

Three Essays in Mental Health Economics: Education and Labor Market Outcomes

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A Thesis
In the Department of
Economics

Presented in Partial Fulfillment of the Requirements
for the Degree of
Doctor of Philosophy (Economics) at
Concordia University
Montreal, Quebec, Canada

June 2025

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CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

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Entitled: **Three Essays in Mental Health Economics: Education and Labor Market Outcomes**

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY (Economics)

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Abstract

Three Essays in Mental Health Economics: Education and Labor Market Outcomes

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This dissertation explores how mental and physical health influence key economic outcomes over the life course, focusing on education, occupational outcomes, and workplace productivity. Using longitudinal data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), the study employs advanced modeling techniques, including Generalized Structural Equation Modeling (GSEM) and mixed-effects regression, to construct latent health measures and quantify their economic consequences.

The first chapter examines the impact of adolescent mental health on academic achievement, particularly high school completion and college enrollment. It addresses the limitations of using narrow diagnostic proxies for mental health by applying a factor-analytic approach to create latent constructs. The findings reveal that better mental health significantly improves educational attainment, with a stronger effect on college entry than on high school completion.

The second chapter investigates how health status shapes occupational sorting across two major classifications: white-collar and full-time employment. It finds that individuals with poor mental health are disproportionately concentrated in low skill, physically demanding, blue-collar jobs, while those with better health are more likely to enter cognitively intensive, white-collar occupations. Physical health also influences job type, reinforcing disparities in labor market access and long-term mobility.

The third chapter evaluates the effect of mental health on workplace productivity. By constructing a composite latent productivity score, based on job satisfaction, hours worked, and income, the study estimates the long-term effects of lagged health status. A one standard deviation increase in mental health is associated with a 0.0251 rise in latent productivity and a 0.0201 increase in wage measure of productivity, confirming the strong and persistent influence of psychological well-being.

Together, these chapters show that mental health is a critical determinant of economic opportunity, shaping individual outcomes from adolescence through adulthood.

Acknowledgements

This dissertation has been more than just an academic pursuit. It has been a journey of growth, resilience, and self-discovery, and I could not have made it through without the support, encouragement, and kindness of so many wonderful people along the way.

First and foremost, I am deeply grateful to my supervisor, Professor Tatyana Koreshkova, for her steady guidance, thoughtful advice, and trust in me. Her mentorship carried me through every phase of this work, and I feel incredibly lucky to have had her by my side throughout this process.

I sincerely thank my internal committee members, Professors James McIntosh, Ian Irvine, and Panos Margaritis, for their generous time and invaluable feedback. I am also thankful to my external examiner, Professor Julia Witt, for her close reading and insightful suggestions. Special thanks to Professor Axel Watanabe for chairing my defense and to Professor Christian Sigouin, our Graduate Program Director, for his consistent support during my time in the program.

I would also like to thank Professors Paul Gomme and Dipjyoti Majumdar for their guidance during my coursework and early research years. I am grateful to Professor Jorgen Hansen, Chair of the Department, for his support and leadership, and to Elise Melancon, the former Graduate Program Assistant, whose kindness and dedication made a lasting difference.

To my dear friend and colleague, Sati Semnanizadeh, thank you for walking beside me throughout this journey. Your friendship, sharp insights, and constant support made the difficult days bearable and the good days even better.

Lastly, and most importantly, I thank my family: Mashael Muwanis, my children, Abdulrahman and Jana, and my parents, brothers, and sisters. Your endless support, strength, and patience gave me the foundation to persevere and succeed.

To all of you, thank you. This dissertation stands as an echo of your support and belief in me.

Contributions of Authors

This thesis contains co-authored material. Chapter 1 is a joint work with my colleague, Sati Semnanizadeh. All authors have contributed equally and share equal responsibility for the work. Chapters 2 and 3 are solely authored by me.

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Introduction

Mental health is increasingly recognized as a pivotal determinant of economic outcomes, influencing an individual's educational trajectory, occupational outcomes, and workplace productivity. As rates of depression, anxiety, and psychological distress continue to rise globally, the need for a deeper economic understanding of how mental health intersects with labor market behavior has become urgent. Traditionally, economic research has treated health, particularly mental health, as a secondary or exogenous factor. However, this dissertation repositions mental health as a central variable, arguing that its effects ripple across multiple stages of economic life. Using a combination of Generalized Structural Equation Modeling (GSEM), and mixed-effects logistic regressions, this dissertation explores three distinct yet interconnected domains: educational attainment, occupational outcomes, and workplace productivity.

The first chapter, focuses on the long-term impact of childhood mental health on educational attainment. Utilizing data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), the study constructs latent variables for mental health, physical health, ability, and activity using GSEM. These latent constructs are derived from observed indicators such as ADHD, depression, substance use, BMI, and self-reported health measures. Unlike studies relying on simplistic binary measures, this chapter builds a multifactorial structure to better capture the complexity of health inputs into educational success. The chapter then applies a two-step framework to estimate the effects of these latent health factors on high school completion and college enrollment. The findings reveal that a one standard deviation increase in poor mental health is associated with a 2.2 percentage point decrease in high school completion and a 3.9 percentage point decrease in college enrollment. These results provide empirical support for the hypothesis that mental health during adolescence is a critical input into the formation of human capital and long-term economic potential.

The second chapter shifts the focus to occupational outcomes. While existing literature has established links between mental health and employment status or earnings, little is known about

how mental and physical health affect the types of jobs individuals select into. This chapter addresses that gap by modeling occupational outcomes across two major classifications: white-collar versus blue-collar and full-time versus part-time employment. Using mixed-effects logistic regression models, the chapter incorporates both fixed and random effects to account for intra- and inter-individual variability over time. Latent variables for mental and physical health are once again constructed via GSEM, with mental health encompassing indicators such as ADHD, depression, suicidal ideation, and unhappiness. The occupational categories are derived from Standard Occupational Classification (SOC) codes and grouped based on shared work contexts and required skill sets using O*NET data. This provides a more granular view of occupational sorting. The empirical results demonstrate that individuals with poor mental health are more likely to select into physically demanding, low-skill, blue-collar occupations, while those with better mental health are more likely to work in high-skilled, white-collar roles. A similar pattern holds for physical health. The results also hold for full-time occupations, where those with better mental health have higher probability of securing full-time employment. These findings underscore the role of mental health as a sorting mechanism in the labor market, affecting not just employment status but the quality and nature of occupational roles.

The third chapter turns to workplace productivity. While traditional measures of productivity in economic literature often rely on income, hours worked, or output, this study develops a more holistic latent productivity score. Constructed via GSEM, the latent productivity variable integrates three observed indicators: job satisfaction, weekly income (logged), and weekly hours worked. This multidimensional approach captures not only output but also worker engagement and subjective well-being, while accounting for a part of productivity that may not be generally compensated for through wages. Latent variables for mental and physical health are carried forward and included in a mixed-effects regression model that controls for both time-varying covariates and unobserved individual heterogeneity. The results reveal a robust and statistically significant association between lagged mental health and productivity. A full-range improvement in mental health (from zero to one) is associated with a 0.0251 increase in latent productivity and a 0.0201 increase in wage-measure of productivity. These findings provide clear evidence that mental health directly influences an individual's performance in the workplace, independent of physical health or socioeconomic background.

To further reinforce the empirical findings, the third chapter also explores how health-productivity relationships vary by sex, race, and education level. The heterogeneity analysis indicates that the productivity effects of mental health are more pronounced among individuals with lower education and among racial minorities, highlighting important equity dimensions of labor market performance. These results offer additional justification for mental health investments not only as a matter of efficiency but also equity.

Taken together, the three chapters of this dissertation build a cohesive narrative around the centrality of mental health in economic life. Each chapter contributes to a broader understanding of how psychological well-being shapes long-term outcomes across education, occupation, and productivity. The consistent use of latent variable modeling across chapters ensures methodological coherence and allows for a more accurate measurement of complex, multidimensional constructs. The reliance on longitudinal panel data from Add Health provides a rich empirical foundation, enabling the identification of causal pathways and dynamic effects that unfold over time.

This dissertation also has important policy implications. First, it suggests that early interventions aimed at improving mental health can generate long-term returns in terms of educational success and labor market performance. Second, it highlights the need for labor policies that support mental well-being in the workplace, such as counseling services, flexible work arrangements, and mental health days. Finally, it underscores the importance of designing occupational health policies that account for both mental and physical health as key drivers of career outcomes. These insights should inform both public and private sector decision-making as policymakers and employers grapple with the rising costs and consequences of untreated mental health conditions.

By integrating insights from labor and health economics, this dissertation lays the groundwork for a more inclusive and realistic model of health. The findings call for a paradigm shift in how economists conceptualize productivity, employability, and educational success, moving beyond single indicators to account for the complex interplay between psychological well-being and economic behavior. In doing so, it not only contributes to academic literature but also equips policymakers and institutions with the analytical tools necessary for evidence-based mental health interventions that can enhance individual well-being and collective economic outcomes.

Chapter 1.

