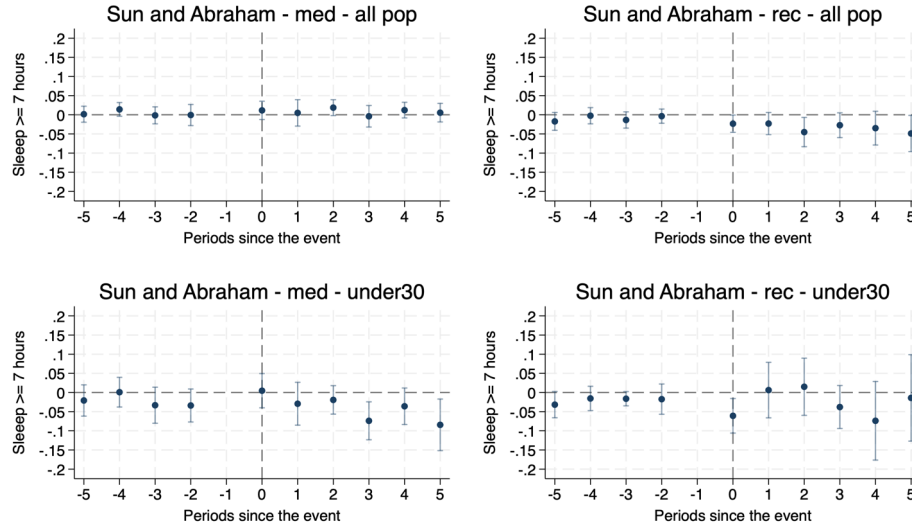


Figure 3.3: Regression Results Dynamic Sun and Abraham by age Groups: all population and Under 30

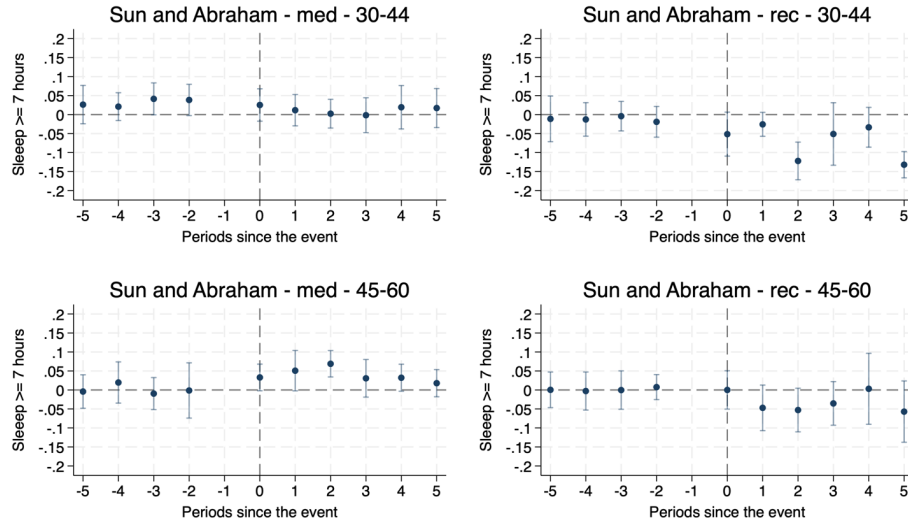


Figure 3.4: Regression Results Dynamic TWFE by age Groups: 30-44 and 45-60

relative to the mean of 0.761, while Sun–Abraham confirms a positive effect of 0.017 ($p < 0.05$), corresponding to a 2.24% increase. Recreational cannabis is not statistically significant in either specification. For adults aged 60+ (Column 6), neither policy yields significant effects.

Medical cannabis is robustly associated with a 2–3% increase in the probability of sleeping at least seven hours among adults aged 45–60, while recreational cannabis is

associated with economically meaningful sleep declines of 2.6–5% among adults aged 30–44. These patterns point to distinct, age-specific effects of medical versus recreational cannabis on sleep.

Table 3.5: Result Regression: TWFE analysis by Age Groups

	All 15+	15–20	21–29	30–44	45–60	>60
medmar	0.011* (0.006)	-0.013 (0.013)	0.032 (0.021)	0.007 (0.008)	0.025** (0.010)	-0.001 (0.007)
recmar	-0.008 (0.007)	-0.005 (0.017)	0.010 (0.017)	-0.020* (0.011)	-0.016 (0.014)	0.002 (0.008)
Mean of Dep. Var.	.806	.862	.820	.778	.761	.857
SE Clusters	51	51	51	51	51	51
Observations	110992	6948	11454	32101	28533	31956

Notes: This table reports coefficients from TWFE regressions of introduction of medical and recreational cannabis on sleep more than 7 hours per night on average spited by age groups. All regressions control for gender, race/ethnicity, years of education, and total household income (in levels), employment status, age, day in which the information is collected by individuals for the diary. Specifications include country-by-year fixed effects. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6: Results Static Regression Medical Cannabis: Sun and Abraham by Age Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	All 15+	15–20	21–29	30–44	45–60	>60
post_med	0.00387 (0.00693)	0.00313 (0.0193)	-0.00649 (0.0147)	0.00330 (0.0126)	0.0173** (0.00726)	0.00564 (0.00808)
Observations	36507	2209	3674	10533	10140	25966
SE Cluster	38	38	38	38	38	38
Mean Dep. Var.	0.803	0.867	0.817	0.779	0.760	0.784

Notes: This table reports coefficients from Sun-Abraham regressions of introduction of medical and recreational cannabis on sleep more than 7 hours per night on average spited by age groups. All regressions control for gender, race/ethnicity, years of education, and total household income (in levels), employment status, age, day in which the information is collected by individuals for the diary. Specifications include country-by-year fixed effects. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7: Results Static Regression Recreational Cannabis: Sun and Abraham by Age Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	All 15+	15-20	21-29	30-44	45-60	> 60
post_rec	-0.0104 (0.00970)	-0.0334 (0.0474)	-0.0122 (0.0354)	-0.0393* (0.0209)	-0.000381 (0.0284)	-0.0170 (0.0114)
Observations	20880	1156	1910	5748	5575	14013
SE Clusters	24	22	24	24	24	24
Mean Dep. Var.	0.829	0.894	0.857	0.804	0.790	0.813

Notes: This table reports coefficients from Sun-Abraham regressions of introduction of medical and recreational cannabis on sleep more than 7 hours per night on average spited by age groups. All regressions control for gender, race/ethnicity, years of education, and total household income (in levels), employment status, age, day in which the information is collected by individuals for the diary. Specifications include country-by-year fixed effects. Standard errors, clustered at the country level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.6 Conclusion

This study sheds new light on the impact of cannabis legalization in the United States, offering what, to our knowledge, is the first causal evidence of how these policies affect Americans' sleep. Combining twenty years of legislative changes with data from the American Time Use Survey, a far from uniform picture emerges: legalization cannot be considered a homogeneous health event. On the contrary, its effects are deeply fragmented and crucially dependent on both the type of law adopted and the age of those who use it. These data seriously call into question the idea of a universal impact, prompting us to look more closely at the different motivations driving different segments of the population.

The numbers, moreover, speak clearly. The medical approach appears to provide concrete support to adults between the ages of 45 and 60, leading to a roughly 3% increase in the likelihood of getting the required seven hours of sleep. This finding lends weight to the self-medication hypothesis: for those facing a phase of life often marked by chronic pain and accumulated fatigue, regulated access to cannabis can become a valuable alternative to traditional medications, or at least a way to tame symptoms that would otherwise ruin their night's sleep. The situation is radically different with recreational legalization. Among young adults (30-44 years), free access appears to go hand in hand with worsening sleep, with a decrease in the likelihood of getting sufficient rest ranging between 2.6% and 5%. It's reasonable to assume that non-therapeutic use leads to less attentive sleep hygiene habits, perhaps precisely because of the high THC content that medical literature associates with REM sleep disruption.

All of this has considerable weight for lawmakers and for public health. While medical cannabis is proving to be a harm reduction tool for older adults, the negative effect on

younger workers raises serious questions about long-term productivity and well-being, given the now well-established link between poor sleep and cognitive decline. Of course, there are limitations: for the 15-29 age group, the paucity of data requires extreme caution before drawing definitive conclusions. Looking ahead, further research, it would be interesting to use data from wearable devices to understand how workplace stress influences these patterns. Ultimately, with this study we highlights how is important that effective regulation can no longer afford to be "standard" or one-size-fits-all; instead, it must be differentiated, protecting the sleep of younger people without denying therapeutic benefits to those who need them most.

One aspect to consider when interpreting these results concerns the nature of the variation utilized for identification. Having leveraged legislative differences across various states, our analysis focuses on a source of variation that is necessarily aggregated relative to the complexity of individual behaviors. Consequently, it is likely that the estimates reflect average population-level trends and may therefore appear more modest than what would emerge from more granular, micro-level individual data. Nevertheless, the fact that the effects remain statistically significant and possess clear economic relevance—particularly for the 30–60 age demographic—confirms the robustness of the empirical framework that has emerged. From this perspective, future research could incorporate even more specific individual-level data or objective measures of sleep, thereby shedding further light on the mechanisms through which legalization impacts daily habits and mapping with even greater precision the nuances across different population subgroups.

References

- Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. *Neuropsychiatr Dis Treat*, 3(5), 553–567.
- Amaral, A., & et al. (2023). Medical cannabis use and sleep outcomes in patients with chronic conditions. *Sleep Medicine*.
- AminiLari, M., Wang, L., Neumark, S., Adli, T., Couban, R. J., Giangregorio, A., Carney, C. E., & Busse, J. W. (2022). Medical cannabis and cannabinoids for impaired sleep: A systematic review and meta-analysis of randomized clinical trials. *Sleep*, 45(2), zsab234.
- Anderson, D. M., Matsuzawa, K., & Sabia, J. J. (2020). Cigarette taxes and teen marijuana use. *National Tax Journal*, 73(2), 475–510. <https://doi.org/10.17310/ntj.2020.2.06>
- Anderson, D. M., & Rees, D. I. (2023). The public health effects of legalizing marijuana. *Journal of Economic Literature*, 61(1), 86–143.
- Anderson, D. M., Rees, D. I., Sabia, J. J., & Safford, S. (2021). Association of marijuana legalization with marijuana use among us high school students, 1993-2019. *JAMA Network Open*, 4, e210180–e210180.
- Avery, M., Giuntella, O., & Jiao, P. (2025). Why don't we sleep enough? a field experiment among college students. *The Review of Economics and Statistics*, 107(1), 65–77. https://doi.org/10.1162/rest_a.01242
- Babson, K. A., Sottile, J., & Morabito, D. (2017). Cannabis, cannabinoids, and sleep: A review of the literature. *Curr Psychiatry Rep*, 19(4), 23. <https://doi.org/10.1007/s11920-017-0885-7>
- Bachhuber, M. A., Saloner, B., Cunningham, C., & Barry, C. L. (2014). Medical cannabis laws and opioid analgesic overdose mortality in the united states, 1999–2010. *JAMA Internal Medicine*, 174(10), 1668–1673. <https://doi.org/10.1001/jamainternmed.2014.4005>
- Boehnke, K. F., Litinas, E., & Clauw, D. J. (2016). Medical cannabis use is associated with decreased opiate medication use in a retrospective cross-sectional survey of patients with chronic pain. *The Journal of Pain*, 17(6), 739–744.
- Bonn-Miller, M. O., Boden, M. T., Bucossi, M. M., & Babson, K. A. (2014). Self-reported cannabis use characteristics, patterns and helpfulness among medical cannabis users. *Am J Drug Alcohol Abuse*, 40(1), 23–30.
- Bradford, A. C., & Bradford, W. D. (2016). Medical marijuana laws reduce prescription medication use in medicare part d. *Health Affairs*, 35(7), 1230–1236. <https://doi.org/10.1377/hlthaff.2015.1661>
- Bradford, A. C., & Bradford, W. D. (2017). Medical marijuana laws may be associated with a decline in the number of prescriptions for medicaid enrollees. *Health Affairs*, 36(5), 945–951. <https://doi.org/10.1377/hlthaff.2016.1661>
- Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>

- Cappuccio, F. P., Cooper, D., D'Elia, L., Strazzullo, P., & Miller, M. A. (2011). Sleep duration predicts cardiovascular outcomes: A systematic review and meta-analysis of prospective studies. *Eur Heart J*, 32(12), 1484–1492. <https://doi.org/10.1093/eurheartj/ehr007>
- Carrieri, V., Madio, L., & Principe, F. (2020). Do-it-yourself medicine? the impact of light cannabis liberalization on prescription drugs. *Journal of Health Economics*, 74, 102371. <https://doi.org/10.1016/j.jhealeco.2020.102371>
- CDC. (2011). Effect of short sleep duration on daily activities—united states, 2005–2008. *MMWR*, 60(8), 239–242.
- CDC - Centers for Disease Control and Prevention. (2024a, February). State medical cannabis laws.
- CDC - Centers for Disease Control and Prevention. (2024b, May). Faststats: Sleep in adults.
- CDC - Centers for Disease Control and Prevention. (2024c, May). Faststats: Sleep in high school students.
- Choi, A., Dave, D., & Sabia, J. J. (2019). Smoke gets in your eyes: Medical marijuana laws and tobacco cigarette use. *American Journal of Health Economics*, 5(3), 303–333.
- Chong, Y., Fryar, C. D., & Gu, Q. (2013). *Prescription sleep aid use among adults: United states, 2005–2010* (NCHS data brief No. 127). National Center for Health Statistics. Hyattsville, MD.
- Colten, H. R., & Altevogt, B. M. (Eds.). (2006). *Sleep disorders and sleep deprivation: An unmet public health problem*. National Academies Press (US). <https://doi.org/10.17226/11617>
- Costa-Font, J., Fleche, S., & Pagan, R. (2024). The labour market returns to sleep. *Journal of Health Economics*, 93, 102840.
- Darden, M., & Papageorge, N. (2024). Rational self-medication. *Economics & Human Biology*, 53, 101350. <https://doi.org/10.1016/j.ehb.2024.101350>
- Dave, D., Liang, Y., Pesko, M. F., Phillips, S., & Sabia, J. J. (2023). Have recreational marijuana laws undermined public health progress on adult tobacco use? *Journal of Health Economics*, 90, 102756.
- Drake, C., Wen, J., Hinde, J., & Wen, H. (2021). Recreational cannabis laws and opioid-related emergency department visit rates. *Health Econ*, 30(10), 2595–2605. <https://doi.org/10.1002/hec.4377>
- Finan, P. H., Goodin, B. R., & Smith, M. T. (2013). The association of sleep and pain: An update and a path forward. *The journal of pain*, 14(12), 1539–1552.
- Fletcher, J. M., Sindelar, J. L., & Yamaguchi, S. (2011). Cumulative effects of job characteristics on health. *Health economics*, 20(5), 553–570.
- Gavin, K. (2024, September). Cannabis & older adults: Poll looks at use, beliefs and risk. *University of Michigan – Michigan Medicine*.
- Gibson, M., & Shrader, J. (2018). Time use and labor productivity: The returns to sleep. *Review of Economics and Statistics*, 100(5), 783–798.