The Silent Barrier to Education: The Impact of Adolescent Mental Health on Academic Success

1.1. Introduction

Mental health disorders are ranked amongst the top causes of societal and economic burden worldwide. The economic burden such as loss in human capital, low adult earnings, high unemployment, lost tax income, high Medicare and welfare reliance, and high levels of criminal activity has been increasing in recent years. As of 2018 data, 16.5% of students under the age of 18 are diagnosed with at least one mental health condition (Whitney and Peterson 2019), while only about 40% of them graduate from high school, highest dropout rate of all students with disabilities (US Dept of Ed, 2011). The escalating economic and societal burdens associated with mental health disorders necessitate a focused examination of their impacts, specifically among children. Childhood developmental stage is crucial for psychological and emotional maturation as well as cognitive and noncognitive skill development. Childhood mental health negatively impacts child's development, influencing her future academic and personal outcomes. The prevalence of mental health conditions among children under 18, as evidenced by Whitney and Peterson (2019), presents a significant concern for public health and education policy. Moreover, the disproportionately high dropout rates among students with mental health conditions, underscore the severity of this issue. This paper aims to systematically explore the correlation between childhood mental health disorders and subsequent educational attainment, specifically high school completion and college enrollment.

By analyzing this linkage, the research seeks to contribute to a more comprehensive understanding of how early mental health issues impact long-term educational trajectories. Such insights are vital for developing targeted interventions that can mitigate the adverse effects of childhood mental health disorders on educational outcomes, thereby addressing larger economic and social challenges. In fact, some medicine and psychology papers have found that early childhood interventions can positively affect schooling outcomes. For instance, a paper by Wong et al. (2023) examines whether emotional regulation capacities within schools affect future academic success among Canadian children between the ages 4-8 years old. They find levels of academic success and schooling attainment is positively associated with emotional intervention and regulation within schools. Another study by Bolinski et al. (2020), through randomized controlled trials, finds that internet mental health interventions have a positive effect on depression and improve college and university outcomes. The present study augments the findings of existing

medical and psychological research to offer policymakers guidance on specific targeted mental and physical health interventions that can enhance academic outcomes. It achieves this by quantifying the distinct effects of various determinants of mental and physical health on educational achievement.

Current economics research on children's mental health and human capital accumulation primarily focuses on two distinct areas. One area examines the impact on adult earnings, often neglecting the role of academic achievements. The other, investigates the reverse channel, examining how employment prospects and income levels affect mental health. The limited studies that explore the effects of childhood mental health on schooling outcomes use methodologies flawed by measurement error and unidimensionality. Moreover, these methodologies generally overlook the critical issue of endogeneity concerning mental health in both schooling and earnings equations. In fact, instead of structured measures, an exogenous noisy proxy of mental health is generally included in these equations, leading to underestimated parameters. This paper aims at addressing these issues by employing an exploratory factor analysis (EFA) approach through a Generalized Structural Equation modelling (GSEM), to construct latent variables that capture multifaceted nature of mental health. We construct four latent variables to represent mental health, physical health, ability, and activity. Each of these latent factors are determined by a set of observed indicators from the National Longitudinal Study of Adolescent to Adult Health (Add Health) data. The study then investigates the interplay between mental health, physical health, ability, and activity to arrive at a more accurate understanding of the impacts of children mental health on educational attainment, particularly the probability of high school completion and college entrance. The factor scores for each latent variable from this step are then computed and used in a second step to explain the probability of high school completion and college entrance through two separate logistic regressions. Our findings indicate a modest, but statistically significant impact of mental health on the likelihood of both completing high school and entering college. The results indicate a one standard deviation increase in poor mental health score, is linked to a decrease of about 2.2 percentage points in the likelihood of graduating from high school. The effect increases to 3.9 percentage points when examining the probability of college entrance. However, it's important to note that a portion of mental health's effect in our model is captured by the influence of factors like ability, as well as other latent variables including activity levels and physical health.

The subsequent section of the paper presents a review of the existing literature on the intersection of children's mental health and the accumulation of human capital. Section 1.3 outlines the details of our data along with variable constructs and a comprehensive descriptive analysis. Section 1.4 outlines our theoretical GSEM model and describes the two-step estimation process. Section 1.5 presents the results. Section 1.6 concludes.

1.2. Literature Review

Mental health and human capital accumulation has garnered substantial attention in recent literature. The growing interest in this area has resulted in an expanding body of literature, with an influx of studies examining different dimensions of human capital accumulation and mental health. However, much attention has been given to the impact of human capital and its subsequent effects on income and mental health, as well as the influence of mental health on adulthood job performance and earnings (Bruffaerts, 2009, Lee et al., 2010, Rugulies et al., 2023, Arpin et al., 2023). Some have also examined the effect of short-term shocks, such as civil wars, parental job loss, earthquakes, and cash transfers on mental health and human capital accumulation (Baez, 2011, Mörk et al., 2020, Bertinelli et al., 2023, Hidrobo et al., 2023). Nonetheless, research examining the influence of childhood mental health on subsequent human capital accumulation has been notably scarce. Furthermore, the existing studies primarily focus on the medical perspective (e.g. Zendarski et al., 2022), often lacking in-depth utilization of advanced statistical methods or comprehensive economic analysis.

Among the limited economics literature on childhood mental health and its effects on human capital accumulation, Currie and Stabile (2006, 2009) utilized National Longitudinal Survey of Youth (NLSY79) to examine the impact of Attention Deficit Hyperactivity Disorder (ADHD) on test scores and educational attainment. Using both OLS and sibling fixed effect regressions, the authors find that childhood ADHD is associated with 6-7% higher probability of grade repetition, and conduct disorders (i.e. depression) also negatively affect grade completion. They also claim that mental health has a greater effect on educational outcomes compare to physical health. Fletcher and Wolfe (2008) aimed to build upon the findings of Currie and Stabile (2006) by examining older children and a wider array of human capital indicators, utilizing data from the National Longitudinal Study of Adolescent Health (Add Health) from the 1990s. They relied on the self-

reported experiences of young adults regarding ADHD during childhood, discovering that the significant negative effects of ADHD on outcomes, identified through ordinary least squares (OLS) estimates, diminished when sibling fixed effects were included. Conversely, Fletcher (2014) investigated the relationship between childhood ADHD and labor market outcomes, finding that ADHD was linked to substantial decreases in employment and earnings despite the inclusion of family fixed effects. He finds having ADHD is associated with a 10-14% drop in employment and a 33% decrease in earnings.

Retaining a similar approach, Aizer (2008) utilizes Early Childhood Longitudinal Survey – Kindergarten Cohort (ECLS-K) of students in kindergarten, first, third, fifth and eighth grades to estimate and compare the impact of having classmates with ADD before and after diagnosis. Using fixed effect regressions, he has found that with one standard deviation increase in the number of children with undiagnosed ADD, the average test scores in the classroom decrease by 10 to 20% of a standard deviation. Salm and Schunk (2012) have used German administrative data and employ sibling fixed effect models to estimate the effect of a diverse list of diagnosed childhood health conditions on the cognitive and verbal ability of pre-school child from four thousand children. They have found that while childhood physical illnesses are not significantly correlated with cognitive ability, mental disorders such as hyperactivity have a substantial impact on cognitive development during school. Using administrative US data and unique policy rules under which youth are assigned to behavioral treatment programs, Cuellar and Dave (2015) find that early behavioral interventions can reduce the probability of school dropout by 3.1 percentage points and positively influence grade completion among youth who suffer from mental health conditions.

Other papers have investigated the effect of children mental health not on academic achievements, but on employment prospects and earnings. Fletcher (2014) utilized Add Health data and finds that presence of ADHD among children reduces adulthood income by 33% and employment by 10-14%. Currie et al. (2010) use administrative health insurance archives of approximately fifty thousand children born in Manitoba. They find that early mental health has predictive power for young adult outcomes, even conditional on future health and health at birth, while childhood physical health only affects adult outcomes through impacts on young adult health. A similar finding is supported by Almond, et al. (2018). Smith and Smith (2010) uses PSID data that surveys siblings and finds that children diagnosed with mental health illnesses earn \$10,400

less in income, accumulate \$18,000 less household assets, and incur a lifetime loss in family income of \$300,000. In line with these findings, Yuda (2020) uncovers that reduced childhood health impacts mid-term promotion prospects as well as long term labor participation. Using Japanese panel survey data (JLPS), his findings show that poor health in childhood leads to worse health outcomes later in life, with negative effects on both mental and physical health growing stronger with age. Additionally, having poor health as a child can reduce chances for job promotions in the medium term and lower the likelihood of working in the long term. The results also reveal that having a low family income directly worsens mental health in both the medium and long terms, exacerbating employment prospects.

Even the limited economics body of literature that analyze the impact of childhood mental health on human capital accumulation, suffer from various major drawbacks, in particular measurement error, a unidimensional approach, and not accounting for endogeneity of mental health in schooling and earning equations. The issue of measurement error arises from the fact that many of these studies use one or two mental health conditions as a noisy proxy for mental health. These proxies often contain a substantial amount of error and do not accurately capture the true variation of the underlying mental health variable they are supposed to represent, which may also lead to potentially misleading inferences when it comes to interpreting the results. The use of a unidimensional approach presents another challenge, undermining the effectiveness of current research on the relationship between children's mental health and their educational outcomes. All existing studies measure the direct impact of mental health on academic achievement, without analyzing the channels through which childhood mental health affects these outcomes. In fact, they only focus on association rather than causal effects. Lastly, the existing literature utilize simple one-step fixed effects or OLS regression methods, and do not account for endogeneity of mental health. Mental health is a complex subject that is identified by several factors, and influences an individual's physical health, ability, and activity. Hence, treating mental health as an exogenous variable through the use of noisy proxies is not sufficient to quantify its true impacts on schooling outcomes. This study attempts to fill the gap in the existing literature by evaluating the impact of childhood mental health on educational achievement through a multifaceted structural model with an endogenous latent variable for mental health.