- Giuntella, O., Han, W., & Mazzonna, F. (2017). Circadian rhythms, sleep, and cognitive skills: Evidence from an unsleeping giant. *Demography*, 54(5), 1715–1742.
- Giuntella, O., & Mazzonna, F. (2019). Sunset time and the economic effects of social jetlag: Evidence from us time zone borders. *Journal of Health Economics*, 65, 210–226.
- Giuntella, O., Saccardo, S., & Sadoff, S. (2024). Sleep: Educational impact and habit formation. *National Bureau of Economic Research Working Paper*, (32550). <http://www.nber.org/papers/w32550>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277.
- Grandner, M. A., Hale, L., Moore, M., & Patel, N. P. (2010). Mortality associated with short sleep duration: The evidence, the possible mechanisms, and the future. *Sleep Med Rev*, 14(3), 191–203. <https://doi.org/10.1016/j.smrv.2009.07.006>
- Han, B. H., & Palamar, J. J. (2020). Trends in cannabis use among older adults in the united states, 2015–2018. *JAMA Internal Medicine*, 180(4), 609–611.
- Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O'Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V., Ware, J. C., ... Kapur, V. K. (2015). National sleep foundation's updated sleep duration recommendations: Methodology and results summary. *Sleep Health*, 1(4), 233–243. <https://doi.org/10.1016/j.sleh.2015.10.004>
- Hollingsworth, A., Wing, C., & Bradford, A. C. (2022). Comparative effects of recreational and medical marijuana laws on drug use among adults and adolescents. *The Journal of Law and Economics*, 65(3), 515–554.
- Karasek, R. (1990). Stress, productivity, and the reconstruction of working life. *Health work*.
- Knutson, K. L., & Van Cauter, E. (2008). Associations between sleep loss and increased risk of obesity and diabetes. *Annals of the New York Academy of Sciences*, 1129(1), 287–304.
- Lauderdale, D. S., Knutson, K. L., Yan, L. L., Liu, K., & Rathouz, P. J. (2008). Self-reported and measured sleep duration: How similar are they? *Epidemiology*, 19(6), 838–845.
- Lozano-Rojas, F., Abraham, A. J., Gupta, S., & Bradford, W. D. (2022). The effect of cannabis laws on access to pain medications among commercially insured patients in the united states. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4299449>
- Mazzonna, F., & Peracchi, F. (2017). Unhealthy retirement? *Journal of Human Resources*, 52(1), 128–151.
- National Academies of Sciences, Engineering, and Medicine. (2017). *The health effects of cannabis and cannabinoids: The current state of evidence and recommendations for research*. The National Academies Press.
- Pacula, R. L., & Smart, R. (2017). Medical marijuana and marijuana legalization. *Annual review of clinical psychology*, 13(1), 397–419.

- Panel: C. C., Watson, N. F., Badr, M. S., Belenky, G., Bliwise, D. L., Buxton, O. M., Buysse, D., Dinges, D. F., Gangwisch, J., Grandner, M. A., et al. (2015). Joint consensus statement of the american academy of sleep medicine and sleep research society on the recommended amount of sleep for a healthy adult: Methodology and discussion. *Journal of Clinical Sleep Medicine*, 11(8), 931–952.
- Patel, S. R., & Hu, F. B. (2008). Short sleep duration and weight gain: A systematic review. *Obesity (Silver Spring)*, 16(3), 643–653. <https://doi.org/10.1038/oby.2007.118>
- Powell, D., Pacula, R. L., & Jacobson, M. (2018). Do medical marijuana laws reduce addictions and deaths related to pain killers? *Journal of health economics*, 58, 29–42.
- Raman, S., & Bradford, A. C. (2022). Recreational cannabis legalizations associated with reductions in prescription drug utilization among medicaid enrollees. *Health Econ*, 31(7), 1513–1521. <https://doi.org/10.1002/hec.4519>
- Raman, S., Maclean, J. C., Bradford, W. D., & Drake, C. (2023). Recreational cannabis and opioid distribution. *Health Econ*, 32(4), 747–754. <https://doi.org/10.1002/hec.4652>
- Ried, K., Tamanna, T., Matthews, S., & Sali, A. (2023a). Medicinal cannabis improves sleep in adults with insomnia: A randomised double-blind placebo-controlled crossover study. *Journal of Sleep Research*, 32(1), e13793.
- Ried, K., Tamanna, T., Matthews, S., & Sali, A. (2023b). Medicinal cannabis improves sleep in adults with insomnia: A randomised double-blind placebo-controlled crossover study. *Journal of sleep research*, 32(3), e13793.
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199. <https://doi.org/10.1016/j.jeconom.2020.09.006>
- van Cauter, E., Holmback, U., Knutson, K., Leproult, R., Miller, A., Nedeltcheva, A., & et al. (2007). Impact of sleep and sleep loss on neuroendocrine and metabolic function. *Horm Res*, 67(Suppl 1), 2–9.
- Walker, M., Lake, S., Tempero, J., Ong, K., & Lucas, P. (2024). Age-related Patterns of Medical Cannabis Use: A Survey of Authorized Patients in Canada. *Cannabis (Albuquerque, N.M.)*, 7(2), 135–149. <https://doi.org/10.26828/cannabis/2024/000208>
- Walsh, Z., Callaway, R., Belle-Isle, L., Capler, R., Kay, R., Lucas, P., & Holtzman, S. (2013). Cannabis for therapeutic purposes: Patient characteristics, access, and reasons for use. *International Journal of Drug Policy*, 24(6), 511–516.
- Wang, M., Faust, M., Abbott, S., Patel, V., Chang, E., Clark, J. I., Stella, N., & Muchowski, P. J. (2025). Effects of a cannabidiol/terpene formulation on sleep in individuals with insomnia: A double-blind, placebo-controlled, randomized, crossover study. *Journal of Clinical Sleep Medicine: JCSM: Official Publication of the American Academy of Sleep Medicine*, 21(1), 69–80. <https://doi.org/10.5664/jcsm.11324>

- Whiting, P. F., Wolff, R. F., Deshpande, S., Di Nisio, M., Duffy, S., Hernandez, A. V., Keurentjes, J. C., Lang, S., Misso, M., Ryder, S., Schmidtkofer, S., Westwood, M., & Kleijnen, J. (2015). Cannabinoids for medical use: A systematic review and meta-analysis. *JAMA*, *313*(24), 2456–2473. <https://doi.org/10.1001/jama.2015.6358>
- Xu, C., & Sturman, Z. (2025). The Effects of Cannabis Access Laws on Sleep in the U.S. *AJPM Focus*, *4*(5), 100387. <https://doi.org/10.1016/j.focus.2025.100387>

Appendix A. Tables

Table A.3.1: Number of Observations per State per Year

State	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
AK	47	30	31	25	32	22	33	21	19	20	24	17	16	22	20	15	14	25	16	22	21
AL	361	277	231	212	181	207	186	218	207	209	193	204	181	193	200	181	179	184	174	138	146
AR	223	138	147	139	112	137	140	137	134	107	138	130	111	117	108	112	116	96	103	96	109
AZ	380	266	241	235	203	238	207	219	212	211	186	186	191	237	226	226	209	209	209	183	157
CA	1940	1308	1178	1341	1234	1277	1341	1367	1312	1293	1167	1195	1075	995	977	902	855	817	803	754	810
CO	385	263	258	232	235	262	270	250	236	250	223	205	209	172	173	161	157	126	148	148	155
CT	285	181	172	147	143	148	171	175	139	155	146	115	122	125	123	100	115	118	117	99	94
DE	51	30	30	25	36	32	40	30	28	31	32	36	27	33	28	20	25	23	29	27	24
DC	68	46	40	34	42	46	40	36	40	42	38	27	34	27	20	30	29	29	33	33	31
FL	1251	817	712	687	637	672	637	685	698	665	627	621	606	619	606	513	496	465	480	426	476
GA	412	304	293	373	340	376	345	388	361	388	309	297	316	340	314	299	308	253	275	215	202
HI	65	42	39	44	36	39	32	39	34	40	33	44	29	35	29	38	28	27	36	26	30
IA	291	182	179	161	163	165	145	165	168	157	131	162	151	142	152	130	156	130	136	128	133
ID	221	122	81	79	83	65	80	75	70	68	77	63	61	68	76	68	65	76	52	60	58
IL	876	598	596	554	484	515	556	577	500	524	497	473	471	442	399	361	375	310	342	278	345
IN	415	302	324	282	281	260	291	316	250	287	252	272	256	244	260	232	244	205	199	198	198
KS	255	183	152	159	149	161	147	150	151	128	138	140	113	134	123	133	87	109	118	109	126
KY	382	220	216	210	214	210	231	207	205	198	202	185	184	181	164	177	174	159	143	148	151
LA	336	207	165	169	154	173	192	202	167	181	159	169	160	169	158	142	144	123	154	120	130
MA	487	332	297	253	243	229	293	292	266	272	213	240	209	203	218	230	236	230	235	218	232
MD	304	238	250	285	233	258	270	275	269	280	237	271	225	188	193	174	160	158	155	158	148
ME	133	73	62	62	60	59	67	65	59	62	55	51	55	48	41	49	43	44	50	42	50
MI	828	537	500	440	442	448	456	436	401	410	412	377	377	329	313	323	326	289	288	240	262
MN	489	328	308	286	287	288	295	315	281	282	265	269	236	227	185	200	192	184	166	173	171
MO	392	257	299	317	285	300	329	304	297	270	234	257	222	198	190	199	173	185	194	156	184
MS	212	158	144	136	107	134	147	128	116	147	105	128	127	134	116	91	105	81	79	89	97
MT	85	58	43	43	54	49	47	46	53	45	42	43	41	39	37	44	31	27	49	51	27
NC	661	442	418	399	365	375	399	403	383	383	339	356	367	313	324	290	297	271	275	252	284
ND	68	48	33	34	29	35	39	34	30	34	29	29	28	34	23	33	30	32	28	33	26
NE	160	117	100	97	85	93	105	88	92	91	82	73	91	74	69	82	78	77	73	58	74
NH	134	70	68	61	49	69	62	64	63	51	55	51	44	37	46	45	50	40	44	44	42
NJ	620	397	394	326	353	324	342	356	321	319	297	304	281	311	295	218	237	199	238	207	184
NM	156	112	112	84	94	100	118	111	86	72	96	82	79	103	104	74	75	77	94	74	71
NV	176	114	110	94	89	112	120	113	115	106	100	112	114	92	105	83	86	84	100	73	84
NY	1337	878	738	731	685	670	738	724	678	602	603	648	562	527	507	458	458	440	415	373	353
OH	911	607	585	499	499	500	494	510	465	442	420	419	383	356	346	371	339	313	327	279	305
OK	307	170	166	191	179	180	182	182	167	176	155	144	154	147	139	158	147	117	129	111	120
OR	309	214	177	187	176	177	202	200	183	170	191	177	152	169	174	167	149	160	178	156	177
PA	967	692	628	564	542	528	576	544	549	531	484	491	421	424	394	369	343	329	339	316	330
RI	96	63	53	48	31	44	43	47	48	46	38	41	44	35	32	36	26	35	29	25	28
SC	300	183	187	211	193	203	200	222	193	235	183	199	200	203	208	168	180	153	183	174	170
SD	77	44	53	30	42	44	46	43	42	35	29	39	40	31	40	44	26	37	34	34	32
TN	367	254	233	238	249	257	262	249	241	231	214	189	227	242	238	246	225	228	240	195	213
TX	1282	917	815	910	888	941	945	934	922	965	827	895	814	803	794	740	696	641	651	596	639
UT	181	149	129	126	122	137	134	123	129	125	122	120	118	110	120	107	121	112	114	103	117
VA	470	332	349	388	383	404	393	386	392	349	365	352	351	297	259	288	266	268	276	220	215
VT	60	29	30	35	27	34	19	31	23	23	27	28	21	21	18	19	22	21	26	21	20
WA	367	233	282	315	294	304	305	328	292	324	259	273	268	233	241	229	263	230	256	219	221
WI	445	309	277	314	302	294	319	327	294	288	275	297	249	195	205	185	184	160	172	166	196
WV	148	106	93	98	90	84	78	95	76	91	56	79	67	63	70	62	73	51	66	51	63
WY	46	37	22	29	30	29	29	28	24	23	18	19	18	21	15	24	25	25	21	21	17

Notes: This table reports the number of ATUS observations by state and year. The number of observations varies across state-year cells due to the ATUS sampling structure and the disaggregation of the data at the state-year level. These counts are reported to document the sample coverage used in the empirical analysis.

Table A.3.2: Number of Observations by Year, Treatment Status, and Age Group

Panel A: Medical Cannabis Legalization (MCL)																					
Age Group & MCL Status	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
15-20 – Not Treated (MCL=0)	1306	864	821	868	752	729	681	690	601	522	438	369	340	233	206	166	153	141	138	85	88
15-20 – Treated (MCL=1)	292	184	194	243	216	229	207	267	265	254	279	316	270	369	329	303	265	283	281	209	220
21-29 – Not Treated (MCL=0)	1825	1249	1239	1117	1088	1077	1078	1037	990	953	723	650	633	389	399	350	328	261	243	221	215
21-29 – Treated (MCL=1)	439	279	235	253	233	304	347	397	350	334	417	514	464	615	550	508	545	513	592	504	524
30-44 – Not Treated (MCL=0)	5536	3521	3483	3301	2984	2964	2998	2849	2559	2545	2050	1683	1588	1105	1119	886	873	704	699	570	538
30-44 – Treated (MCL=1)	1182	754	747	810	765	919	939	1067	1017	1094	1166	1479	1340	1732	1637	1645	1530	1554	1664	1400	1369
45-60 – Not Treated (MCL=0)	4817	3247	2915	2883	2813	2708	2897	2842	2556	2436	2063	1801	1728	1123	1062	935	876	701	602	569	559
45-60 – Treated (MCL=1)	928	706	627	658	662	844	832	946	991	1037	1149	1473	1410	1727	1730	1557	1559	1496	1522	1371	1369
61+ – Not Treated (MCL=0)	3814	2728	2370	2348	2249	2318	2426	2402	2311	2368	1980	1824	1734	1218	1220	1240	1238	945	935	875	1061
61+ – Treated (MCL=1)	581	441	407	462	486	631	728	763	839	900	1120	1483	1398	1982	1971	2003	2068	2184	2411	2332	2605
Panel B: Recreational Cannabis Legalization (RCL)																					
Age Group & RCL Status	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
15-20 – Not Treated (RCL=0)	1598	1048	1015	1111	968	958	888	957	866	741	685	647	582	483	425	364	309	291	238	166	151
15-20 – Treated (RCL=1)	.	.	.	.	.	.	.	.	.	35	32	38	28	119	110	105	109	133	181	128	157
21-29 – Not Treated (RCL=0)	2264	1528	1474	1370	1321	1381	1425	1434	1340	1239	1096	1108	1036	816	771	663	681	540	495	423	377
21-29 – Treated (RCL=1)	.	.	.	.	.	.	.	.	.	48	44	56	61	188	178	195	192	234	340	302	362
30-44 – Not Treated (RCL=0)	6718	4275	4230	4111	3749	3883	3937	3916	3576	3450	3061	3003	2722	2315	2215	1882	1840	1559	1322	1115	912
30-44 – Treated (RCL=1)	.	.	.	.	.	.	.	.	.	189	155	159	206	522	541	649	563	699	1041	855	995
45-60 – Not Treated (RCL=0)	5745	3953	3542	3541	3475	3552	3729	3788	3547	3302	3079	3146	2961	2356	2245	1934	1857	1557	1209	1146	1004
45-60 – Treated (RCL=1)	.	.	.	.	.	.	.	.	.	171	133	128	177	494	547	558	578	640	915	794	924
61+ – Not Treated (RCL=0)	4395	3169	2777	2810	2735	2949	3154	3165	3150	3137	2982	3174	2932	2696	2631	2552	2572	2267	1954	1856	1919
61+ – Treated (RCL=1)	.	.	.	.	.	.	.	.	.	131	118	133	200	504	560	691	734	862	1392	1351	1747

Notes: This table reports the number of AFUS observations by year, treatment status, and age group. Panel A refers to medical cannabis legalization (MCL); treated states have MCL in effect (medmar=1), untreated states do not (medmar=0). Panel B refers to recreational cannabis legalization (RCL); treated states have RCL in effect (reclmar=1), untreated states do not (reclmar=0). The sample excludes weekends and the year 2020. Recreational cannabis was first introduced in 2012, so there are no observations for recreational cannabis before that year. It is also important to note that younger cohorts (ages 15–20 and 21–29) may contain relatively few observations, which can reduce statistical power. Results for these age groups should therefore be interpreted with caution.