1.3. Data and Variables

Following an extensive review of multiple data sources that encompass adolescent mental health conditions, the decision was made to utilize the National Longitudinal Study of Adolescent to Adult Health (Add Health) for our research. The dataset is a school-based longitudinal survey of a nationally representative sample of youth in grades 7-12 in the United States in 1994-95. The panel structure of the data follows observations for 20 years and includes surveys from adolescents, their peers, school administrators, parents, siblings, friends, and romantic partners. It hence encompasses several waves of data collection, tracking respondents from adolescence into adulthood. Its rich content covers a range of modules, including mental health, socio-economic status, and educational achievements. The primary strength of Add Health lies in its extensive coverage and longitudinal insight, offering a unique opportunity to observe developmental changes and causal relationships over a significant portion of the lifespan. The dataset's substantial size and detailed health information, particularly regarding mental health metrics, provide a robust foundation for our research. The dynamic nature of the data, with its age-specific analysis across different waves, is particularly relevant to studying the evolution of mental health issues and their influence on educational outcomes.

The data collection for the study spans across five distinct waves, each capturing different stages of the participants' lives. The initial wave, Wave I, conducted in 1994-1995, focuses on a sample of adolescents in grades 7-12. The subsequent wave, Wave II, conducted in 1996, revisits the same cohort, who are then in grades 8-12. Wave III, occurring in 2001-2002, shifts the focus to these individuals as young adults, now aged between 18 and 26 years. Wave IV, carried out between 2008-2009, continues to track this group, now matured into young adults aged 24-32. Finally, Wave V, taking place between 2016-2018, surveys these participants who have reached the ages of 33 to 43, offering a comprehensive longitudinal perspective on their development from adolescence into mid-adulthood.

For this research, we utilize cross-sectional data from Waves I, III, and IV of the dataset, as they provide pertinent information relevant to our analysis. Most explanatory variables, including indicators of childhood mental health, academic performance, and demographic controls, are derived from Wave I, which surveys respondents in grades 7–12. The key outcome variables, high

school completion and college enrolment, are drawn from Waves III and IV. Given that there is an approximately eight-year gap between each wave, this temporal structure supports a causal interpretation of the effects of early mental health on later academic outcomes. After a meticulous examination and cleaning of the Add Health data, we finalized a sample of 3,959 individuals who were originally surveyed in Wave I.

The selection and cleaning process was guided by several key criteria aimed at ensuring the integrity and applicability of our data for examining the effects of adolescent mental health on academic achievements, such as the probability of high school completion and college enrollment. We prioritized observations that included complete information on the observed variables used to construct the four latent variables (physical health, mental health, activity, and ability) through factor analysis, which was crucial to accurately model the constructs and ensure their reliability. Observations lacking data on high school completion and college enrollment (assessed by Waves III and IV) were excluded to maintain the focus on our primary research outcomes. For observations with missing data on variables of secondary interest, we employed data imputation techniques where appropriate, based on the pattern and mechanism of missingness, to maximize the use of available data without compromising the validity of our analysis. We also reviewed the dataset for outliers and inconsistencies, particularly in the reported academic achievements and health-related variables. Where possible, outliers were corrected or excluded based on a predefined rationale to prevent undue influence on the model outcomes. These criteria were designed to ensure that our dataset accurately represented the target population of adolescents and their experiences with mental health and academic achievements.

1.3.1. Latent Variables

1.3.1.1. Mental Health

Mental health is defined as a state of well-being in which an individual realizes their own abilities, can cope with the normal stresses of life, and can work productively. The prevalent mental health conditions affecting youth include a range of disorders, among which the most important ones are depression and anxiety, behavioral disorders, and suicidal behaviors and thoughts. Depression and anxiety are leading causes of illness and disability among adolescents worldwide. Depression affects a significant proportion of both younger (10-14 years) and older (15-19 years)

adolescents. Anxiety disorders, including fear and excessive worry, are also common, particularly among older adolescents. As for behavioral disorders, Attention Deficit Hyperactivity Disorder (ADHD) and conduct disorders are more common among younger adolescents. ADHD is characterized by difficulty in paying attention, excessive activity, and impulsivity, and can significantly impact educational outcomes. In terms of suicidal thoughts, there has been a notable increase in sadness, hopelessness, and suicidal thoughts and behaviors among young people, with suicide being a leading cause of death in the 15-29 age group. (Mental Health America, 2023; World Health Organization, 2021; American Psychological Association, 2023). Supporting these findings and using a factor analysis approach to decide on the number of factors, we have used indicators, *ADHD*, *Depressed*, *Fearful*, *Unhappy*, and *Suicide* to construct our latent variable, *Poor Mental Health*. Each indicator is described below.

ADHD: This data is taken from waves III and IV, where respondents are asked “Have you been taking prescription medication for attention problems or ADD or ADHD in the past 12 months?” and “Has a doctor, nurse or other health care provider ever told you that you have or had attention problems or ADD or ADHD?”. For those who responded with “yes” to any of the above questions, a binary variable is constructed taking the value of one, while it is set to zero for all other answers.

Depressed: This variable is constructed based on the answers to the question: “How often had you felt depressed during the past week?”. A binary variable is created which equals one for those who answered, “a lot of the time”, “most of the time”, or “all of the time”, and zero otherwise.

Fearful: Respondents were asked “How often had you felt fearful during the past week?”. A binary variable is formed, where individuals who responded with “a lot of the time”, “most of the time”, or “all of the time” are assigned a value of one, and all others are assigned a value of zero.

Unhappy: The construction of this variable is based on the responses given to “How often had you enjoyed life during the past week?”. A binary variable is created, which generates one for those who answered “never” or “rarely”, and zero otherwise.

Suicide: This variable is formulated using the responses to the question, “During the past 12 months, did you ever seriously think about committing suicide?”. A binary variable is established,

assigning a value of one to participants who indicated “yes” as their response, and a value of zero to all other responses.

1.3.1.2. Physical Health

Physical health is a broad concept that encompasses the well-being of the body and the proper functioning of an organism. A key aspect of sustaining good physical health involves lifestyle choices, including maintaining a balanced diet, engaging in physical activity (captured by another latent variable described below), and refraining from harmful substances. For our research, we concentrated on lifestyle and behavioral variables linked to physical health instead of relying on diagnosed diseases. This decision was influenced by the limited variability in disease diagnoses in the early waves of the Add Health dataset. Additionally, we included a general health variable that asks individuals whether they feel healthy. The response to this question provides a comprehensive overview, encompassing all symptomatic diagnosed diseases that may influence school performance. By focusing on lifestyle and behavioral aspects, such as dietary habits and substance use (including tobacco, marijuana, and alcohol), we aimed to capture a broader and more dynamic picture of factors influencing physical health in the adolescent population. We have constructed a latent Poor Physical Health factor based on observed variables *Poor Health*, *Tobacco*, *Alcohol*, *Marijuana*, and *Poor BMI* described below.

Poor Health: Respondents were asked a general question “how is your health?” In order to capture any physical conditions, those who answered “fair”, or “poor” are given a value of 1, as having poor physical health, and those that answered “excellent, very good, or good” are assigned a value of zero and considered healthy.

Tobacco: Participants were asked whether they “ever smoked cigarettes on a regular basis”. A binary variable is then created assigning a value of one for those who answered “yes”, and zero otherwise.

Alcohol: A binary variable was generated based on responses to the question “During the past 12 months, on how many days did you drink alcohol?”. Those who answered “every day” or “almost every day” or “weekly” were assigned a value of one, where others received a value of zero.

Marijuana: The respondents were asked “During your life, how many times have you used marijuana?”. A binary variable is established, assigning a value of one to participants who indicated any value “equal or more than 3 times” as their response, and a value of zero to all other responses.

Poor BMI: Body Mass Index (BMI) has been calculated using individual's weight and height from the original dataset. A binary variable is then generated assigning individuals who were underweight (i.e. a BMI lower than 18.499), overweight, or obese (i.e. a BMI higher than 24.999) a value of one as having a poor BMI. Others were assigned a value of zero and considered to be of normal, healthy weight.

1.3.1.3. Activity

The dataset identifies variables *Bicycle*, *Sport*, and *Exercise* as key indicators correlated with physical activity. These variables are considered to capture a significant portion of the physical activities typically engaged in by adolescents as they encompass light, medium, and intense levels of activity in different fields. A detailed explanation of each of these variables is provided below, offering insights into their respective roles in representing adolescent physical activity.

Bicycle: Respondents were asked “during the past week, how many times did you go roller-blading, roller-skating, skate-boarding, or bicycling?” Answers that were at least “one time” are assigned a value of one, and zero otherwise.