Appendix B

Table B.3.1: Medical Cannabis – Sun and Abraham Estimates by Age Group (Wild Cluster Bootstrap)

	(1) All Pop	(2) 15-20	(3) 21-29	(4) 30-44	(5) 45-60	(6) >60
post_med	0.00387 (0.00693)	0.00313 (0.0193)	-0.00649 (0.0147)	0.00330 (0.0126)	0.0173** (0.00726)	-0.00700 (0.0101)
N_obs	36507	2209	3674	10533	10140	9951
N_cluster	38	38	38	38	38	38
Mean_DV	0.803	0.867	0.817	0.779	0.760	0.853

Notes: This table reports coefficients from Sun and Abraham regressions estimating the effect of the introduction of medical cannabis laws (MCL) on the probability of sleeping seven or more hours per night, separately by age group. All regressions control for gender, race/ethnicity, years of education, total household income (in levels), employment status, age, and the diary day. Specifications include state and year fixed effects. Standard errors, clustered at the state level, are reported in parentheses. To address concerns about inference with a limited number of clusters (38 for MCL), p-values are obtained using Wild Cluster Bootstrap procedures. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3.2: Recreational Cannabis – Sun and Abraham Estimates by Age Group (Wild Cluster Bootstrap)

	(1) All Pop	(2) 15-20	(3) 21-29	(4) 30-44	(5) 45-60	(6) >60
post_rec	-0.0104 (0.00970)	-0.0334 (0.0474)	-0.0122 (0.0354)	-0.0393* (0.0209)	-0.000381 (0.0284)	0.00371 (0.0144)
N_obs	20880	1156	1910	5748	5575	6490
N_cluster	24	22	24	24	24	24
Mean_DV	0.829	0.894	0.857	0.804	0.790	0.864

Notes: This table reports coefficients from Sun and Abraham regressions estimating the effect of the introduction of recreational cannabis laws (RCL) on the probability of sleeping seven or more hours per night, separately by age group. All regressions control for gender, race/ethnicity, years of education, total household income (in levels), employment status, age, and the diary day. Specifications include state and year fixed effects. Standard errors, clustered at the state level, are reported in parentheses. To address concerns about inference with a limited number of clusters (24 for RCL), p-values are obtained using Wild Cluster Bootstrap procedures (Cameron et al., 2008). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 4

Early unemployment and long-term effects on health and risky health behaviors

Ilaria Prometti*
Francesco Principe**

* Corresponding author. Department of Economics, University of Pavia, Italy. E-mail: ilaria.prometti01@universitadipavia.it

** Department of Economics, University of Bergamo, Italy. E-mail: francesco.principe@unibg.it

Abstract

This paper examines the long-term effects of youth unemployment (ages 18–25) on adult health behaviors, chronic conditions, and occupational outcomes. Using harmonized SHARE panel data linked to country-specific unemployment rates, we analyze how early labor-market shocks influence smoking, alcohol use, diet, physical activity, chronic disease, and job characteristics. We find that higher youth unemployment raises the probability of daily smoking by 3.25% and prolongs smoking duration, while reducing heavy drinking by 4.7%, vigorous physical activity by 1%, and frequent fruit and vegetable consumption by 0.5%. Cumulative exposure also increases the likelihood of working in physically demanding jobs and lowers adult income. Effects are strongest among lower-educated individuals, with additional persistence among high-income adults and slightly higher susceptibility among women. These results highlight that early economic adversity shapes adult health and labor outcomes through stress, behavioral, and occupational pathways, with lasting implications for health inequality and long-term economic well-being.

4.1 Introduction

Early adulthood is a critical window for modeling health behaviors that persist across the life course and that are able to influence long-term morbidity, productivity, and longevity (Becker & Murphy, 1988; Grossman, 1972). Behaviors such as smoking, excessive alcohol consumption, physical inactivity, and insufficient fruit and vegetable intake are not only key determinants of health, but also generate substantial economic burdens on healthcare systems (e.g., £3.3 bn for smoking, £3.3 bn for alcohol, £5.8 bn for poor diet, £0.9 bn for physical inactivity in the UK; Candari et al. 2017; Heron et al. 2019; Scarborough et al. 2011). These data highlight the public health and economic relevance of understanding factors that influence risky health behaviors, such as early-life economic shocks.

Prior research documents persistent economic scarring from entering the labor market during recessions, but less is known about behavioral, health, and labor-market consequences in the long-term. This paper wants to investigate the effects of youth unemployment (ages 18–25) on adult smoking, alcohol use, diet, physical activity, chronic disease, and occupational outcomes, using harmonized SHARE data linked to country-specific unemployment rates. The analysis focuses on cohorts for which detailed youth unemployment data are available (namely individuals born in the 1940s and later).

Our results show that exposure to high youth unemployment increases the probability of daily smoking by 3.25% relative to the sample mean and prolongs smoking duration, reduces heavy drinking by 4.7%, and slightly diminishes vigorous physical activity (1%) and frequent fruit and vegetable consumption (0.5%). Heterogeneity analyses indicate stronger smoking effects for lower-educated individuals ($\beta_{\text{Unemp} \times \text{Edu}} = -0.001$, $p < 0.05$), marginally higher susceptibility among women ($\beta_{\text{Unemp} \times \text{Female}} = 0.007$, $p < 0.10$), and persistent smoking duration among high-income adults ($\beta_{\text{Unemp} \times \text{Income Q4}} = 0.593$, $p < 0.05$). Robustness checks confirm that these patterns are consistent across alternative unemployment measures and when restricting the sample to individuals who never moved countries (even though this sample was very small).

Beyond behaviors, youth unemployment leaves lasting health and labor scars. In fact, exposure at age 17 increases the number of chronic conditions in adulthood ($\beta = 0.017$, $p < 0.05$) and the probability of having more than two chronic diseases by 1.79% from the population mean ($\beta = 0.006$, $p < 0.01$). On the same line, the exposure at age 18 raises comorbidity by 1.37% from the population mean. While, the cumulative exposure, average unemployment between ages 18 - 25 increases the probability of working in physically demanding jobs by 2.84% (with age-18 exposure alone produces a 3.50% increase). Additionally and consequently, we observe a reduction in adult income ($\beta = -327.34$, $p < 0.05$).

To understand these patterns, we explore potential behavioral and socio-economic mechanisms. Early labor-market shocks appear to increase stress-induced smoking, reduce engagement in health-promoting behaviors through financial and social con-

straints, and channel individuals into more physically demanding occupations, amplifying chronic disease risk. Stress and coping mechanisms may explain why smoking persists even as other health behaviors decline; in fact, financial and social capital constraints reduce diet quality, physical activity, and discretionary alcohol consumption. Therefore, time allocation and environmental constraints further limit opportunities for healthy behaviors, showing a negative effect in short-run, but especially reinforcing the long-term health impacts of early unemployment.

Our findings suggest that there is a causal relationship between early adulthood unemployment and later health behaviors and conditions, even modest increases in risky behaviors due to youth unemployment can translate into substantial long-term health-care costs. Therefore, a potential targeted interventions during youth recessions could mitigate long-term health and economic scars.

The remainder of the paper is structured as follows. Section 4.2 reviews the literature. Section 4.3 describes the data. Section 4.4 outlines the empirical strategy. Section 4.5 presents the main findings. Section 4.6 explores mechanisms. Section 4.7 presents heterogeneity and robustness checks. Section 4.8 discusses additional long-term outcomes. Section 4.9 concludes.

4.2 Related Literature

A large empirical literature documents that cohorts entering the labor market during recessions experience persistent penalties in wages, employment stability, and career trajectories. Seminal contributions show that adverse macroeconomic conditions at entry reduce early-career earnings and job quality, with mechanisms linked to early-career skill depreciation (Arellano-Bover, 2022), loss of firm-specific human capital, weaker firm-worker matching, and slower occupational progression (Kahn, 2010; Oreopoulos et al., 2012a; Oyer, 2006; Schwandt & von Wachter, 2019a). Beyond economic outcomes, recent research has highlighted broader “social scarring” effects, showing that early exposure to unemployment shocks can shape fertility decisions (Currie & Schwandt, 2014), criminal behavior (B. Bell et al., 2018), and mental health outcomes over the life course (Frijters et al., 2005; Schwandt, 2016). These findings suggest that adverse entry conditions may also influence preferences, expectations, and risk attitudes—factors that are central to the formation of long-term health behaviors.

While the evidence on labor-market scarring is extensive, less attention has been paid to its potential behavioral and health consequences. Longitudinal studies indicate that youth unemployment predicts poorer physical health and higher mortality in adulthood (Frijters et al., 2005; Schwandt, 2016), implying that health behaviors could represent a key transmission channel through which early labor-market shocks translate into long-run health inequality. This perspective naturally connects to the theoretical framework of health capital, which emphasizes the cumulative nature of health investments over

the life cycle (Becker & Murphy, 1988; Conti & Heckman, 2010; Grossman, 1972). According to this view, early-life environments and constraints shape individual health trajectories by influencing education, parental inputs, and time preferences. Neuroscientific and behavioral evidence further identifies adolescence and early adulthood (roughly ages 16–25) as a sensitive window for habit formation and the consolidation of risk preferences (Casey et al., 2008; Conrod, 2016; Cunha & Heckman, 2007; Sawyer et al., 2018; Steinberg, 2008). Exposure to economic adversity during this developmental stage may therefore leave lasting imprints on individuals’ behavioral capital—the ability to plan, sustain, and invest in one’s health.

At the macro level, the relationship between business cycles and health behaviors has long been debated. Classic studies find pro-cyclical patterns in mortality and risky behaviors, with health outcomes often improving during recessions due to reduced traffic, workplace accidents, and pollution exposure (Ruhm, 2000). This pro-cyclical pattern is further supported by evidence of decreased smoking and alcohol consumption (Ruhm, 2005), lower obesity prevalence (Neumayer, 2004), and improved dietary quality (Di Pietro, 2018; Xu, 2013). Additional studies emphasize health gains from reduced air pollution and decreased work-related stress during recessions (Stevens et al., 2015). Yet these average patterns mask substantial heterogeneity: micro-level and longitudinal evidence shows that individuals directly affected by job loss—particularly young entrants facing prolonged or involuntary unemployment—tend to experience mental health deterioration and adopt less healthy behaviors such as increased smoking, poorer diet, and reduced physical activity (Colman & Dave, 2018; Cutler & Lleras-Muney, 2006; Deb et al., 2011; Haushofer & Fehr, 2014). Evidence also suggests that exposure to macroeconomic downturns during the working life can have persistent negative consequences for health outcomes later in life (Antonova et al., 2017). The magnitude and direction of these effects vary systematically by age, education, gender, and welfare institutions. Findings from SHARE countries also link early-life adversity with later-life unhealthy lifestyle adoption (Brugiavini et al., 2022). Moreover, evidence from the post-Great Recession period points to a weakening or even reversal of pro-cyclical relationships, especially among vulnerable groups and young adults (Hall et al., 2021). These findings motivate a focus on the labor-market entry phase as a critical period not only for professional development but also for the establishment of long-term health habits.

Several mechanisms may explain the persistence of unhealthy behaviors triggered by early economic hardship. Economic insecurity shortens individuals’ perceived time horizon, inducing present-biased choices and lower investment in health capital (Haushofer & Fehr, 2014; Matthews & Gallo, 2011). Unstable employment trajectories also generate chronic stress and erode economic, social, and behavioral resources, creating a “vulnerability trap” in which detrimental habits become self-reinforcing over time (Becker & Murphy, 1988; Conti & Heckman, 2010). These processes can be interpreted as a gradual erosion of behavioral capital, linking early labor-market shocks to enduring differences in health-related behaviors.

Despite the growing body of evidence on scarring and health capital formation, there remains limited direct and comparative evidence linking local youth unemployment exposure to adult health behaviors. Few studies exploit harmonized cross-country data with region-specific unemployment measures, and none systematically analyze heterogeneity by institutional context. This paper addresses these gaps by combining harmonized SHARE data with regional unemployment indicators to estimate the long-term effects of youth exposure (ages 16–25) on adult health behaviors—including smoking, alcohol consumption, physical activity and vegetables and fruit intake. The analysis further examines underlying mechanisms (income, mental health, and occupational trajectories) and explores heterogeneity by education, gender, and welfare regime.

This study contributes to two distinct literatures. First, it extends the scarring literature by considering long-term behavioral health outcomes as part of the broader consequences of early labor-market conditions (Kahn, 2010; Oreopoulos et al., 2012a). Second, it integrates the health capital framework with the notion that the macroeconomic context during formative years constitutes a key input in the development of behavioral capital (Becker & Murphy, 1988; Grossman, 1972). The resulting evidence provides new insights into how early economic environments shape health inequalities over the life course and suggests policy implications for labor-market and preventive health interventions aimed at mitigating long-term disparities.

4.3 Data

We combine individual-level data from the Survey of Health, Ageing and Retirement in Europe (SHARE) with official national unemployment statistics to construct a harmonized dataset linking early labor-market conditions to adult health behaviors. SHARE is a multidisciplinary longitudinal survey of individuals aged 50, and their partners, and over that collects detailed information on health, socioeconomic status, and demographics across European countries and Israel. We pool all available waves, excluding the SHARELIFE datasets in Wave 3 and part of Wave 7, which lack behavioral outcome data. The resulting harmonized sample includes respondents born between the 1940s and the 1970s, as well as their partners.

Our primary outcomes capture key health-related behaviors associated with long-term morbidity and mortality: smoking, alcohol consumption, physical activity, and fruit and vegetable intake. These behaviors represent both risky (smoking, heavy drinking, sedentary lifestyle) and protective (healthy diet) habits, offering a broad measure of behavioral health capital in later adulthood. Summary statistics for each outcome are reported in Tables A.1- A.4.

Across all health outcomes, the demographic composition of the analytical samples remains broadly comparable. The mean age of respondents consistently falls between 54 and 60 years. Females constitute between 56% and 58% of the participants in most samples, with the notable exception of the 'Smoke Duration' sample, where the female share

is slightly lower at 49% (Table A.1). The average educational attainment is approximately 12 to 13 years, aligning with the completion of secondary education, and mean household income levels robustly cluster around the third quartile of the within-country income distribution. Sample size varies across outcomes, ranging from approximately 10,000 (e.g., Moderate Physical Activity) to 23,000 (e.g., Eating Fruit Often). These variations reflect differences in item-specific non response rather than systemic attrition (in fact some questions are asked only in some waves). Country representation is heterogeneous but broad, as detailed from Table A.1 to Table A.4. Belgium, France, and Spain are relatively overrepresented, with Belgium consistently exhibiting the highest country share (approx. 21%–22% across samples). This heterogeneity is characterized by the clear over representation of Belgium (21%–22%), France (15%–19%), and Spain (13%–18%), which is balanced by the under representation of countries such as Cyprus (0%–2%), Greece (1%–5%), and Finland (0%–5%). This general consistency across key covariates supports the comparability of the data across distinct outcome-specific subsamples.

Each health behavior is defined using standardized self-reported measures harmonized across countries and survey waves. Smoking is coded as one if the respondent reports ever having been a daily smoker. Drinking is a dummy variable equal to one if the respondent reports consuming more than one glass of alcohol per day, in line with WHO thresholds for risky drinking (World Health Organization - WHO, 2018). Physical inactivity is coded as one if the respondent engages in neither moderate nor vigorous physical activity more than once per week, in line with WHO recommendations (World Health Organization - WHO, 2010). Fruit and vegetable intake is coded as one if the respondent reports consuming more than 3–6 portions of fruits or vegetables per week. Descriptive distributions and sample compositions for all variables are presented in Tables A.1–A.4.

Covariates include gender, age, years of education, the respondent’s position in the within-country income quartile distribution, and wave fixed effect. All specifications include country and birth-cohort fixed effects to absorb cross-country heterogeneity in health systems and generational differences in behaviors. All missing data were eliminated from the analysis.

We measure early labor market exposure using age-specific national unemployment rates to capture the effect of macroeconomic conditions on later-life health behaviors. Our primary window of interest is ages 18–25, widely recognized as the critical period for labor market entry (“critical window”), when human capital accumulation and first-job outcomes are most sensitive to economic shocks (Arellano-Bover, 2022; Kahn, 2010; Oreopoulos et al., 2012a). High unemployment during this period can reduce initial job quality and limit skill accumulation, generating persistent effects on earnings and health.

We also consider earlier ages (16–18) to control for potential strategic responses to labor market conditions, such as delayed school completion or postponed labor market

entry (Sievertsen, 2016). Including these younger age windows allows us to isolate the direct effect of unemployment at entry (18–25) from indirect effects mediated through educational decisions (16–18).

Formally, for each respondent, we construct the average national unemployment rate for ages 18–25, complemented by separate rates for ages 16, 17, and 18 as robustness checks. This setup exploits cross-cohort and cross-country variation in macroeconomic exposure while controlling for country and cohort fixed effects.

While it would be interesting to measure exposure to youth unemployment at the regional level, historical data covering ages 16–25 for cohorts born between 1940 and 1970 are not available. As a result, we rely on national unemployment rates as a broad measure of macroeconomic conditions during the initial phase of labor market entry. The choice of these cohorts is motivated by our aim to observe long-term effects of early labor market conditions on adult health.

We also highlight that gender-specific historical unemployment rates are not available for the cohorts and countries analyzed. Therefore, our analysis relies on aggregate national unemployment rates, although incorporating gender-specific measures could be an important extension for future work.

Figure 4.1 shows the evolution of unemployment rates by country, while Figure 4.2 summarizes their cross-country range and coverage.

The final analytic sample covers ten countries: Belgium, Cyprus, Denmark, Finland, France, Greece, Israel, Italy, Spain, and Sweden. Average youth unemployment exposure is 5.5% (SD = 3.1 pp), ranging from 0.7% (Denmark) to 19.2% (Spain), providing substantial variation for identification. Data from additional SHARE countries were excluded due to missing historical unemployment series or inconsistent governance periods.

Health behaviors are measured contemporaneously at the survey waves, while unemployment exposure is constructed retrospectively using respondents' birth year and country. This design allows us to estimate the long-term association between early macroeconomic conditions and adult health behaviors, exploiting both cross-country and cross-cohort variation.

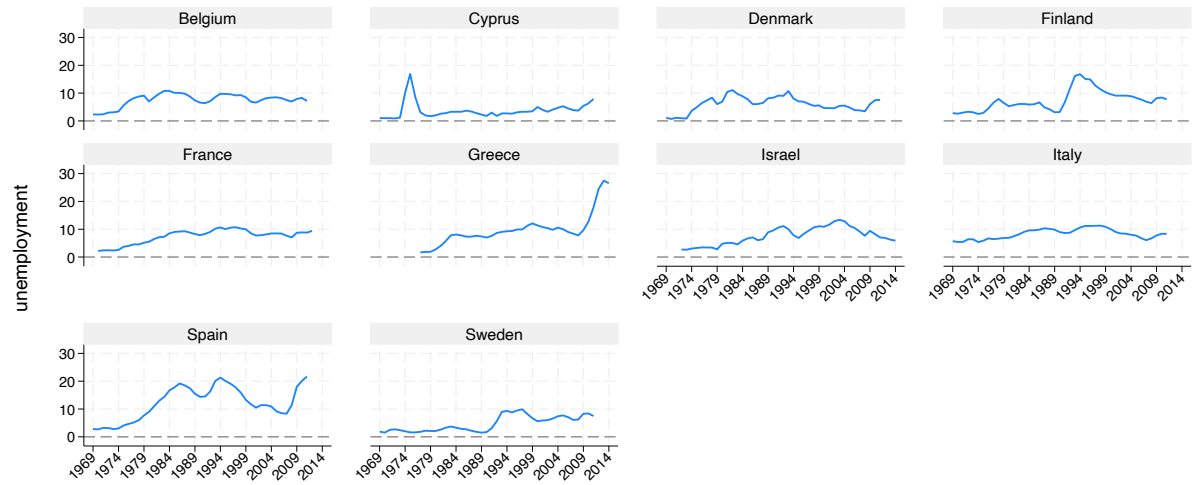


Figure 4.1: Unemployment by Country

Notes: Time series graphs related to unemployment for each country in the sample. Our analysis is restricted to the population covered by the SHARE survey.

Country	MinRate	MaxRate	StartYear	EndYear
Sweden	1.50	5.60	1969	1992
Spain	2.68	19.20	1969	1992
Italy	5.38	10.35	1969	1992
France	2.23	9.28	1970	1992
Denmark	0.73	11.09	1969	1992
Greece	1.69	8.66	1977	1992
Belgium	2.30	10.80	1969	1992
Israel	2.64	11.16	1972	1992
Cyprus	0.90	16.90	1969	1992
Finland	2.50	11.60	1969	1992

Figure 4.2: Unemployment Series Information and Year by Country

Notes: Minimum unemployment rate, maximum unemployment rate, start year, and end year of the unemployment rate series for each country in the sample. The countries are limited to those covered by the SHARE survey. The data come from the OECD, the Statistical Service of Cyprus, the IMF, the ILO, and the Italian National Institute of Statistics.

4.4 Empirical Strategy

To examine the long-run effects of entering the labor market during periods of high unemployment on adult health behaviors, we estimate the following equation:

$$y_{ica} = \beta U_{ic}^{18-25} + \delta_c + \delta_a + \delta_{ca} + \delta_{ca}^2 + X_i' \gamma + \omega_w + \varepsilon_{ica} \quad (4.1)$$

The dependent variable y_{ica} denotes a health-related outcome for individual i , born in cohort (year) a and living in country c , observed in survey wave w . These outcomes include binary indicators for ever smoking (1 if the respondent has ever smoked daily), alcohol abuse (1 if the respondent drink more than 1 glass of alcohol per day on average), and physical activity moderate (numerical variable of moderate number of activities per month or binary variable equal to 1 if the respondents reports vigorous physical activity more than once per week), and daily consumption of fruit and vegetables (binary variable equal to 1 if the respondent reports eating fruit and vegetables more than 3-6 times per week).

Our main regressor of interest, U_{ic}^{18-25} , measures the average exposure to unemployment between ages 18 and 25 for individual i in country c . This variable captures macroeconomic conditions at labor market entry, a critical period for the formation of habits and long-term preferences. In alternative specifications, we replace U_{ic}^{18-25} with unemployment rates at specific ages (U_i^{16} , U_i^{17} , or U_i^{18}) to assess sensitivity to the timing of exposure.

The vector X_i includes standard individual-level controls: a gender indicator equal to one for female respondents, years of completed education (as a continuous variable), and dummy variables for household income quartiles. Income quartiles are constructed based on total household income and range from 1 (lowest) to 4 (highest), capturing the respondent's relative socioeconomic position within the national income distribution.

The specification incorporates a rich set of fixed effects to absorb potential confounding variation. In particular, we include country fixed effects (δ_c) to control for time-invariant country characteristics, cohort fixed effects (δ_a) to capture life-cycle or generational patterns, and country-specific linear and quadratic cohort trends (δ_{ca} and δ_{ca}^2) to flexibly account for differential cohort profiles across countries. In addition, we include survey wave fixed effects (ω_w) to absorb common time shocks across countries and cohorts.

This empirical strategy exploits variation in macroeconomic conditions across countries and cohorts to identify the causal effect of early labor market exposure. The identifying assumption is that, conditional on the rich set of controls and fixed effects, the average exposure to unemployment between ages 18 and 25 is orthogonal to unobserved determinants of adult health behaviors. This assumption is plausible given the inclusion of country and wave fixed effects, flexible country-specific cohort trends, and individual socioeconomic controls.

It is important to acknowledge that our identification strategy may be influenced by certain selection mechanisms. Specifically, the presence of phenomena such as selective attrition, premature mortality, or occupational selection risks introducing non-negligible distortions into the analysis of the long-term effects of youth unemployment. Indeed, it is reasonable to hypothesize that individuals exposed to more severe episodes of unemployment—or those characterized by more fragile health—are less likely to remain within the sample into adulthood or to actively participate in data collection surveys.

Therefore, our analysis would end up focusing on a subset of intrinsically more resilient individuals, underrepresenting the most vulnerable segments of the original population. Likewise, it cannot be ruled out that the difficulties experienced during youth influence subsequent career trajectories, intertwining health outcomes with the type of occupation held in adulthood. Overall, these dynamics suggest that our results should be interpreted as a conservative estimate: the actual negative effect of youth unemployment could be significantly greater than what was detected, given that the observed group represents the most robust and least affected component of the initial sample.

Our specification, which isolates the effect of labor market conditions at the time of entry (U_{18-25}) through the inclusion of country, cohort, and year fixed effects, is framed within the causal identification framework proposed by Arellano-Bover, 2022.

We estimate linear probability models for binary outcomes and OLS regressions for continuous ones. Standard errors are clustered at the country-by-cohort level (defined by the interaction of country and birth year) to account for potential within-cell correlation in unobserved determinants and to reflect the level of variation in our main regressor.

Our study adds to the growing evidence that economic conditions experienced in early life can have lasting consequences in adulthood (e.g., Oreopoulos et al., 2012b; Schwandt and von Wachter, 2019b). While prior work has focused on labor market outcomes, mortality, and general health, we extend this research by documenting behavioral responses—such as smoking, physical inactivity, and diet—that may serve as key mechanisms linking early economic conditions to long-term health disparities.

4.5 Results

4.5.1 Smoking Behavior

Looking at the results in Table 4.1, we can see a persistent scarring effect of adverse labor market entry conditions on adult smoking behavior.

People who faced higher national unemployment rates between ages 18 and 25 were more likely to become daily smokers as adults. The association is strong and statistically significant ($\beta = 0.016$, $p < 0.01$). So, in other words, a one-percentage-point rise in youth unemployment is associated with roughly a 1.6% higher chance of becoming a

daily smoker later in life. Relative to the sample mean ($\bar{Y} \approx 49.3\%$), this absolute increase represents a 3.25% increase in the probability of being a daily smoker.

Unlike earlier studies that looked only at whether people start smoking, we find that the impact of early labor market conditions can last well into adulthood. The U_i^{18-25} measure is also associated with a significantly longer smoking duration ($\beta = 0.427$, $p < 0.05$), corresponding to roughly five additional months of cumulative smoking over the life course. Compared to the mean smoking duration ($\bar{Y} \approx 25.7$ years), this translates to a 1.66% increase in the total duration of smoking. Robustness checks using single-age unemployment rates (ages 16–18) show no consistent significant associations, indicating that the scarring effect arises from cumulative exposure rather than isolated shocks.

Table 4.1: Effects of Youth Unemployment on Smoking

	ever smoke daily				smoking duration			
u(16)	0.004 (0.003)				0.087 (0.192)			
u(17)	0.004 (0.003)				0.067 (0.196)			
u(18)	0.005 (0.003)				0.161 (0.173)			
u(18-25)	0.016*** (0.003)				0.427** (0.180)			
mean(Y)	.488	.49	.492	.493	25.265	25.433	25.633	25.745
SE Clusters	261	271	281	291	204	215	226	236
N	16335	18018	19852	21632	2477	2741	3031	3299

Notes: This table reports coefficients from regressions of health behaviors (ever smoke daily and smoking duration) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.2 Alcohol Consumption

The pattern for alcohol consumption differs from that of smoking (Table 4.2). Exposure to youth unemployment (U_i^{18-25}) is significantly negatively associated with the probability of heavy drinking ($\beta = -0.008$, $p < 0.05$), corresponding to a 0.8 percentage point decrease. Relative to the mean probability of heavy alcohol consumption ($\bar{Y} \approx 17.0\%$), this is equivalent to a 4.71% decrease in the probability of excessive drinking. This reduction is consistent with the pro-cyclicality of alcohol consumption documented in

prior work (D. N. Bell & Blanchflower, 2011; Popovici & French, 2013; Ruhm, 2000). Unlike earlier studies, our results show that these behavioral adjustments are sustained over the long term, rather than reflecting only short-term reactions to economic stress.