Sport: A binary variable was generated considering answers to the question “during the past week, how many times did you play an active sport, such as baseball, softball, basketball, soccer, swimming, or football?” Those who answered at least “one time” received a value of one, others were reported as zero.

Exercise: To capture lighter levels of activity in comparison to the *Sport* variable, respondents are asked “during the past week, how many times did you do exercise, such as jogging, walking, karate, jumping rope, gymnastics, or dancing?” A binary variable is established assigning a value of one to participants who indicated at least “one time” as their response, and a value of zero to all other responses.

1.3.1.4. Ability

In academic and psychological research, test scores are often used as indicators of ability, consistent with a broad consensus in the literature. This perspective is rooted in the understanding that standardized tests, particularly those measuring cognitive abilities, can provide a quantifiable measure of certain aspects of an individual's intellectual capability. This is because standardized tests provide a uniform metric for evaluating all students based on the same tasks under similar conditions, offering a level playing field for assessment. In our research, we also adopted this established approach, using test scores as observable indicators of the latent variable *Ability*. This decision aligns with the view that test scores, while not encompassing the entirety of an individual's abilities, offer a practical and widely accepted means of approximating cognitive skills and academic potential. For this purpose, we use students' **English Score**, **Math Score**, **History Score**, and **Science Score** as observed in the data. These variables are continuous and range from zero to four. We also add an additional variable **Senior Student**. This variable is generated based on the student's age and compares it to 'A Comprehensive Guide to Schooling Ages' (Education World Wide, 2023) to check if the student is in the appropriate grade. This variable is meant to capture grade repetition, which is also an important determinant of academic performance and ability.

1.3.2. High School Completion and College Entrance

High school completion and college entrance are outcome variables in our research. Basically, the main question of the research is to analyze the effect of mental health and other latent variables (i.e. physical health, activity, and ability) on children's educational achievement, meaning the likelihood of completing high school and entering college. We have generated two binary variables for each, based on the answers to the two specific questions: "what is your high school graduation status?" and "what is the highest level of education that you have achieved to date?" Answers "finished high school with diploma" were assigned a value of one for the binary *High School* variable (zero otherwise). Answers that indicated "some college" or higher received a value of one for *College* binary variable, reflecting college entrance, whereas all other answers were reported as zero.

The two outcome variables are then regressed on the following observed demographic characteristics:

Female: It identifies the sex of the individual (i.e. *Female* = 1 if the individual is female, zero otherwise).

Black: It identifies the race of the individual (i.e. *Black* = 1 if the individual is black, zero otherwise).

Age: This variable has been calculated using individual's date of birth and the interview date.

Mom's College: This variable indicates whether the individual's mother has completed a college degree (i.e. if the individual's mother has completed college, *Mom's College* = 1, zero otherwise).

Family Income (ln): This is a continuous variable, which has been calculated using the log of family income.

1.3.3. Descriptive Statistics

Table 1.1 presents descriptive statistics comparing proportion of individuals who completed high school (entered college) to those who dropped out of high school (did not enter college) in each category. The grouping is based on variables that possess largest amount of variability, such as health status, tobacco use, alcohol consumption, marijuana use, body mass index (BMI), and mental health indicators like ADHD, depression, fearfulness, unhappiness, and suicidal tendencies. This table also includes data statistics on sports participation and exercise habits, offering a comprehensive overview of various factors that might influence educational outcomes. The data is presented in mean values with standard errors in parentheses, providing a clear statistical summary for each variable.

Figures A.1 and A.2 in Appendix A depict the schooling decisions of students with and without mental health issues respectively. It presents statistics on high school completion, dropping out, completing a GED, and entering college. The data is divided to show percentages for all students as well as those specifically identified with mental health conditions. This visual representation

effectively illustrates how mental health impacts key educational milestones in adolescence, providing valuable insights into the academic paths chosen by this demographic.

Table 1.1. Comparative Descriptive Statistics

	No High School Diploma	High School Diploma	No College Education	College Education	Total
Male	0.524 (0.500)	0.442 (0.497)	0.534 (0.499)	0.414 (0.493)	0.452 (0.498)
Female	0.476 (0.500)	0.558 (0.497)	0.466 (0.499)	0.586 (0.493)	0.548 (0.498)
Health	0.871 (0.335)	0.940 (0.238)	0.891 (0.311)	0.950 (0.218)	0.931 (0.253)
Tobacco	0.357 (0.480)	0.169 (0.375)	0.289 (0.454)	0.147 (0.354)	0.192 (0.394)
Alcohol	0.245 (0.431)	0.157 (0.364)	0.189 (0.392)	0.158 (0.365)	0.168 (0.374)
Marijuana	0.329 (0.470)	0.179 (0.383)	0.247 (0.431)	0.175 (0.380)	0.198 (0.398)
BMI	23.13 (4.689)	22.47 (4.513)	23.14 (4.848)	22.28 (4.362)	22.56 (4.540)
ADHD	0.0964 (0.295)	0.0480 (0.214)	0.0607 (0.239)	0.0509 (0.220)	0.0541 (0.226)
Depressed	0.157 (0.364)	0.0809 (0.273)	0.125 (0.331)	0.0740 (0.262)	0.0904 (0.287)
Fearful	0.0562 (0.231)	0.0312 (0.174)	0.0426 (0.202)	0.0305 (0.172)	0.0344 (0.182)
Unhappy	0.287 (0.453)	0.169 (0.375)	0.247 (0.432)	0.154 (0.361)	0.184 (0.388)
Suicide	0.181 (0.385)	0.123 (0.328)	0.144 (0.351)	0.123 (0.329)	0.130 (0.336)
Sport	0.663 (0.473)	0.724 (0.447)	0.673 (0.469)	0.737 (0.440)	0.717 (0.451)
Exercise	0.831 (0.375)	0.848 (0.359)	0.815 (0.389)	0.860 (0.347)	0.846 (0.361)
<i>N</i>	498	3461	1269	2690	3959

Mean coefficients, standard errors in parentheses.

1.4. Structural Model

This model aims to build on efforts by Currie and Stabile (2006) and Fletcher and Wolfe (2008) that examine the effects of childhood ADHD on adult outcomes through fixed effect regressions. However, it attempts to construct some comprehensive measures of mental health using a factor analysis approach within a structural framework, where individuals face varying probabilities of completing high school and entering college based on their mental health and other unobserved measures such as physical health, activity, and ability.

The model follows Cunha and Heckman (2008) and attempts to deal with the following three issues that existing models in the literature suffer from: measurement problems related to health variables, unidimensionality of mental health, and mental health endogeneity in high school completion and college entrance equations. Observed variables from Wave I are used to construct four unobserved latent measures that are believed to affect the probability of high school and college in Waves III and IV through modelling heterogeneity. Instead of using subjective data as proxies for mental health, physical health, activity, and ability, our model utilizes a factor analysis approach to construct latent variables for each of these measures. An exploratory factor analysis (EFA) approach is employed to identify these factors.

We then use data from Waves III and IV to obtain information on high school completion and college entrance. Given that the latent variables are not observed to the econometrician, we integrate over their respective distributions to investigate how they influence high school completion and college entrance probabilities. Additionally, the model measures the exclusive effects of the four latent characteristics on these two probabilities, delineating the portions attributable to each of the unobserved constructs and the observed demographic characteristics. The model is estimated in two steps, using a combination of structural equation modelling and logistic regressions. The details are outlined below.

1.4.1. Measurement System

The measurement part of the model focuses on composing four comprehensive measures of mental health, physical health, activity, and ability. The challenge is that these characteristics are latent and unobserved. Instead of using subjective measures of mental health, physical health,

activity, and ability used by the existing literature, we utilize an exploratory factor analysis approach to extract these unobserved factors from the data using a variance covariance matrix. This approach models each observed variable as a function of the underlying latent factors plus unique variance (which includes unique variance of the variable and error). It focuses on the shared variance among variables to identify the underlying factors. In our analysis, we utilized a scree plot for each of the four latent variables to determine the optimal number of factors. This method involves identifying a point on the plot, known as the 'elbow', where the addition of more factors contributes minimally to explaining the variance, thereby guiding the selection of the most meaningful factors for each latent variable.

The first latent factor is *Poor Mental Health*, which is identified by binary indicators, ADHD, depression, fearfulness, unhappiness, and suicidal thoughts through a logistic regression:

$$\log \left(\frac{P(Y_{i,m}=1)}{1-P(Y_{i,m}=1)} \right) = \beta_{0,m} + \beta_{1,m} M_i , \quad (1.1)$$

where $Y_{i,m}$ represents the m^{th} binary indicator for the i^{th} observation, $\beta_{0,m}$ is the intercept for the m^{th} binary indicator, $\beta_{1,m}$ is the factor loading of the latent variable, *Poor Mental Health*, on the m^{th} indicator, M_i represents the latent variable *Poor Mental Health* for the i^{th} observation, and $m = \{1,2,3,4,5\} = \{ADHD, Depressed, Fearful, Unhappy, Suicide\}$.