Table 4.2: Effects of Youth Unemployment on Drinking

	drinking			
u(16)	-0.002 (0.003)			
u(17)	-0.001 (0.003)			
u(18)	0.000 (0.003)			
u(18-25)	-0.008** (0.004)			
mean(Y)	.171	.17	.17	.17
SE Clusters	257	268	277	288
N	16375	18218	20023	21894

Notes: This table reports coefficients of from regressions of health behaviors (drink 2 or more glasses of alcohol per day - less recent data) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.3 Physical Activity

Youth unemployment negatively affects vigorous physical activity but not overall inactivity (Table 4.3). Specifically, U_i^{18-25} is associated with a lower probability of engaging in vigorous exercise more than once per week ($\beta = -0.008$, $p < 0.01$), equivalent to a 0.8 percentage point decrease. Relative to the sample mean ($\bar{Y} \approx 78.3\%$), this effect represents a 1.02% reduction in the probability of engaging in vigorous physical activity. Significant negative effects are also observed for unemployment at age 18 alone ($\beta = -0.004$, $p < 0.05$). Our findings highlight long-lasting reductions in time-intensive leisure behaviors due to early labor market shocks, extending prior evidence that focused mainly on immediate responses.

Table 4.3: Effects of Youth Unemployment on Physical Activities

	N Moderate physical activities				Vigorous phys.act. more 1xweek			
u(16)	-0.018* (0.009)				-0.004 (0.002)			
u(17)	-0.013* (0.007)				-0.003 (0.002)			
u(18)	-0.007 (0.007)				-0.004** (0.002)			
u(18-25)	0.006 (0.008)				-0.008*** (0.002)			
mean(Y)	1.552	1.558	1.556	1.562	.789	.787	.784	.783
SE Clusters	238	248	258	268	267	277	287	297
N	7261	8148	9120	10043	18887	20795	22866	24865

Notes: This table reports coefficients from regressions of health behaviors (Number of moderate physical activities in a month and Vigorous activities more than one per week) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5.4 Fruit and Vegetable Intake

Individuals who experienced youth unemployment also tend to have slightly poorer diets, indicating lasting effects on eating habits (Table 4.4). U_i^{18-25} is negatively and significantly correlated with frequent consumption of fruits and vegetables ($\beta = -0.005$, $p < 0.01$), corresponding to a 0.5 percentage point reduction in the probability of consuming these items more than three times per week. Relative to the sample mean

($\bar{Y} \approx 93.6\%$), this is equivalent to a 0.53% decrease in the probability of frequent consumption. By examining long-term dietary patterns, our results complement prior studies that primarily document short-term nutritional responses to economic constraints.

Table 4.4: Effects of Youth Unemployment on Physical Inactivity and Consumption of Fruit and vegetables

	Consumption of fruit and vegetables often			
u(16)	0.000 (0.001)			
u(17)	-0.000 (0.001)			
u(18)	-0.001 (0.001)			
u(18-25)	-0.005*** (0.002)			
mean(Y)	.937	.938	.937	.936
SE Clusters	231	241	251	261
N	15477	16928	18501	20024

Notes: This table reports coefficients from regressions of health behaviors (consumption of fruit and vegetables often) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our findings demonstrate that adverse labor market conditions during the transition to adulthood have long-lasting and behavior-specific effects on adult health. Early exposure to high unemployment increases the probability of being a daily smoker by 3.25% (relative to the mean) and significantly lengthens smoking duration; on the other hand, it decreases the probability of heavy drinking by 4.71% and leads to small but significant reductions in healthy behaviors, such as a 1.02% drop in vigorous physical activity and a 0.53% decrease in frequent fruit and vegetable consumption.

Our results suggest that the effects of early economic shocks are not just short-term, but they can have effect also later in life, since last into mid-adulthood, leaving a kind of lasting ‘scar’ on behavior. These patterns emphasize heterogeneous behavioral responses and provide novel evidence on the long-term health consequences of youth labor market conditions.

4.6 Mechanisms

While the main empirical results document a relationship between youth unemployment exposure and adult health behaviors, the mechanisms linking these outcomes cannot be fully identified within our empirical framework. The analyses presented in this section should therefore be interpreted as suggestive evidence on potential channels rather than as definitive causal mediation effects.

The retrospective life-history information collected in the SHARELIFE waves (wave 3 e wave 7) allows us to reconstruct episodes of stress and mental health conditions over the life course. Although SHARELIFE waves are not used for the main behavioral outcomes, these data provide valuable information to explore potential pathways linking early labor market conditions to later-life health behaviors.

To unpack the pathways underlying our main results, this section examines the channels through which youth exposure to unemployment (U_i^{18-25}) affects adult health-related behaviors. Drawing on contemporary economic and public-health literature, we focus on three principal mechanisms: *psychological stress and coping*, *financial and social capital constraints*, and *time-allocation and environmental constraints*. Each mechanism is then linked to our empirical evidence.

4.6.1 Psychological Stress and Coping

Previous studies suggest that economic shocks in early adulthood can create lasting stress, which may lead people to adopt unhealthy behaviors as a way of coping (De Vogli & Santinello, 2005; Falba et al., 2005; Gruber & Köszegi, 2001; Richards et al., 2011). For example, youth unemployment has been linked to higher smoking initiation and lower cessation rates.

In our sample, we find strong empirical support for this mechanism. Exposure to U_i^{18-25}

is positively associated with the probability of experiencing at least one stressful life event (“ever stress”) with $\beta = 0.008$, $p < 0.10$, and significantly associated with longer stress duration (“stress dur”) with $\beta = 0.473$, $p < 0.05$ (from Table 4.5 to Table 4.7). Economically, this implies that youth labour-market adversity increases adult stress duration by approximately five to six months on average.

Additionally, we observe a positive association between U_i^{18-25} and self-reported depressive symptoms in adulthood (“ever depressed”), with a coefficient of $\beta = 0.006$, $p < 0.10$ (Table 4.8). Economically, this implies that youth labour-market adversity increases both stress and depression duration, raising the overall psychological burden by several months on average.

These findings are consistent with the hypothesis that persistent stress may increase reliance on coping behaviors such as smoking and it could reduce the capacity or willingness to invest in healthier long-term behavior. Within a rational-addiction framework (Becker & Murphy, 1988), smoking habits adopted as a coping response become locked-in, explaining why we observe a positive effect of youth unemployment on adult smoking even when other health behaviors move in the opposite direction.

Table 4.5: Effects of Youth Unemployment on Smoking
- Stress Mechanism

	everstress				stress_dur			
u(16)	0.010 (0.012)				0.510* (0.306)			
u(17)	0.003 (0.013)				0.560** (0.257)			
u(18)	0.009 (0.011)				0.582** (0.244)			
u(18-25)	0.008 (0.011)				0.473* (0.248)			
mean(Y)	.611	.603	.604	.605	8.17	8.394	8.602	8.569
SE Clusters	157	166	175	182	143	151	159	167
N	1858	2323	2846	3327	1115	1374	1684	1970

Notes: This table reports coefficients from regressions of health behaviors (ever stress period and stress duration) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.6: Effects of Youth Unemployment on Smoking
Stress Mechanism

	stress start				stress end			
u(16)	-0.098 (0.338)				0.349 (0.385)			
u(17)	-0.129 (0.337)				0.329 (0.347)			
u(18)	0.051 (0.307)				0.565* (0.324)			
u(18-25)	0.060 (0.334)				0.619* (0.348)			
mean(Y)	38.683	38.825	39.262	39.546	46.834	47.176	47.834	48.083
SE Clusters	145	153	162	170	145	153	161	169
N	1129	1391	1706	1997	1127	1389	1702	1993

Notes: This table reports coefficients from regressions of health behaviors (stress start and stress end) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.7: Effects of Youth Unemployment on Smoking
- Stress Mechanism

	stress now			
u(16)	0.013 (0.015)			
u(17)	0.022* (0.013)			
u(18)	0.023* (0.012)			
u(18-25)	0.020 (0.014)			
mean(Y)	.267	.266	.266	.26
SE Clusters	145	153	161	169
N	1127	1389	1702	1993

Notes: This table reports coefficients from regressions of health behaviors (current stress period) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.8: Effects of Youth Unemployment on Smoking - Depression Potential Mechanism

	high depression			
u(16)	-0.001 (0.001)			
u(17)		0.001 (0.001)		
u(18)			0.002 (0.001)	
u(18-25)				0.003* (0.002)
mean(Y)	.172	.171	.169	.169
SE Clusters	267	277	287	297
N	18888	20796	22867	24865

Notes: This table reports coefficients from regressions of health behaviors (high level of depression in general during their life stress period) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6.2 Financial Constraints and Social Participation

A second mechanism concerns enduring budget constraints and diminished social capital stemming from early labour-market setbacks. Prior work indicates that consumption of discretionary goods—alcohol, fruits, and vegetables—declines during economic slumps, and that social interaction plays a key role in shaping health behaviors (Arellano-Bover, 2022; D. N. Bell & Blanchflower, 2011; Popovici & French, 2013; Ruhm, 2000).

It should be noted that the financial and social variables used in this section are measured in adulthood. Therefore, they describe what could be the mechanism affecting current behavior, and we cannot assume that this mechanism has been fully consolidated or persistent over the life course. We simply note that the budget-constraint hypothesis is compatible with the evidence: individuals who experienced higher levels of youth unemployment are also those who later in life exhibit lower wealth and income. As such, the evidence from these variables should be interpreted as suggestive and interpretative.

Our results show that exposure to youth unemployment (U_i^{18-25}) has persistent effects on adult economic outcomes. Total adult income is significantly lower, with $\beta = -327.34$ ($p < 0.05$, Table 4.9), and wealth—proxied by house value—is also reduced, $\beta = -8,770.78$ ($p < 0.01$, Table 4.10). This evidence of long-term scarring implies tighter lifetime budget constraints for those exposed to early unemployment.

In addition to lower income and wealth, individuals exposed to youth unemployment also display a lower accumulation of pension wealth and higher reliance on unemployment benefits in adulthood (Table 4.11). These patterns are consistent with the expectation that early labor-market shocks constrain long-term savings, reduce contributions to pension schemes, and increase dependency on public transfers, reinforcing the lifetime budget constraints that shape health behaviors.

Table 4.9: Effects of Youth Unemployment on Employment and Self Empl Income

	ydip				ytot			
u(16)	101.38 (112.95)				126.69 (123.04)			
u(17)	52.99 (101.93)				39.61 (112.09)			
u(18)	-24.85 (95.42)				-1.28 (106.36)			
u(18-25)	-213.65** (91.88)				-327.34** (148.13)			
mean(Y)	10812	10260	9716	9257	12666	12063	11468	10959
SE Clusters	267	277	287	297	267	277	287	297
N	18890	20798	22869	24867	18890	20798	22869	24867

Notes: This table reports coefficients from regressions of Employment and Self-Employment Job Income on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.10: Effects of Youth Unemployment on Home Value

	home value			
u(16)	-3439.239** (1693.456)			
u(17)	-3635.913** (1534.492)			
u(18)	-4411.935*** (1414.942)			
u(18-25)	-8770.775*** (1185.690)			
mean(Y)	195187.551	194449.968	194437.558	194563.936
SE Clusters	267	277	287	297
N	18890	20798	22869	24867

Notes: This table reports coefficients from regressions of Employment and Self-Employment Job Income on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.11: Effects of Youth Unemployment on Pension and Unemployment benefits

	Private and Occ Pension				Unemployment Benefits			
u(16)	-19.060 (11.584)				-14.482 (18.621)			
u(17)	-11.192 (12.287)				6.775 (15.495)			
u(18)	-17.663* (10.103)				5.296 (17.875)			
u(18-25)	-21.532 (14.479)				61.241*** (21.477)			
mean(Y)	304.006	372.44	426.467	471.985	421.588	416.293	401.213	378.953
SE Clusters	267	277	287	297	267	277	287	297
N	18890	20798	22869	24867	18890	20798	22869	24867

Notes: This table reports coefficients from regressions of Number of children on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We further document that U_i^{18-25} is negatively associated with adult social participation ($\beta = -0.012$, $p < 0.05$, Table 4.12), indicating reduced social networks and opportunities for group-based or socially mediated activities.

In this situation, alcohol consumption tends to decline: it is a non-essential, socially driven expense that people with limited resources are more likely to cut. Fruit and vegetable intake declines due to higher price-elasticity and the time required for preparation. Vigorous physical activity decreases as social capital and available resources are reduced, though overall inactivity does not rise.

These results indicate that both budget constraints and social capital losses help explain observed declines in alcohol use, diet quality, and vigorous exercise following youth unemployment.

Table 4.12: Effects of Youth Unemployment on Drinking
- Sociality Possible Mechanism

	N Social activities last y				Vigorous phys.act. more 1xweek			
u(16)	-0.008 (0.009)				-0.004 (0.002)			
u(17)	-0.018** (0.007)				-0.003 (0.002)			
u(18)	-0.011* (0.007)				-0.004** (0.002)			
u(18-25)	-0.008 (0.009)				-0.008*** (0.002)			
mean(Y)	2.17	2.155	2.142	2.128	.789	.787	.784	.783
SE Clusters	237	247	257	267	267	277	287	297
N	17714	19355	21124	22818	18887	20795	22866	24865

Notes: This table reports coefficients from regressions of health behaviors (Vigorous Physical activities more than 1 per week now) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6.3 Placebo Tests: Early-Life Conditions

To further assess the plausibility of a causal interpretation of our main results, we implement placebo tests using pre-determined childhood characteristics. If exposure to youth unemployment were capturing unobserved individual traits or pre-existing socioeconomic conditions, we might observe a correlation between U_i^{18-25} and variables determined well before labor-market entry.

Using the retrospective SHARELIFE information (wave 3 and wave 7), we therefore test whether youth unemployment exposure predicts two early-life conditions: self-reported health status at age 15 and the occupation of the main household breadwinner when the respondent was ten years old. These variables are determined prior to the age window in which youth unemployment exposure occurs and should therefore not be affected by it.

The empirical specification mirrors our baseline regressions. If the estimated coefficients on U_i^{18-25} are statistically insignificant, this supports the interpretation that our main results are not driven by pre-existing childhood disadvantages but instead reflect the impact of early labor-market conditions.

The results of these placebo regressions are summarized in Table 4.13. As we can see

from the table, exposure to youth unemployment shows no statistical association with either health status at age 15 or the occupational position of the household head during the respondent’s childhood. Across all specifications, the estimated coefficients are of negligible magnitude and are not statistically distinguishable from zero.

This evidence confirms the robustness of our framework: indeed, it is unlikely that the link between youth employment shocks and health behaviors in adulthood is mediated by pre-existing childhood disadvantages or by latent characteristics of the family background. In particular, the absence of a systematic correlation with parental socioeconomic status and early-life health conditions suggests that our estimates are not simply capturing differences inherited prior to labor market entry.

Overall, the outcome of these tests reinforces the credibility of our empirical strategy. The results support the notion that the effects documented in the main analysis reflect the genuine impact of conditions encountered during the early stages of one’s career, rather than individual trajectories already predetermined by prior factors.

Table 4.13: Placebo Tests: Pre-Determined Childhood Characteristics

	MainParent_job_w3				health15			
u(16)	0.043 (0.076)				-0.000 (0.000)			
u(17)	0.045 (0.071)				0.000 (0.000)			
u(18)	0.074 (0.059)				0.000 (0.000)			
u(18-25)	-0.069 (0.055)				0.000 (0.001)			
mean(Y)	6.25	6.264	6.275	6.292	.922	.923	.923	.924
SE Clusters	155	164	173	180	267	277	287	297
N	1831	2285	2799	3281	18889	20797	22868	24866

Notes: The table reports placebo regressions using pre-determined childhood characteristics as dependent variables: the occupation of the main household breadwinner at age 10 (columns 1–4) and self-reported health status at age 15 (columns 5–8). The empirical specification mirrors the baseline regressions. Data are drawn from SHARELIFE (waves 3 and 7). Standard errors clustered at the region-cohort level in parentheses. ***p<0.01; **p<0.05; *p<0.1.

4.6.4 Behavioral Trade-offs and Policy Implications

Our evidence suggests that early exposure to unemployment can shape adult health behaviors through multiple interacting channels. The increase in adult smoking ap-

pears to be primarily driven by psychological stress and coping, individuals exposed to youth unemployment experience persistent stress, which they mitigate through smoking, leading to habits that are reinforced and persist over time. In contrast, declines in alcohol consumption, fruit and vegetable intake, and vigorous physical activity could be largely explained by budgetary and social time constraints.

These mechanisms are not mutually exclusive, in fact, early labor-market adversity may simultaneously raise stress, limit resources, reduce social engagement, and change how people allocate their time, leading to heterogeneous behavioral responses across different health behaviors. Investigating and try to recognize these different channels is essential in order to understand how to intervene, especially from a policy design prospective. Interventions may need to address stress-relief and addiction prevention for smoking, while targeting resources, social-network restoration, and habit formation for diet, activity, and alcohol-use pathways.

4.7 Heterogeneity and Robustness Checks

In order to investigate our main results, we implement some analysis related to the heterogeneity of our results in different subgroups and we implement some robustness check on our previous analysis. For the heterogeneity analysis we focus on smoking outcomes in order to describe better the only behavior that is moving in the opposite way rather than the others health behaviors. The analyses in this section serve both to validate the causal interpretation of the effects and to shed light on mechanisms through which youth unemployment (U_i^{18-25}) translates into long-term health behaviors.

4.7.1 Heterogeneity by Education, Gender, and Income

We begin by examining the role of key socioeconomic and demographic characteristics in shaping susceptibility to smoking as a coping response. Our estimates indicate that the scarring effect of youth unemployment on the probability of ever smoking daily is significantly moderated by educational attainment. In particular, the interaction between U_i^{18-25} and years of education (Edu) is negative and statistically significant ($\beta = -0.001$, $p < 0.05$; Table 4.14), suggesting that individuals with lower levels of education experience more pronounced behavioral scarring. This pattern is in line with the idea that higher education confers psychological resilience, improved long-term planning, and a greater awareness of the health costs of smoking, making highly educated individuals less vulnerable to stress-induced unhealthy behaviors.

Also for gender differences, there is a relevant disparities. The interaction between U_i^{18-25} and a female indicator (Female) is positive and marginally significant ($\beta = 0.007$, $p < 0.1$; Table 4.15), suggesting that women are slightly more affected to smoking initiation following youth unemployment. This finding is consistent with prior evidence on gender-specific stress responses and coping mechanisms, whereby women may internalize stress differently and exhibit stronger behavioral reactions in the form of health-risk behaviors.

Finally, we explore heterogeneity by adult income as a measure of ex-post economic recovery. Surprisingly, the interaction between U_i^{18-25} and the highest adult income quartile (Income Q4) is positive and significant for smoking duration ($\beta = 0.593$, $p < 0.05$; Table 4.16). This implies that even among individuals who recover economically, the smoking habit acquired during stressful youth unemployment persists. This persistence may reflect a locked-in coping mechanism, where the financial cost of maintaining the habit is negligible for individuals with higher income, underling that behavioral scars related to stress are not fully mitigated by subsequent income gains, otherwise can be support by them.

These heterogeneity analyses are in line and highlights the possible centrality of persistent psychological stress in driving the smoking response, and they identify lower education, female gender, and high-income adults (conditional on smoking) as key groups experiencing differentiated effects in long-term. These results are consistent with

Table 4.14: Heterogeneity of the Effect of Youth Unemployment on Smoking by Education

	daily smoking	smoke duration
U 18–25	0.023*** (0.005)	0.290 (0.329)
Education Years	0.001 (0.002)	-0.540*** (0.140)
Unemp $\times$ Edu	-0.001** (0.000)	0.012 (0.020)
N	21633	3300
Controls	V	V
Mean(Y)	0.493	25.742
SD(Y)	0.500	13.372
Clusters	291	236

Notes: This table reports coefficients of heterogeneity test by Education from regressions of health behaviors (daily smoking and smoke duration in year) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.15: Heterogeneity of the Effect of Youth Unemployment on Smoking by Gender

	daily smoking	smoke duration
Unemployment 18–25	0.011*** (0.004)	0.307 (0.217)
Female	-0.180*** (0.020)	-3.728*** (1.259)
Unemployment $\times$ Female	0.007*** (0.003)	0.227 (0.181)
N	21631	3298
Controls	V	V
Mean(Y)	0.492	25.744
SD(Y)	0.500	13.372
Clusters	291	236

Notes: This table reports coefficients of the heterogeneity test by Gender from regressions of health behaviors (daily smoking and smoke duration in year) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the broader mechanisms analysis: stress-coping primarily shapes smoking outcomes, whereas budget and social capital constraints dominate alcohol, diet, and physical-activity channels.

4.7.2 Robustness Check

We conduct an extensive set of robustness analyses to ensure that our findings are not driven by model specification, measurement choices, or sample composition. All robustness tables are reported in Appendix B, except for those related to robustness check 4.7.2, which appear in Section 4.5.

Alternative Measures of Youth Unemployment Exposure

As a first step, we check whether our results change depending on how we define exposure to youth unemployment. The tables in the section results report estimates using one-year unemployment rates at ages 16, 17, and 18, as well as the cumulative average over ages 18–25. Looking at all the outcomes, being exposed to tough labor market conditions between ages 18 and 25 seems to have a lasting impact on adult health behaviors. In contrast, experiencing unemployment in just one year between ages 16 and 18 doesn’t show clear or consistent effects, (except for some changes in moderate and vigorous physical activity).

For daily smoking (Table 4.1), unemployment at ages 16–18 remains positive but yields small and statistically insignificant coefficients. This aligns with the idea, where one-year exposures show no meaningful association with the probability of ever smoking daily. In contrast, the cumulative measure U_i^{18-25} remains positive and highly significant.

For smoking duration (Table 4.1), the pattern is similar: the single-year unemployment coefficients at ages 16, 17, and 18 remain positive, but are smaller in magnitude and statistically insignificant. Again, the cumulative measure exhibits a large and highly significant coefficient.

For alcohol consumption (Table 4.2), the cumulative measure of exposure consistently emerges as the strongest predictor of later behavior. For heavy drinking—the outcome analyzed in the main text—the cumulative measure U_i^{18-25} is significantly negative, whereas single-age exposures are negative, but smaller and statistically insignificant.

Physical activity (Table 4.3) is the only domain showing a different pattern. For moderate physical activity, the coefficients are negative and significant for unemployment at ages 16 and 17, while for age 18 and cumulative exposure over ages 18–25 the coefficients are not statistically significant. For vigorous physical activity, the opposite pattern emerges: unemployment at age 18 and cumulative exposure over ages 18–25 generate negative and significant coefficients, whereas unemployment at ages 16 and 17 remains negative but statistically insignificant. Our results suggest that cumulative ex-

Table 4.16: Heterogeneity of the Effect of Youth Unemployment on Smoking by Income

	daily smoking	smoke duration
u18_25	0.017*** (0.005)	0.004 (0.300)
Income Q2	-0.006 (0.030)	-1.257 (2.104)
Income Q3	0.028 (0.029)	-5.210*** (1.969)
Income Q4	-0.033 (0.031)	-7.231*** (1.853)
Unemp $\times$ Income Q2	0.000 (0.005)	0.054 (0.277)
Unemp $\times$ Income Q3	-0.005 (0.004)	0.469 (0.299)
Unemp $\times$ Income Q4	-0.001 (0.005)	0.593** (0.266)
N	21631	3298
Controls	V	V
Mean(Y)	0.492	25.744
SD(Y)	0.500	13.372
Clusters	291	236

Notes: This table reports coefficients of heterogeneity test by Income from regressions of health behaviors (daily smoking and smoke duration in year) on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

posure has the largest and most consistent impact on vigorous activity, while moderate activity does not show a comparable long-term response.

The robustness checks for dietary behavior (Table 4.4) reveal a consistent negative association only for the cumulative measure U_i^{18-25} . All single-age exposures remain negative, but small and statistically insignificant.

These findings reinforce the conclusion that persistent exposure—rather than isolated annual shocks—drives long-term health behavior patterns.

Robustness Check: Controlling for Lifetime Country Mobility

To further validate our core findings, we conduct a robustness check by introducing a control for whether individuals have never changed their country of residence over their lifetime. This approach ensures that exposure to local youth unemployment rates across different age cohorts is consistent for each individual, thereby eliminating potential biases introduced by mobility. A summary figure for these analyses is presented 4.3, while additional, more detailed tables are available in 4.9 of the paper.

The estimated coefficients remain broadly consistent in direction with the main results, although statistical significance is reduced in many cases due to the smaller sample size. In particular, the reduction in observations is substantial for smoking duration, where the number of individuals decreases from over 10,000 to approximately 657 for u(16), which likely contributes to the loss of statistical significance.

For ever smoking daily (Table B.1), the youngest cohort u(18–25) retains a positive and highly significant coefficient ($\beta = 0.020$; $p < 0.001$; $\text{mean}(Y) = 0.480$), corresponding to a +4.17% increase in the probability of being a daily smoker, confirming the main finding.

Smoking duration (Table B.1) coefficients remain positive across all age groups, ranging from +0.122 (u17) to +0.390 (u16). For unemployment at age 16, this implies a +1.40% increase relative to the sample mean of 27.83. While these coefficients are economically meaningful, statistical significance is largely absent due to the dramatic reduction in sample size, which limits statistical power.

For regular alcohol consumption (Table B.2), the coefficients are not statistically significant. In this case, the only coefficient that retains the magnitude of the main model is for the cumulative cohort u(18–25), which exhibits a negative coefficient ($\beta = -0.009$), representing a -4.55% change relative to the mean. However, again, this effect is not statistically significant.

Physical activity (Table B.3) results for both measures lose their statistical significance. Vigorous activity coefficients are mostly negative, but u(18) is marginally positive and significant ($\beta = +0.014$; $\text{mean}(Y) = 0.592$; $p < 0.10$; +2.36%). Moderate activity shows negative coefficients across the board, but for u(18–25) ($\beta = +0.011$; $\text{mean}(Y) =$

1.557; +0.71%), we observe a positive, non-significant coefficient. It is also important to underline that the sample size is substantially reduced in this case.

For frequent fruit consumption (fruit and vegetables often, Table B.4), the coefficients are consistently negative across all age cohorts. For the youngest cohort, u(16), the coefficient is $\beta = -0.003$, which is weakly significant ($p < 0.10$). The magnitude of the effect is less than -0.5% of the sample mean. Similar coefficients are observed for the cumulative cohort u(18–25) ($\beta = -0.004$) and the other cohorts. Here, we lose half of the population, but the number of observations remains large (N between 9,897 and 13,355).

Therefore, even when we look only at individuals who never moved countries, the main results remain consistent, showing that geographic mobility does not drive our main findings. Although statistical significance is generally not present, the direction and economic magnitude of the estimated effects remain consistent with the baseline analysis. This robustness check is consistent with the interpretation that adverse labor market conditions during the ages of 18–25 exert persistent effects on adult health behaviors.

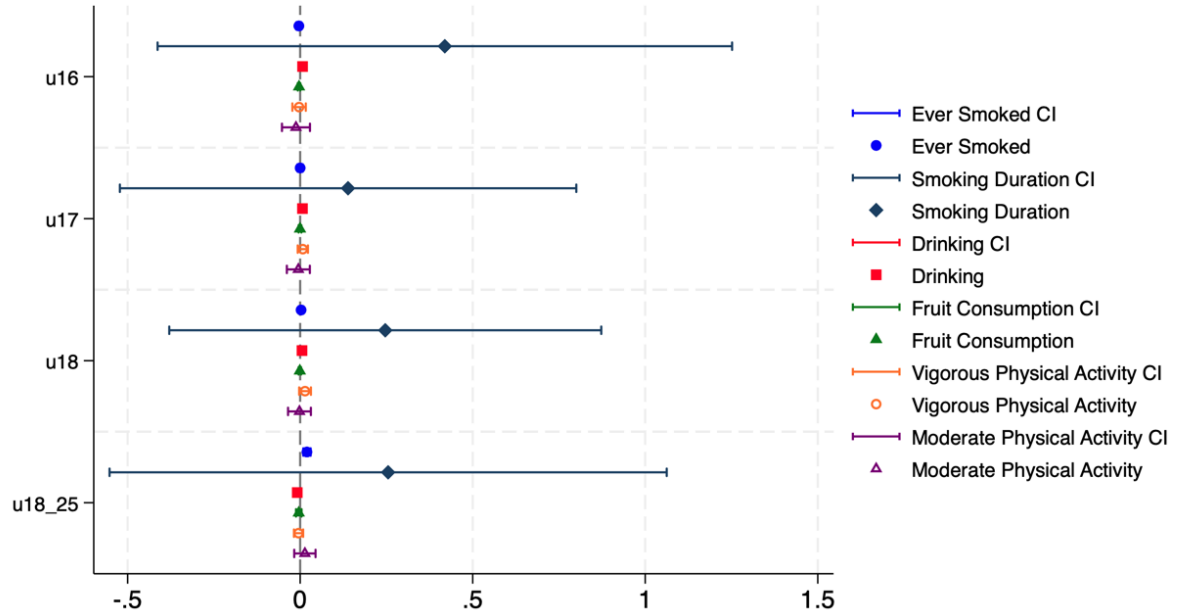


Figure 4.3: Robustness Check - unemployment on Health Behaviors

4.8 Other Long-Term Health and Labor Outcomes

Beyond the behavioral adjustments discussed in Section 4.6 (smoking, alcohol, diet, and physical activity), exposure to youth unemployment (U^{18-25}) has an effect later in

life also on other outcomes, as adult health and labor-market outcomes. This section examines two key dimensions for these fields: chronic disease prevalence and the physical nature of adult work, providing a link between early behavioral responses and long-term health and socioeconomic consequences.