The second latent factor is *Poor Physical Health*, determined by binary indicators, subjective health, alcohol consumption, marijuana and tobacco use, and unhealthy BMI through the following:

$$\log \left(\frac{P(Y_{i,p}=1)}{1-P(Y_{i,p}=1)} \right) = \beta_{0,p} + \beta_{1,p} P_i , \quad (1.2)$$

where $Y_{i,p}$ signifies the p^{th} binary indicator for the i^{th} observation, $\beta_{0,p}$ is the intercept for the p^{th} binary indicator, $\beta_{1,p}$ is the factor loading of the latent variable, *Poor Physical Health*, on the p^{th} indicator, P_i denotes the latent variable *Poor Physical Health* for the i^{th} observation, and $p = \{1,2,3,4,5\} = \{Poor Health, Tobacco, Alcohol, Marijuana, Poor BMI\}$.

The third latent factor is *Activity*, associated with the observed binary variables, cycling, involvement in professional sports, and exercising through the following regression equation:

$$\log \left(\frac{P(Y_{i,a}=1)}{1-P(Y_{i,a}=1)} \right) = \beta_{0,a} + \beta_{1,a} A_i , \quad (1.3)$$

where $Y_{i,a}$ denotes the a^{th} binary indicator for the i^{th} observation, $\beta_{0,a}$ is the intercept for the a^{th} binary indicator, $\beta_{1,a}$ is the factor loading of the latent variable, *Activity*, on the a^{th} indicator, A_i denotes the latent variable *Activity* for the i^{th} observation, and $a = \{1,2,3\} = \{Bicycle, Sport, Exercise\}$.

Lastly, latent variable *Ability* is identified by the observed, continuous test scores for English, Math, History, and Science, as well as the binary indicator, being senior to one's peers, through the following two equations:

$$V_{i,b} = \lambda_{0,b} + \lambda_{1,b} B_i + \epsilon_{i,b} , \quad (1.4)$$

and

$$\log \left(\frac{P(Y_{i,Senior Student}=1)}{1-P(Y_{i,Senior Student}=1)} \right) = \beta_{0,Senior Student} + \beta_{1,Senior Student} B_i , \quad (1.5)$$

where in the first equation $V_{i,b}$ represents ability's continuous indicators, English, Math, Science, and History scores, $\lambda_{0,b}$ is the intercept for b^{th} continuous variable, $\lambda_{1,b}$ is the factor loading of *Ability* regressed on its b^{th} continuous variable, $\epsilon_{i,b}$ is the residual associated with the i^{th} observation and b^{th} continuous variable and is independent of B_i (i.e. $\epsilon_{i,b} \perp B_i$), and $b = \{1,2,3,4\} = \{English Score, Math Score, History Score, Science Score\}$. In the second equation, $Y_{i,Senior Student}$ denotes the binary indicator, *Senior Student*, for the i^{th} observation, $\beta_{0,sen}$ is the intercept for *Senior Student*, $\beta_{1,Senior Student}$ is the factor loading of the latent variable, *Ability*, and B_i denotes the latent variable *Ability* for the i^{th} observation. A detailed description of each equation is provided in Appendix B under Model Equations.

In general, in the measurement part of our model, all binary indicators follow a logistic function to estimate the probability of the binary outcome as a function of the predictors, which ensures that the predicted probabilities are bounded between zero and one:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}} \quad (1.6)$$

To minimize the mis-classification rate, we should predict $Y = 1$ when $P \geq 0.5$ and $Y = 0$ when $P < 0.5$. This means guessing 1 whenever $\beta_0 + \beta_1 X$ is non-negative, and 0 otherwise. This probabilistic modeling is crucial for understanding the association between the likelihood of various binary indicators given variations in the latent variables. Our continuous test scores for the latent variable *Ability*, follow a normal distribution:

$$f(V_i|B_i) = \frac{1}{\sqrt{2\sigma_{ub}^2\pi}} \exp \left(-\frac{(V_{ib} - \lambda_{0,b} - \lambda_{1,b}B_i)^2}{2\sigma_{ub}^2} \right) \quad (1.7)$$

Identification of the model requires that $L \geq 2k + 1$, where L is the number of observed indicators and k is the number of latent factors (Cunha and Heckman, 2008). Our model ensures this condition is satisfied since there are a total of eighteen observed indicators (a minimum of three for each latent variable) and four latent factors. Identification also requires imposing constraints on some parameters; In our analysis, we standardize one loading per latent factor to unity. Subsequent loadings are interpreted relative to this, offering a proportional comparison to the standardized coefficient. In particular, we set $\beta_{1,Unhappy} = 1$ in the equation for *Poor Mental Health*, $\beta_{1,Marijuana} = 1$ in the equation for *Poor Physical Health*, $\beta_{1,Bicycle} = 1$ for *Activity*, and $\beta_{1,Science Score} = 1$ for *Ability*.

1.4.2. Educational Outcomes

The latent factors constructed in the previous part are used to model our two education outcome variables: high school completion and college entrance. They are each estimated separately within two independent GSEM frameworks. *High School* is a binary outcome variable estimated through the following general logistic form:

$$\log \left(\frac{P(H_i=1)}{1-P(H_i=1)} \right) = \alpha_{0,H} + \alpha_{1,H} M_i + \alpha_{2,H} P_i + \alpha_{3,H} A_i + \alpha_{4,H} B_i + \sum_{j=1}^5 \gamma_{j,H} D_{i,j} , \quad (1.8)$$

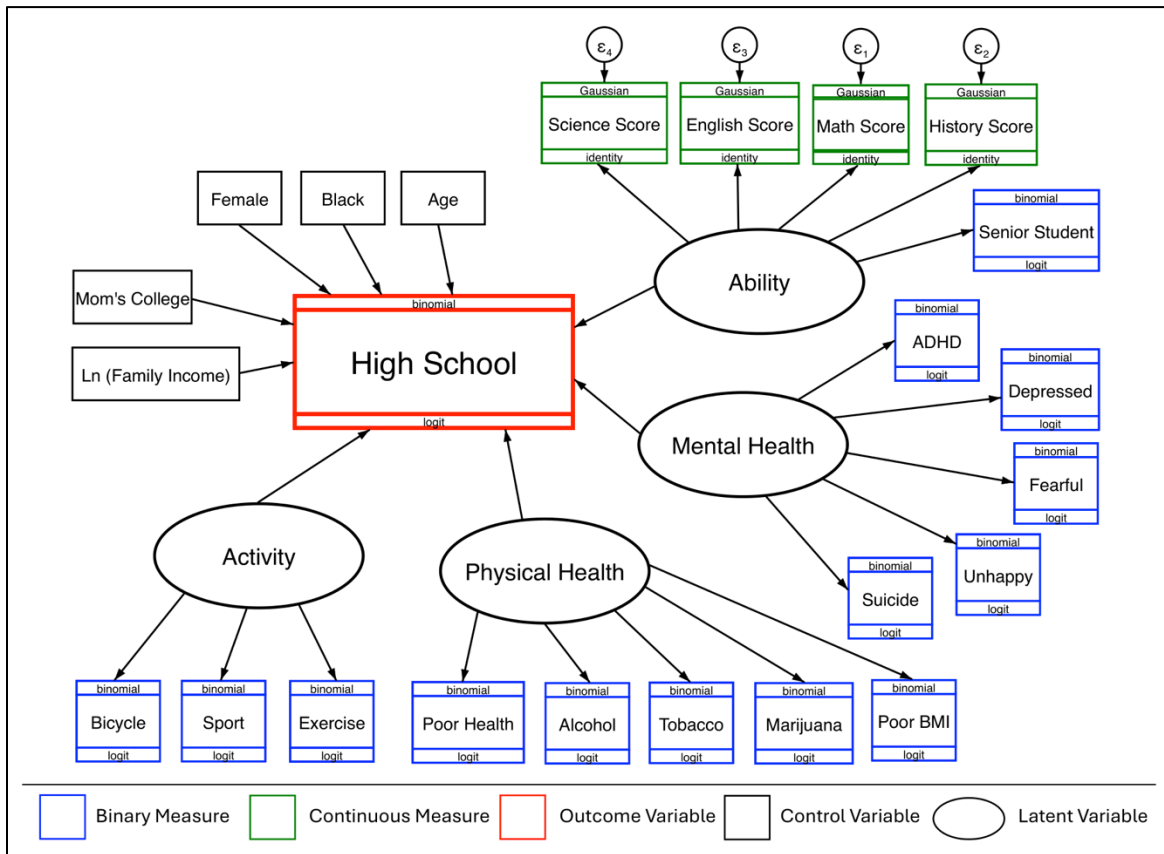
where H_i is the probability of completing high school for the i^{th} observation, α_0 is a constant, $\alpha_1, \alpha_2, \alpha_3$, and α_4 are the coefficients of *Poor Mental Health*, *Poor Physical Health*, *Activity*, and *Ability*, respectively, for the i^{th} observation; γ_j is the coefficient of each demographic

covariate (i.e. sex, age, mother's college completion, race, and family income), and $D_{i,j}$ represents demographic covariate j for the i^{th} observation with $j = \{1,2,3,4,5\} = \{Female, Age, Mom's College, Black, Family Income (ln)\}$. The equation for college follows the exact same form and interpretation, except that here, the response variable, C_i , denotes the probability of entering college:

$$\log \left(\frac{P(C_i=1)}{1-P(C_i=1)} \right) = \alpha_{0,C} + \alpha_{1,C} M_i + \alpha_{2,C} P_i + \alpha_{3,C} A_i + \alpha_{4,C} B_i + \sum_{j=1}^5 \gamma_{j,C} D_{i,j} \quad (1.9)$$

Figure 1.1 offers a visual overview of our GSEM model's structure, highlighting the interactions between observed indicators and latent constructs, as well as the relationships between the latent constructs and the high school completion outcome variable. The structure for the college entrance outcome variable is very similar and, therefore, is not depicted here.

Figure 1.1. Visual Overview of the GSEM Model's Structure



The terms at the top of each outcome variable are the family (i.e. Gaussian, binomial), and the terms at the bottom of each outcome variable represent the link (i.e. logit, identity). For any model of the form: $g\{E(y_i)\} = X_i\beta$, $y_i \sim F$, F is the family and $g(\cdot)$ is the link.

1.4.3. Estimation

Estimation is carried out through two crucial stages as explained below.

Stage 1: Equations 1.1-1.5, 1.8, and 1.9 constitute our Generalized Structural Equation Modelling, through which the log odds of high school completion and college entrance are exclusively estimated. The distributions of the latent factors may follow various forms; however, we assume a normal distribution to facilitate estimation of our model:

$$f(U) = f(U|\mu, \Omega),$$

where μ and Ω are the mean and covariance of each latent variable $U = \{M, P, A, B\}$. Each latent variable is inferred from the pattern of responses to its corresponding indicators, as indicated by the factor loadings. These loadings, alongside measures of model fit, suggest that the latent constructs were reliably captured by the observed indicators.

Let ψ denote all the parameters in our model, $\psi = \{\beta, \lambda, \alpha, \gamma, \sigma, \mu, \Omega\}$, $U = \{M, P, A, B\}$ be the vector of latent factors, D be the vector of observed demographic variables for high school and college, and q be the vector of all observed indicators determining each latent variable. The full model likelihood functions for *High School* and *College*, respectively, are hence:

$$\mathcal{L}_H(\psi) = \sum_{i=1}^n [\sum_q \ln P(Y_{i,q}, V_{i,q} | U_i, \psi) + \ln P(H_i | U_i, \psi, D_i)], \quad (1.10)$$

and

$$\mathcal{L}_C(\psi) = \sum_{i=1}^n [\sum_q \ln P(Y_{i,q}, V_{i,q} | U_i, \psi) + \ln P(C_i | U_i, \psi, D_i)] \quad (1.11)$$

Considering the latent characteristics of the factors, we compute the likelihood function across the distributions of these non-observable elements. The log-likelihood functions, as shown in equations 10 and 11, are determined via Maximum Likelihood Estimation (MLE) methods.

Stage 2: In the subsequent phase, factor scores for each of the four latent variables derived from the Generalized Structural Equation Model are computed. These factor scores are then utilized as predictor variables in two distinct logistic regression analyses to predict the likelihoods of completing high school and entering college, respectively, through the following:

$$\log \left(\frac{P(H_i=1)}{1-P(H_i=1)} \right) = \emptyset_{0,H} + \emptyset_{1,H} MS_i + \emptyset_{2,H} PS_i + \emptyset_{3,H} AS_i + \emptyset_{4,H} BS_i + \sum_{j=1}^5 \vartheta_{j,H} D_{i,j}, \quad (1.12)$$

and

$$\log \left(\frac{P(C_i=1)}{1-P(C_i=1)} \right) = \emptyset_{0,C} + \emptyset_{1,C} MS_i + \emptyset_{2,C} PS_i + \emptyset_{3,C} AS_i + \emptyset_{4,C} BS_i + \sum_{j=1}^5 \vartheta_{j,C} D_{i,j}, \quad (1.13)$$

where H_i and C_i are probabilities of high school completion and college entrance, respectively, MS_i , PS_i , AS_i , BS_i , are the computed latent factor scores of *Poor Mental Health*, *Poor Physical Health*, *Activity*, and *Ability*, for individual i , from Step 1 of the estimation process (GSEM model). $\emptyset_{0,H}$ and $\emptyset_{0,C}$ are constants, $\emptyset_{1,H}$ and $\emptyset_{1,C}$, $\emptyset_{2,H}$ and $\emptyset_{2,C}$, $\emptyset_{3,H}$ and $\emptyset_{3,C}$, $\emptyset_{4,H}$ and $\emptyset_{4,C}$ are the coefficients of *Poor Mental Health Score*, *Poor Physical Health Score*, *Activity Score*, and *Ability Score*, respectively, for the i^{th} observation; $\vartheta_{j,H}$ and $\vartheta_{j,C}$ are the coefficients of demographic covariates (i.e. sex, age, mother's college completion, race, and family income), and $D_{i,j}$ is the j^{th} demographic factor for individual i , with $j = \{1,2,3,4,5\} = \{Female, Age, Mom's College, Black, Family Income (ln)\}$.

1.5. Results

1.5.1. Measurement System

In our Generalized Structural Equation Model (GSEM), the measurement component crucially quantifies the relationships between the latent variables—*Poor Mental Health*, *Poor Physical Health*, *Activity*, and *Ability*—and their observed indicators. This component constructs latent factors and explains how each observed variable contributes to and reflects the underlying latent concept.

For the latent variable *Poor Mental Health*, explained by equation 1.1, we consider indicators such as ADHD, depression, fearfulness, unhappiness, and suicidal tendencies. The Average Marginal Effect (AME) for each of these indicators as well as the raw coefficients $\beta_{1,m}$, are reported in Table 1.2.a. The AME values tell us the average change in the probability of exhibiting any of the reported symptoms (i.e. *ADHD*, *Depressed*, *Fearful*, *Unhappy*, *Suicide*), for a one-unit increase in the latent construct *Poor Mental Health*, while holding all other variables constant. For instance, the AME for ADHD represents a unit increase in the latent factor, Poor

Mental Health Score, is associated with an average change of 0.054, in the probability of having ADHD symptoms. Based on the results, compared to other indicators, unhappiness, with an AME of 0.185, contributes the most to the overall construct of *Poor Mental Health*. Similarly, the AMEs for depression (0.090), fearfulness (0.035), and suicidal tendencies (0.131) each reflect how changes in these specific mental states contribute to and are indicative of the overall level of an individual's mental health.

Table 1.2.a. Measurement System - Mental Health

	ADHD	Depressed	Fearful	Unhappy	Suicide
Panel A: Estimated parameters					
Constant	- 2.934*** (0.079)	- 4.353*** (0.319)	- 4.183*** (0.183)	- 2.178*** (0.101)	- 2.529*** (0.098)
Poor Mental Health	0.238*** (0.062)	1.605*** (0.218)	0.829*** (0.107)	1	0.843*** (0.092)
Panel B: Average Marginal Effects of Factors (AME)					
Poor Mental Health AME	0.054*** (0.004)	0.090*** (0.005)	0.035*** (0.003)	0.185*** (0.006)	0.131*** (0.005)
<i>N</i>	3959	3959	3959	3959	3959

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

Tables 1.2.b, 1.2.c, and 1.2.d, each report similar results for the other three latent variables *Poor Physical Health*, *Activity*, and *Ability*. Among the binary indicators included for *Poor Physical Health*, explained by equation 1.2, *Poor BMI*, with an AME of 0.365, shows the strongest average association. This means that, on average, a shift in BMI status (from normal to poor) has a more substantial impact on the probability of being classified under *poor physical health* than changes in the other binary indicators like subjective health (i.e. *Poor Health*), tobacco, marijuana, or alcohol consumption. However, all five indicators positively and significantly influence the probability of having poor physical health, which is consistent with our intuitive hypotheses.

Table 1.2.b. Measurement System - Physical Health

	Poor Health	Tobacco	Alcohol	Marijuana	Poor BMI
Panel A: Estimated parameters					
Constant	- 2.816*** (0.081)	- 2.585*** (0.141)	- 2.228*** (0.085)	- 2.677*** (0.163)	- 0.548*** (0.033)
Poor Physical Health	0.274*** (0.041)	0.920*** (0.114)	0.594*** (0.055)	1	- 0.013 (0.017)
Panel B: Average Marginal Effects of Factors (AME)					
Poor Physical Health AME	0.070*** (0.004)	0.204*** (0.006)	0.179*** (0.006)	0.271*** (0.001)	0.365*** (0.008)
<i>N</i>	3959	3959	3959	3959	3959

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

Table 1.2.c. Measurement System - Activity

	Bicycle	Sport	Exercise
Panel A: Estimated parameters			
Constant	- 0.604*** (0.041)	1.131*** (0.058)	1.913*** (0.067)
Activity	1	1.235*** (0.218)	0.951*** (0.161)
Panel B: Average Marginal Effects of Factors (AME)			
Activity AME	0.373*** (0.008)	0.717*** (0.007)	0.846*** (0.006)
<i>N</i>	3959	3959	3959

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

The latent factor, *Activity*, is identified by observed indicators, *Bicycle*, *Sport*, and *Exercise*, among which the latter has the most influential effect on this latent construct. Cycling and being

involved in any team sports, such as baseball, are also positively correlated with physical activity and are significant at the 99% confidence interval.