4.8.1 Health Outcomes: Chronic Diseases

We first examine long-term health outcomes, measured by both the mean number of reported chronic conditions and the probability of reporting more than two chronic conditions, which has a sample mean of approximately 37.1%. The effects of youth unemployment on chronic disease are concentrated at specific ages rather than across the full U^{18-25} exposure. In particular, unemployment at age 17 (U^{17}) is associated with an increase in the mean number of chronic conditions in adulthood by 1.7% (Table 4.17). When focusing on comorbidity, U^{17} increases the probability of having more than two chronic conditions by 0.6%, corresponding to a 1.69% rise over the sample mean. Exposure at age 18 (U^{18}) also shows a significant effect on comorbidity, 0.5%, implying a 1.35% increase over the mean. These our findings suggest that early labor-market shocks influence long-term health not only through the adoption of risky behaviors, such as smoking as a stress-coping mechanism (Section 4.6.1), but also other health related conditions in long-term through critical windows.

4.8.2 Labor-Market Outcomes: Physically Demanding Work

Additionally, through our analysis we can see that also adult occupational characteristics are affected by early unemployment. Higher average exposure to youth cumulative unemployment (U^{18-25}) increases the probability of working in physically demanding jobs by $\beta = 0.013^{**}$, corresponding to a 2.84% increase the mean per percentage point of youth unemployment (Table 4.18). Exposure at age 18 (U^{18}) has an even larger effect, with $\beta = 0.016^{***}$, which translates to a 3.50% higher probability of being employed in a physically demanding occupation from the mean. This occupational outcome coincides with a reduction in total adult income of $\beta = -327.34^{**}$ (annual income after tax in Table 4.9), highlighting that early labor-market shocks channel individuals into lower-quality, more physically demanding occupations. These kind of jobs constitute an additional risk factor for health, reinforcing the effects of earlier behavioral responses and contributing to the accumulation of chronic health conditions.

4.8.3 Integrated Pathways

These results show that exposure to youth unemployment increases psychological stress, which in turn promotes smoking and other coping behaviors. Due to financial and social capital constraints we observe a reduction in engagement in health-promoting behaviors such as diet quality and physical activity. These behavioral changes, combined with labor market conditions, lead to higher rates of chronic disease and a greater likelihood of

Table 4.17: Effects of Youth Unemployment on Chronic Disease

	n chronic disease				More than 2 chronic disease			
u(16)	0.005 (0.008)				0.005** (0.002)			
u(17)	0.017** (0.008)				0.006*** (0.002)			
u(18)	0.012** (0.006)				0.005** (0.002)			
u(18-25)	-0.000 (0.007)				0.001 (0.003)			
mean(Y)	1.294	1.314	1.336	1.36	.35	.356	.363	.371
SE Clusters	267	277	287	297	267	277	287	297
N	18890	20798	22869	24867	18890	20798	22869	24867

Notes: This table reports coefficients from regressions of Employment and Self-Employment Job Income on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses.

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

Table 4.18: Effects of Youth Unemployment on Job Physical Demanding

	jobph_n				jobph_d			
u(16)	0.011 (0.010)				0.009** (0.004)			
u(17)	0.010 (0.011)				0.010** (0.005)			
u(18)	0.020** (0.009)				0.016*** (0.004)			
u(18-25)	0.024** (0.011)				0.013** (0.005)			
mean(Y)	2.411	2.411	2.416	2.421	.451	.452	.455	.457
SE Clusters	239	249	257	265	239	249	257	265
N	5630	5994	6358	6679	5630	5994	6358	6679

Notes: This table reports coefficients from regressions of Job physical demanding on unemployment experience at different ages. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

occupying physically demanding jobs in adulthood. Specifically, early exposure at ages 17 and 18 significantly increases the number of chronic conditions and the probability of comorbidity. While average exposure across ages 18 to 25 raises the probability of physically demanding work by almost 3% per point increase in youth unemployment. The resulting occupational and health outcomes demonstrate how early labor-market adversity propagates through multiple channels to produce long-term disadvantages in both health and economic status.

4.9 Conclusions and Policy Implications

This study examined the long-term effects of adverse labor-market entry conditions, measured through exposure to youth unemployment (ages 18–25), on health behaviors, chronic conditions, and labor-market outcomes in adulthood. Using harmonized panel data from the SHARE project linked to country- and cohort-specific unemployment rates, we provide robust evidence of the persistence of these early economic shocks. Our results show that early economic adversity leaves a lasting and multidimensional impact on individual well-being.

In terms of health, exposure to higher youth unemployment increases the probability of daily smoking by 3.25% and extends smoking duration, while reducing excessive alcohol

consumption (-4.7%), vigorous physical activity (-1%), and frequent fruit and vegetable intake (-0.5%). These changes suggest an overall shift in lifestyle likely driven by stress and reduced resources to maintain healthy habits.

Labor-market outcomes are similarly affected. Cumulative exposure to youth unemployment increases the likelihood of working in physically demanding occupations ($\beta = 0.013$, a 2.84% increase relative to the sample mean) and reduces adult income ($\beta = -327.34$). Early unemployment also diminishes social participation ($\beta = -0.008$) and the accumulation of financial resources, including home wealth ($\beta = -8,770.78$) and private pensions ($\beta = -21.532$), while increasing reliance on unemployment benefits ($\beta = 61.241$).

We also analyze heterogeneity to understand how these effects differ across individuals and why it matters: exposure to early unemployment disproportionately affects those with lower educational attainment and lower initial household income, amplifying pre-existing disparities and showing that early economic shocks interact with socioeconomic conditions to exacerbate long-term inequalities.

These our findings show that approaching and try to address these issues probably requires more than one approach and probably tailored ones. Programs that reduce stress and encourage healthier habits could help, by quitting smoking or staying active. Active labor-market policies, including vocational training, targeted hiring subsidies, and career counseling, can help and redirect affected youth toward less physically demanding and better-compensated occupations. Targeted support for disadvantaged individuals can help to reduce intergenerational inequalities by mitigating the behavioral and occupational consequences of early unemployment. Timely measures and interventions that prevent increased youth unemployment would produce substantial improvements in population health and long-term earnings.

Therefore, in order to prevent the cascading effect by youth unemployment that alter lifestyle choices and career trajectories, we can adopt policies that are able to take care about the heterogeneity of these effect, which have significative long term consequences on health and economic inequalities.

Appendix A - Descriptive Statistics

Table A.1 through Table A.4 report summary statistics for the main analytical samples, including mean, standard deviation, minimum, and maximum values for each variable.

Table A.1: Descriptive Statistics: Ever Smoke and Smoke Duration

	Ever smoked			Smoke duration		
	Count	Mean	SD	Count	Mean	SD
Age	21633	60.07	6.18	3300	56.33	5.84
female	21633	0.57	0.50	3300	0.49	0.50
Years of education	21633	12.46	4.14	3300	12.11	3.93
thinc_quartile	21633	2.95	1.04	3300	2.97	1.06
Belgium	21633	0.22	0.42	3300	0.21	0.41
Cyprus	21633	0.02	0.13	3300	0.00	0.07
Denmark	21633	0.12	0.33	3300	0.14	0.35
Finland	21633	0.05	0.22	3300	0.02	0.15
France	21633	0.16	0.37	3300	0.19	0.39
Greece	21633	0.05	0.21	3300	0.05	0.22
Israel	21633	0.03	0.17	3300	0.04	0.19
Italy	21633	0.13	0.34	3300	0.10	0.31
Spain	21633	0.13	0.33	3300	0.14	0.35
Sweden	21633	0.09	0.28	3300	0.09	0.29

Notes: These are the summary statistics for individuals included in the regression sample for the dependent variable *Ever smoke daily and Smoking duration*, i.e., only those with non-missing values on all covariates and residing in countries with sufficient time-series data on unemployment. The means and standard deviations reported are computed on the estimation sample (i.e., the sample actually used in the regressions). The income variable (*thinc_quartile*) is coded into quartiles based on total household income within each country, with values ranging from 1 (lowest) to 4 (highest). Education is a continuous variable corresponding to completed years of schooling.

Table A.2: Descriptive Statistics: drinking more than 1 glass per day

	Drink more than 1 glass per day		
	Count	Mean	SD
Age	16540	53.85	4.28
female	16540	0.58	0.49
Years of education	16540	12.02	4.12
thinc_quartile	16540	3.01	1.07
Belgium	16540	0.21	0.41
Cyprus	16540	0.00	0.00
Denmark	16540	0.14	0.35
Finland	16540	0.00	0.00
France	16540	0.16	0.37
Greece	16540	0.01	0.10
Israel	16540	0.04	0.20
Italy	16540	0.14	0.35
Spain	16540	0.18	0.39
Sweden	16540	0.11	0.31

Notes: These are the summary statistics for individuals included in the regression sample for the dependent variable *Drinking more than 1 alcohol glass per day*, i.e., only those with non-missing values on all covariates and residing in countries with sufficient time-series data on unemployment. The means and standard deviations reported are computed on the estimation sample (i.e., the sample actually used in the regressions). The income variable (*thinc_quartile*) is coded into quartiles based on total household income within each country, with values ranging from 1 (lowest) to 4 (highest). Education is a continuous variable corresponding to completed years of schooling.

Table A.3: Descriptive Statistics: Moderate and Vigorous Physical Activity

	Moderate PA (N activities)			Vigorous PA (≥ 1 x/week)		
	Count	Mean	SD	Count	Mean	SD
Age	10046	56.84	5.52	21633	60.07	6.18
female	10046	0.57	0.49	21633	0.57	0.50
Years of education	10046	12.09	4.10	21633	12.46	4.15
thinc_quartile	10046	2.94	1.06	21633	2.94	1.04
Belgium	10046	0.21	0.41	21633	0.22	0.42
Cyprus	10046	0.01	0.07	21633	0.02	0.13
Denmark	10046	0.12	0.33	21633	0.12	0.33
Finland	10046	0.02	0.13	21633	0.05	0.22
France	10046	0.19	0.39	21633	0.16	0.37
Greece	10046	0.03	0.18	21633	0.05	0.21
Israel	10046	0.05	0.22	21633	0.03	0.17
Italy	10046	0.12	0.32	21633	0.13	0.34
Spain	10046	0.17	0.37	21633	0.13	0.33
Sweden	10046	0.09	0.29	21633	0.09	0.28

Notes: These are the summary statistics for individuals included in the regression sample for the dependent variable *Number of moderate physical activity per month and binary variable if they are doing vigorous physical activity more than one per week*, i.e., only those with non-missing values on all covariates and residing in countries with sufficient time-series data on unemployment. The means and standard deviations reported are computed on the estimation sample (i.e., the sample actually used in the regressions). The income variable (*thinc_quartile*) is coded into quartiles based on total household income within each country, with values ranging from 1 (lowest) to 4 (highest). Education is a continuous variable corresponding to completed years of schooling.

Table A.4: Descriptive Statistics: Eating Fruit Often

	Eat fruit often		
	Count	Mean	SD
Age	23187	56.25	4.65
female	23187	0.56	0.50
Years of education	23187	12.50	4.15
thinc_quartile	23187	3.00	1.05
Belgium	23187	0.22	0.41
Cyprus	23187	0.02	0.13
Denmark	23187	0.12	0.32
Finland	23187	0.05	0.22
France	23187	0.15	0.35
Greece	23187	0.05	0.21
Israel	23187	0.04	0.20
Italy	23187	0.14	0.34
Spain	23187	0.15	0.36
Sweden	23187	0.08	0.27

Notes: These are the summary statistics for individuals included in the regression sample for the dependent variable *Eating Fruit Often*, i.e., only those with non-missing values on all covariates and residing in countries with sufficient time-series data on unemployment. The means and standard deviations reported are computed on the estimation sample (i.e., the sample actually used in the regressions). The income variable (*thinc_quartile*) is coded into quartiles based on total household income within each country, with values ranging from 1 (lowest) to 4 (highest). Education is a continuous variable corresponding to completed years of schooling.

Appendix B - Robustness check

This section reports the full set of tables underlying the robustness checks discussed in Section 4.7 of the main text. The tables are organized to mirror the sequence of robustness exercises in the paper, allowing readers to assess the consistency of the results across different empirical choices. Unless otherwise noted, estimates follow the same notation and layout as in the baseline tables. To access the additional information required for these analyses, we rely on specific subsamples.

Table B.1: Robustness check - Effects of Youth Unemployment on Ever Smoking and Smoke duration with immigrants control

	ever smoke daily				smoke duration			
u(16)	-0.004 (0.004)				0.443 (0.439)			
u(17)	0.000 (0.004)				0.174 (0.345)			
u(18)	0.003 (0.003)				0.291 (0.326)			
u(18-25)	0.020*** (0.006)				0.304 (0.414)			
mean(Y)	.471	.475	.479	.48	27.83	28.034	28.372	28.381
SE Clusters	210	221	233	243	135	150	162	173
N	7787	8755	9826	10874	657	746	849	932

Notes: This table reports coefficients from regressions of health behaviors (smoking daily and smoke duration in years) on unemployment experience at different ages. This robustness check is including immigrants control. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Robustness check - Effects of Youth Unemployment on Drinking with immigrants control

	drinking			
u(16)	0.007 (0.006)			
u(17)		0.007 (0.005)		
u(18)			0.005 (0.005)	
u(18-25)				-0.009 (0.005)
mean(Y)	.205	.2	.2	.198
SE Clusters	159	167	175	183
N	7212	8177	9142	10172

Notes: This table reports coefficients from regressions of health behaviors (drink more than 1 glass of alcohol per day) on unemployment experience at different ages. This robustness check is including immigrants control. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Robustness check - Effects of Youth Unemployment on Vigorous Physical Activity with immigrants control

	vigorous physical activity				N moderate physical activity			
u(16)	-0.002 (0.010)				-0.014 (0.021)			
u(17)	0.008 (0.007)				-0.006 (0.017)			
u(18)	0.014 (0.009)				-0.003 (0.017)			
u(18-25)	-0.004 (0.007)				0.012 (0.016)			
mean(Y)	.591	.59	.592	.588	1.561	1.569	1.557	1.557
SE Clusters	184	196	208	218	184	196	208	218
N	1982	2317	2704	3045	1984	2321	2708	3050

Notes: This table reports coefficients from regressions of health behaviors (Vigorous Physical Activity more than 1 per week - binary variable and Number Moderate physical activities per month variable) on unemployment experience at different ages. This robustness check is including immigrants control. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Robustness check - Effects of Youth Unemployment on Fruit and Vegetables intake with immigrants control

	fruit and vegetables often			
u(16)	-0.003* (0.002)			
u(17)	-0.001 (0.002)			
u(18)	-0.001 (0.002)			
u(18-25)	-0.004 (0.004)			
mean(Y)	.935	.935	.935	.936
SE Clusters	216	223	236	249
N	9897	11038	12177	13355