Lastly, in our measurement system, *Ability* is described by test scores in four subjects, English, Math, History, and Science, as well as the probability of being senior compared to one's peers. Our initial hypotheses was that the four scores would be positively associated with cognitive ability, while being older compared to one's classmates would be a negative indication of one's ability (i.e. grade repetition). For the most part, the results support the hypotheses, as all four test scores are positively and significantly (at 99% CI) correlated with the latent construct, *Ability*. In particular, an increase of one unit in the *Ability* factor is associated with an average increase of 3.239 units in the student's *English Score*. This indicates a strong positive relationship between English skills and the overall measurement of the individual's ability. However, despite having a negative raw coefficient, consistent with our intuitive hypothesis, *Senior Student* has a positive and significant AME. This implies that across the entire distribution of our data, the average effect of being senior (i.e. older compared to peers) on the probability of having a higher level of ability is positive. We believe this could be related to maturity, experience, or other factors not directly captured by the model.

Table 1.2.d. Measurement System - Ability

	English Score	Math Score	History Score	Science Score	Senior Student
Panel A: Estimated parameters					
Constant	3.239*** (0.014)	2.955*** (0.018)	2.973*** (0.020)	2.941*** (0.020)	0.020 (0.034)
Ability	0.698*** (0.029)	0.879*** (0.035)	0.802*** (0.038)	1	- 0.627*** (0.060)
Panel B: Average Marginal Effects of Factors (AME)					
Ability AME	3.238*** (0.014)	2.955*** (0.018)	2.973*** (0.020)	2.941*** (0.020)	0.505*** (0.008)
<i>N</i>	3959	3959	3959	3959	3959

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

1.5.2. Effects of Mental Health on Educational Outcomes

Table 1.3 reports the effects of our four latent constructs, *Poor Mental Health*, *Poor Physical Health*, *Activity*, and *Ability*, along with other observed demographic variables on the probability of high school completion. Our main variable of interest in this study is mental health. As specified by the results, an increase of one standard deviation in the *Poor Mental Health* score indicating worse mental health, is associated with a decrease of approximately 2.2 percentage points in the likelihood of completing high school. Having poor physical health is also negatively associated with the probability of high school completion with a magnitude similar to mental health (i.e. AME of - 0.027). Furthermore, the AME shows that a one standard deviation increase in the latent factor *Activity*, reflecting higher levels of physical activity, is associated with 3.1 percentage point decrease in the probability of completing high school. The interpretation of activity's coefficient, however, requires more caution as the standard error of 0.013 suggests moderately substantial variability in estimating the AME for this factor. However, if we were to explain this counter-intuitive negative association, we can think about factors such as time allocation tradeoff, shifting priorities, and burnout. Lastly, *Ability* factor score has a highly significant positive effect on the probability of high school completion. A one standard deviation in the *Ability* score increases the likelihood of high school completion by 9.0 percentage points.

Table 1.4 demonstrates similar results for the probability of college entrance. Worsening mental health, indicated by a one standard deviation increase in the *Poor Mental Health* score is associated with a 3.9 percentage point decrease in college entrance probability, suggesting a significant negative impact of poor mental health on higher-education attainment; This value is approximately twice as large as the impact on the likelihood of high school completion. The AME for *Poor Physical Health* score, though quantitatively small, is not statistically significant indicating no discernible impact of physical health status on college entrance within the scope of this model. Additionally, a one standard deviation increase in the *Activity* score, reflecting higher levels of physical activity, is associated with an 8.9 percentage point increase in the likelihood of entering college, pointing to a positive relationship between physical activity and higher education outcomes. A one standard deviation increase in the *Ability* score is linked to a 19.4 percentage

point increase in the probability of college entrance, highlighting the strong influence of academic capabilities on higher education prospects.

Table 1.3. Probability of High School Completion – GSEM and AME

Variables	GSEM Coefficients	Average Marginal Effects
Poor Mental Health	- 0.159*** (0.059)	- 0.022*** (0.005)
Poor Physical Health	- 0.198*** (0.046)	- 0.027*** (0.003)
Activity	- 0.049 (0.144)	- 0.031** (0.013)
Ability	0.764*** (0.121)	0.090*** (0.010)
Female	0.395*** (0.111)	0.031*** (0.010)
Age	0.280*** (0.036)	0.031*** (0.003)
Mom's College	1.107*** (0.152)	0.095*** (0.014)
Black	- 0.374*** (0.128)	- 0.043*** (0.011)
Family Income (<i>ln</i>)	0.021* (0.012)	0.002* (0.001)
Constant	- 2.640*** (0.576)	-
<i>N</i>	3959	

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each variable, holding other variables fixed.

Most demographic factors have a positive effect on both high school completion and college entrance except for the variable *Black*, revealing racial disparities in access to higher education. In both high school and college regressions, *Family Income (ln)* was near the threshold, but ultimately did not reach statistical significance. Among all demographic predictors, mother's

college education has the highest effect on educational success, particularly on college entrance probability. Having a mother with a college education significantly increases the likelihood of college entrance by 24.6 percentage points, highlighting the substantial role of maternal education in shaping educational aspirations and achievements. The raw coefficients of latent factor scores and demographic indicators for the two-step logistic regressions are outlined in Appendix C, Table C.1.

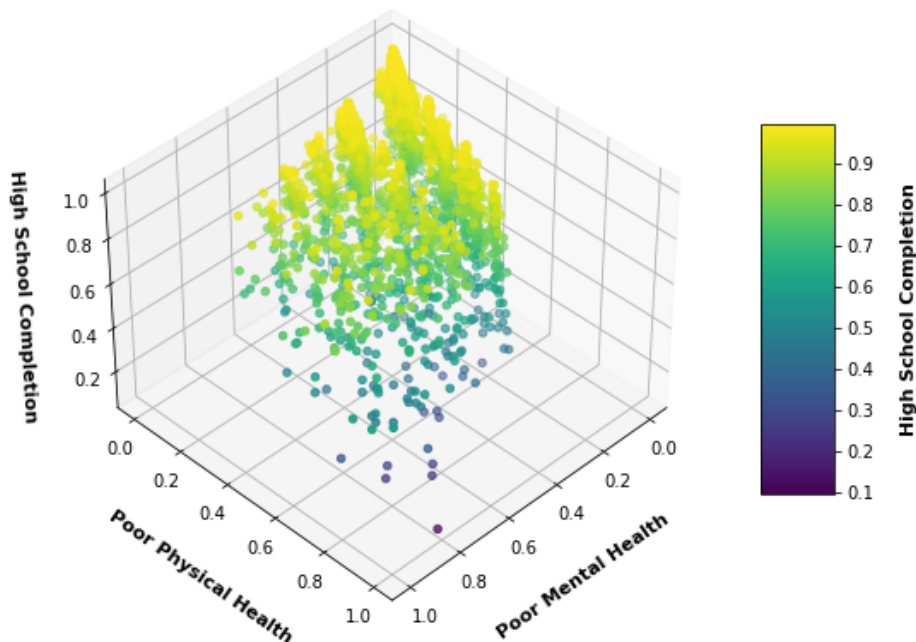
Table 1.4. Probability of College Entrance – GSEM and AME

Variables	GSEM Coefficients	Average Marginal Effects
Poor Mental Health	- 0.120*** (0.046)	- 0.039*** (0.007)
Poor Physical Health	- 0.036 (0.032)	0.005 (0.005)
Activity	0.169 (0.112)	0.089*** (0.017)
Ability	0.841*** (0.099)	0.194*** (0.014)
Female	0.554*** (0.081)	0.100*** (0.013)
Age	0.132*** (0.025)	0.035*** (0.004)
Mom's College	1.539*** (0.105)	0.246*** (0.016)
Black	- 0.293*** (0.094)	- 0.046*** (0.015)
Family Income (<i>ln</i>)	0.014 (0.009)	0.002* (0.001)
Constant	- 1.933*** (0.425)	-
<i>N</i>	3959	

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each variable, holding other variables fixed.

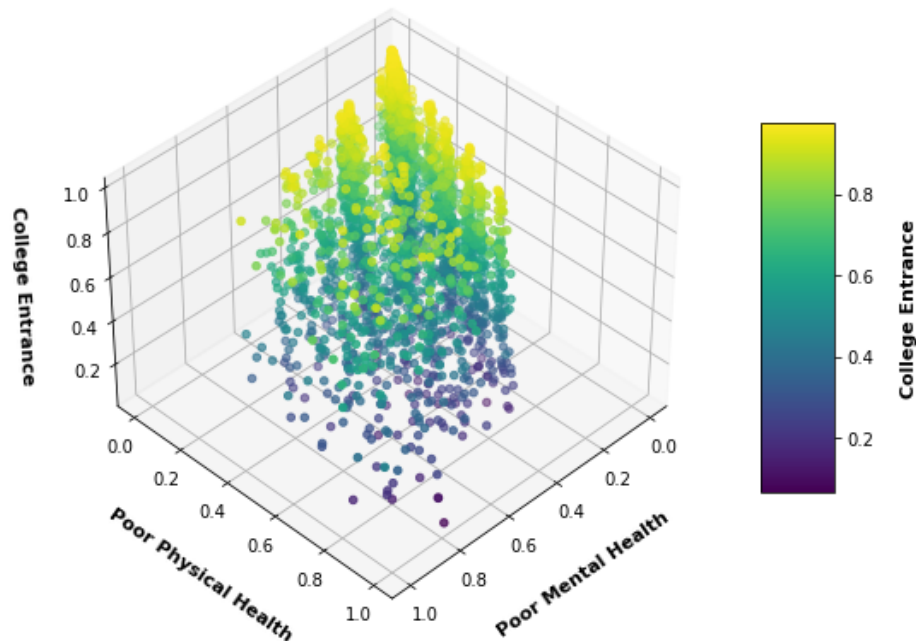
Figures 1.2.a and 1.2.b are 3D scatter plots showing the impact of poor mental and physical health on the distribution of educational outcomes. The first plot, 1.2.a, presents the distribution of high school completion probabilities as a function of poor mental and physical health scores. The 3D scatter plot reveals that as the scores indicating poorer health increase, the likelihood of completing high school appears to decline, as shown by the aggregation of points towards the bottom of the graph. Figure 1.2.b depicts the distribution of college entrance probabilities against the poor mental and physical health scores. It demonstrates a similar pattern to the first plot, where an increase in poor health scores tends to correspond with a decrease in the probabilities of entering college, illustrated by the descending concentration of points. In both plots, the probability scale is represented by a color gradient, which aids in visual depiction of the negative correlation between poor health and the probability of achieving these educational milestones.