Notes: This table reports coefficients from regressions of health behaviors (Fruit and Vegetables intake more than 3-6 times per week) on unemployment experience at different ages. This robustness check is including immigrants control. All regressions control for gender, years of education, and total household income (in country-specific quartiles). Specifications include wave fixed effects and country-by-cohort fixed effects. Standard errors, clustered at the country-by-age level, are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

References

- Antonova, L., Bucher-Koenen, T., & Mazzonna, F. (2017). Long-term health consequences of recessions during working years. *Social Science Medicine*, 187, 134–143. <https://doi.org/10.1016/j.socscimed.2017.06.044>
- Arellano-Bover, J. (2022). The effect of labor market conditions at entry on workers' long-term skills. *The Review of Economics and Statistics*, 104(5), 1028–1045. https://doi.org/10.1162/rest_a_01008
- Becker, G. S., & Murphy, K. M. (1988). A theory of rational addiction. *Journal of Political Economy*, 96(4), 675–700. <https://doi.org/10.1086/261558>
- Bell, B., Bindler, A., & Machin, S. (2018). Crime scars: Recessions and the making of career criminals. *Review of Economics and Statistics*, 100(3), 392–404. https://doi.org/10.1162/REST_a_00698
- Bell, D. N., & Blanchflower, D. G. (2011). Youth unemployment in the great recession. *Oxford Review of Economic Policy*, 27(4), 578–595. <https://doi.org/10.1093/oxrep/grr011>
- Brugiavini, A., Weber, G., & Toson, M. (2022). Adverse childhood experiences and unhealthy lifestyles later in life. *Social Science Medicine*, 297, 114849. <https://doi.org/10.1016/j.socscimed.2022.114849>
- Candari, C. J., Cylus, J., & Nolte, E. (2017). *Assessing the economic costs of unhealthy diets and low physical activity: An evidence review and proposed framework*. European Observatory on Health Systems; Policies.
- Casey, B. J., Getz, S., & Galvan, A. (2008). The adolescent brain. *Developmental Review*, 28(1), 62–77. <https://doi.org/10.1016/j.dr.2007.08.003>
- Colman, G., & Dave, D. (2018). Unemployment and health behaviors over the business cycle: A longitudinal view. *Southern Economic Journal*, 85(1), 93–120. <https://doi.org/10.1002/soej.12283>
- Conrod, P. J. (2016). Personality-targeted interventions for substance use and misuse. *Current Addiction Reports*, 3(4), 426–436. <https://doi.org/10.1007/s40429-016-0127-6>
- Conti, G., & Heckman, J. J. (2010). Understanding the early origins of the education-health gradient: A framework that can also be used to evaluate the role of policies. *Perspectives on Psychological Science*, 5(5), 585–605. <https://doi.org/10.1177/1745691610383505>
- Cunha, F., & Heckman, J. J. (2007). The technology of skill formation. *American Economic Review*, 97(2), 31–47. <https://doi.org/10.1257/aer.97.2.31>
- Currie, J., & Schwandt, H. (2014). Short- and long-term effects of unemployment on fertility. *Proceedings of the National Academy of Sciences*, 111(41), 14734–14739. <https://doi.org/10.1073/pnas.1408975111>
- Cutler, D. M., & Lleras-Muney, A. (2006, June). *Education and health: Evaluating theories and evidence* (NBER Working Paper No. 12352) (JEL No. I1, I2). National Bureau of Economic Research. <http://www.nber.org/papers/w12352>

- De Vogli, R., & Santinello, M. (2005). Unemployment and smoking: Does psychosocial stress matter? *Tobacco Control*, 14(6), 389–395. <https://doi.org/10.1136/tc.2004.010611>
- Deb, P., Gallo, W. T., Ayyagari, P., Fletcher, J. M., & Sindelar, J. L. (2011). The effect of job loss on overweight and drinking. *Journal of Health Economics*, 30(2), 317–327. <https://doi.org/10.1016/j.jhealeco.2010.12.001>
- Di Pietro, G. (2018). Revisiting the impact of macroeconomic conditions on health behaviours. *Economics and Human Biology*, 28, 173–181. <https://www.sciencedirect.com/science/article/pii/S1570677X18300225>
- Falba, T., Teng, H.-M., Sindelar, J. L., & Gallo, W. T. (2005). The effect of involuntary job loss on smoking intensity and relapse. *Addiction*, 100(9), 1330–1339. <https://doi.org/10.1111/j.1360-0443.2005.01150.x>
- Frijters, P., Haisken-DeNew, J. P., & Shields, M. A. (2005). The causal effect of income on health: Evidence from german reunification. *Journal of Health Economics*, 24(5), 997–1017. <https://doi.org/https://doi.org/10.1016/j.jhealeco.2005.01.004>
- Grossman, M. (1972). *On the concept of health capital and the demand for health*. National Bureau of Economic Research. <https://www.nber.org/papers/w739>
- Gruber, J., & Köszegi, B. (2001). Is addiction "rational"? theory and evidence. *The Quarterly Journal of Economics*, 116(4), 1261–1303.
- Hall, J., Goranitis, I., Kigozi, J., & Guariglia, A. (2021). New evidence on the impact of the great recession on health-compromising behaviours. *Economics and Human Biology*, 41, 100980. <https://doi.org/10.1016/j.ehb.2021.100980>
- Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. *Science*, 344(6186), 862–867. <https://doi.org/10.1126/science.1232491>
- Heron, L., O'Neill, C., McAneney, H., Kee, F., & Tully, M. A. (2019). Direct healthcare costs of sedentary behaviour in the uk. *Journal of Epidemiology and Community Health*, 73(7), 625–629. <https://doi.org/10.1136/jech-2018-211758>
- Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2), 303–316. <https://doi.org/10.1016/j.labeco.2009.07.005>
- Matthews, K. A., & Gallo, L. C. (2011). Psychological perspectives on pathways linking socioeconomic status and physical health. *Annual Review of Psychology*, 62, 501–530. <https://doi.org/10.1146/annurev.psych.031809.130711>
- Neumayer, E. (2004). Recessions lower (some) mortality rates. *Social Science Medicine*, 58(6), 1037–1047. [https://doi.org/10.1016/S0277-9536\(03\)00246-4](https://doi.org/10.1016/S0277-9536(03)00246-4)
- Oreopoulos, P., von Wachter, T., & Heisz, A. (2012a). The short- and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1), 1–29. <https://doi.org/10.1257/app.4.1.1>
- Oreopoulos, P., von Wachter, T., & Heisz, A. (2012b). The short- and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1), 1–29. <https://doi.org/10.1257/app.4.1.1>

- Oyer, P. (2006). Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives*, 20(3), 143–160. <https://doi.org/10.1257/jep.20.3.143>
- Popovici, I., & French, M. T. (2013). Does unemployment lead to greater alcohol consumption? *Industrial Relations: A Journal of Economy and Society*, 52(2), 444–466. <https://doi.org/10.1111/irel.12019>
- Richards, J., Stipelman, B. A., Bornovalova, M. A., Daughters, S., Sinha, R., & Lejuez, C. (2011). Biological mechanisms underlying the relationship between stress and smoking: State of the science and directions for future work. *Biological Psychology*, 88(1), 1–12. <https://doi.org/10.1016/j.biopsycho.2011.06.009>
- Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics*, 115(2), 617–650. <https://doi.org/10.1162/003355300554872>
- Ruhm, C. J. (2005). Healthy living in hard times. *Journal of Health Economics*, 24(2), 341–363. <https://doi.org/10.1016/j.jhealeco.2004.09.004>
- Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D., & Patton, G. C. (2018). The age of adolescence. *The Lancet Child Adolescent Health*, 2(3), 223–228. [https://doi.org/10.1016/S2352-4642\(18\)30022-1](https://doi.org/10.1016/S2352-4642(18)30022-1)
- Scarborough, P., Bhatnagar, P., Wickramasinghe, K. K., Allender, S., Foster, C., & Rayner, M. (2011). The economic burden of ill health due to diet, physical inactivity, smoking, alcohol and obesity in the uk: An update to 2006–07 nhs costs. *Journal of Public Health (Oxford, England)*, 33(4), 527–535. <https://doi.org/10.1093/pubmed/fdr033>
- Schwandt, H. (2016). Unmet aspirations as an explanation for the age u-shape in human wellbeing [IZA Discussion Paper No. 7604]. *Journal of Economic Behavior & Organization*, 122, 75–87. <https://doi.org/10.1016/j.jebo.2015.11.010>
- Schwandt, H., & von Wachter, T. (2019a). Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets. *Journal of Labor Economics*, 37(S1), S161–S198. <https://doi.org/10.1086/700589>
- Schwandt, H., & von Wachter, T. (2019b). Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets. *Journal of Labor Economics*, 37(S1), S161–S198. <https://doi.org/10.1086/701053>
- Sievertsen, H. H. (2016). Local unemployment and the timing of post-secondary schooling. *Economics of Education Review*, 50, 17–28. <https://doi.org/10.1016/j.econedurev.2015.11.002>
- Steinberg, L. (2008). A social neuroscience perspective on adolescent risk-taking. *Developmental Review*, 28(1), 78–106. <https://doi.org/10.1016/j.dr.2007.08.002>
- Stevens, A. H., Miller, D. L., Page, M. E., & Filipski, M. (2015). The best of times, the worst of times: Understanding pro-cyclical mortality. *American Economic Journal: Economic Policy*, 7(4), 279–311. <https://doi.org/10.1257/pol.20130057>

- World Health Organization - WHO. (2010). Global recommendations on physical activity for health [<https://www.who.int/dietphysicalactivity/publications/9789241599979/en/>].
- World Health Organization - WHO. (2018). Global status report on alcohol and health 2018 [<https://www.who.int/publications/i/item/9789241565639>].
- Xu, X. (2013). The business cycle and health behaviors. *Social Science & Medicine*, 77, 126–136. <https://doi.org/10.1016/j.socscimed.2012.11.034>

General Conclusions

This dissertation has investigated health-related behaviors, with a specific focus on sleep and lifestyle habits, as a critical form of human capital investment over the life cycle. By combining evidence from a randomized behavioral experiment, staggered Difference-in-Differences policy evaluations, and quasi-experimental analyses of macroeconomic shocks, the thesis contributes to the economics of health literature by showing how informational, institutional, and economic environments jointly shape individual health, productivity, and long-term well-being.

Through the three chapters of the thesis, I provide an overview of how behaviors that can put health at risk are formed in the early stages of life, such as sleep (2) and other habits (4), and how these then consolidate over time, leading to repercussions on health, human capital, income and opportunities. Moreover, we observed how they respond heterogeneously to public policies (3), and how they are persistently affected by economic conditions, especially adverse (4). Therefore, the results highlight that health behaviors are not merely the outcome of individual preferences, but rather the product of constrained choices made within specific institutional, social, and economic contexts.

Main Findings

As we have seen in the first chapter, childhood is a foundational stage for health capital formation and we are able to document persistent racial disparities in children's sleep behaviors in the United States. Using both nationally representative time-use data and a randomized online experiment, we show that Black/African-American children consistently go to bed later than their White counterparts. The gap remain even after accounting for observable socioeconomic characteristics. Through an experiment we demonstrate that low-cost, scalable informational interventions can causally shift parental intentions and behaviors. In particular, Black/African-American mothers react better to the intervention for the subscription to the newsletter than White mothers, suggesting a difference in the treatment effect between the two subgroups. Our findings indicate that the lack of information and the difficulty in finding reliable and readily available information on sleep could be the drivers of our results.

The second chapter evaluates how institutional changes in substance regulation affect adult sleep outcomes, focusing on the staggered adoption of medical and recreational cannabis legalization in the United States. Exploiting variation across states and over time, the analysis provides causal evidence of strong heterogeneity in policy effects. Medical cannabis legalization significantly increases the probability of adequate sleep among adults aged 45–60, in contrast, recreational cannabis legalization reduces adequate sleep primarily among adults aged 30–44. These results demonstrate that the public health effects of cannabis liberalization depends critically on the regulatory framework and age group. The chapter highlights that policies often labeled under a single umbrella term can generate opposing effects across population subgroups.

Through the third chapter we examine youth unemployment as an economic shock with long-lasting effects on both health behaviors and labor-market trajectories. Using harmonized longitudinal SHARE data linked to cohort- and country-specific unemployment rates, our analysis shows that exposure to adverse labor-market conditions between critical window between ages 18 and 25 lead to persistent behavioral, health, and economic scars. In fact, higher youth unemployment increases daily smoking and smoking duration, and simultaneously reducing heavy drinking, vigorous physical activity, and regular fruit and vegetable consumption. These behavioral responses are accompanied by a higher probability of working in physically demanding jobs and by lower adult income and wealth accumulation. Through our results we are able to observe that effects are particularly pronounced among individuals with lower education and lower initial socioeconomic status, indicating that early economic adversity amplifies pre-existing inequalities.

Policy Implications

The collective evidence of this dissertation underscores the need for a stratified and life-cycle-oriented policy approach to health behaviors.

Indeed, the findings from childhood interventions point to the effectiveness of early, low-cost, and scalable behavioral policies. Informational strategies can modify parental intentions and behaviors in populations facing structural and informational barriers. In our perspective, early interventions therefore represent high-return investments in human capital, with the potential to reduce inequalities before they can be reiterated over time.

On the same line, the results on cannabis legalization stress the importance of accounting for age- and policy-specific heterogeneity. We find that medical cannabis bring meaningful sleep benefits for 45-60 adults, whereas recreational cannabis can reduce sleep among younger and 30-44 adults. Policymakers should carefully weigh the therapeutic and labor-market benefits of medical cannabis against the potential cognitive and sleep-related costs associated with recreational use.

Continuing on this path, the evidence on youth unemployment demonstrates that adverse labor-market conditions at the beginning of working life are not merely transitory shocks, but triggers of long-term behavioral and economic trajectories. Also in this analysis we observe the need of tailored interventions over the population, that have different effect by these shocks. The policies aimed at stabilizing youth employment, as well as timely psychosocial, behavioral, and labor-market support during economic downturns, should be viewed as long-term investments in public health and economic equity.

In conclusion, this dissertation shows that health behaviors, and sleep in particular, are shaped by a complex interaction of informational constraints, institutional environments, and economic conditions. Inequalities in health and human capital accumulation emerge early and propagate over the life course, reinforced by heterogeneous responses to policies and macroeconomic shocks. By integrating experimental, policy-based, and macroeconomic evidence, this thesis highlights the central role of health behaviors as both determinants and outcomes of economic inequality.

The findings we achieved invite policymakers to recognize health behaviors not only as a medical issue, but as a core domain of economic policy. Investments aimed at improving health behaviors, as sleep, smoking, alcohol and others or at protecting young individuals from adverse economic shocks can generate substantial long-term gains in individual well-being, labor productivity, and social welfare.