Figure 1.2.a. Mental Health, Physical Health, and High School Completion



3D scatter plots demonstrating the negative correlation between poor mental and physical health scores and the probabilities of high school completion, with color gradients indicating likelihood.

Figure 1.2.b. Mental Health, Physical Health, and College Entrance



3D scatter plots demonstrating the negative correlation between poor mental and physical health scores and the probabilities of college entrance, with color gradients indicating likelihood.

1.5.3. Postestimation

In our study, we recognize the critical importance of validating the reliability and robustness of our econometric model. While some conventional post-estimation validation methods were not feasible due to the model's complexity, we employed all accessible techniques to affirm the accuracy of our approach. Our statistical model was estimated in a sequential, two-step process. After each step, we calculated binned residuals, a method where predicted probabilities are grouped into bins, and residuals (i.e. the differences between predicted and actual outcomes) within these bins are analyzed. This approach is particularly useful in assessing the model's fit across different ranges of the predicted values. In our Generalized Structural Equation Model (GSEM), the predicted probabilities for both high school completion and college entrance closely mirrored the actual probabilities across these bins. Detailed depictions of these comparisons are available in Figures 1.3.a and 1.4.a. We further enhanced our model's predictive accuracy through a two-step estimation procedure, elaborated in Section 1.4 of our paper. This refinement resulted in an even better alignment of our predicted probabilities with the actual values, reinforcing the exceptional

precision of our model. The binned residuals of the two-step estimation are depicted in Figures 1.3.b and 1.4.b, for high school and college respectively. The horizontal axis represents the probability ($0 \leq P \leq 1$) of high school completion and college entrance segmented into five groups at intervals of 0.2. This means the first group covers probabilities from 0 to 0.2, the second from 0.2 to 0.4, the third from 0.4 to 0.6, and so forth. The vertical axis displays both the mean actual and mean predicted probabilities of completing high school and gaining college admission in each bin, as derived from the 1-step and 2-step estimation methods. Figures 1.3.b and 1.4.b clearly demonstrate that the 2-step estimates more closely align with the actual probabilities, reflecting the accuracy and effectiveness of our 2-step methodology.

Moreover, we utilized the Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC) to compare the fit of the one-step and two-step models. These criteria are statistical tools used to evaluate model fit, where lower values indicate a more efficient model in terms of balancing goodness-of-fit and model complexity. The two-step model exhibited lower AIC and BIC values, suggesting an improved model fit. These findings are documented in Appendix C, Tables C.2 and C.3.

Finally, to assess our model's ability to discriminate between different outcomes accurately, we computed Receiver Operating Characteristic (ROC) values after each estimation step. ROC analysis is to evaluate the performance of classification models, with values typically ranging from 0.5 (i.e. no discrimination) to 1 (i.e. perfect discrimination). ROC values above 0.80, which improved even further after the second stage, as shown in the plots in Appendix C, Figures C.1 and C.2, indicate a low rate of false positives and robust model performance in distinguishing between cases. These high ROC values affirm the strong discriminative capacity of our model.

Figure 1.3.a.

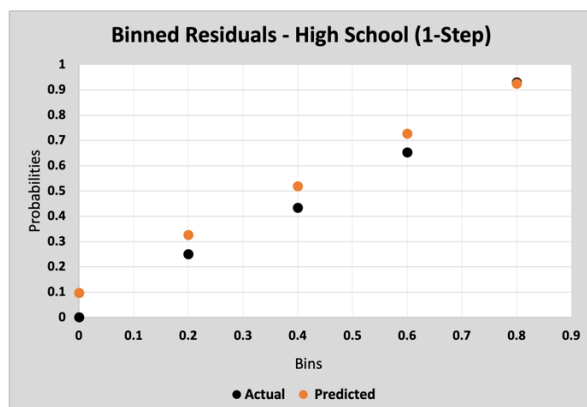
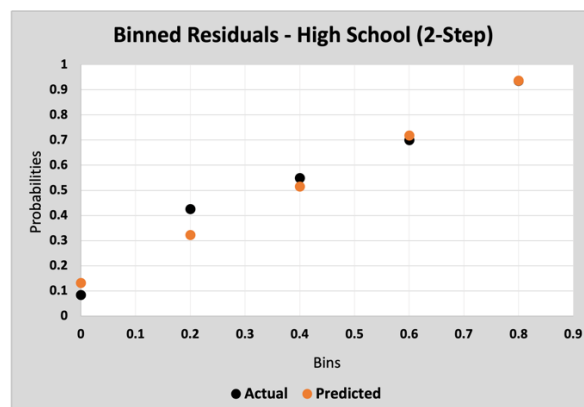


Figure 1.3.b.



The horizontal axis is the probability ($0 \leq P \leq 1$) of high school completion divided into five groups at intervals of 0.2. The vertical axis displays both the mean actual and mean predicted probabilities of completing high school, as derived from the 1-step (2.a) and 2-step (2.b) estimation methods.

Figure 1.4.a.

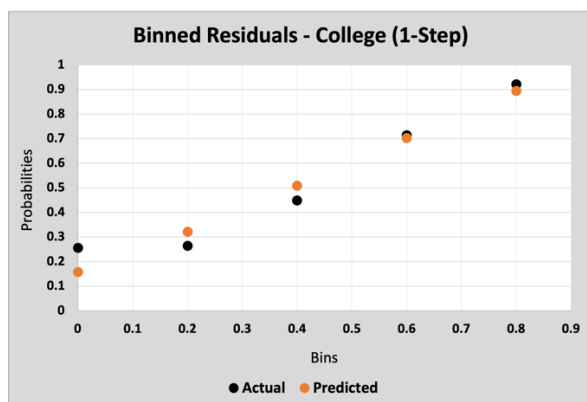
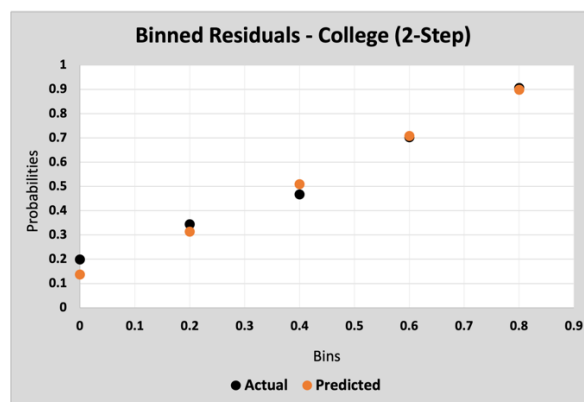


Figure 1.4.b.



The horizontal axis is the probability ($0 \leq P \leq 1$) of college entrance divided into five groups at intervals of 0.2. The vertical axis displays both the mean actual and mean predicted probabilities of college entrance, as derived from the 1-step (3.a) and 2-step (3.b) estimation methods.

1.6. Conclusion

This study delves into the complex relationship between childhood mental health issues and their long-term effects on educational achievements, such as completing high school and pursuing higher education. By analyzing extensive Add Health data and using advanced statistical methods through GSEM and two-step estimation, we have uncovered several important insights that add depth to our understanding of this critical issue. By conceptualizing mental health as an unobserved latent construct and evaluating its impact in conjunction with other key latent characteristics, like

physical health, activity, and ability, this study addresses a critical gap in the existing research. It substantially enhances the current literature, which often oversimplifies mental health by limiting it to observable proxies, by adding depth and complexity to our understanding of its role. Our approach has been unique in considering children who might have undiagnosed mental health conditions, as it investigates different dimensions of mental health, such as comorbidity, and its impact on other unobserved characteristics. This has allowed us to paint a more accurate picture of how mental health interplays with other factors and is vital for creating effective policies and support systems.

Key findings reveal that mental health conditions have a modest, yet noticeable negative impact on a student's educational journey. Specifically, a one standard deviation increase in the worsening of mental health, correlates with a 2.2 percentage point decrease in the likelihood of high school completion. This trend continues into higher education, where a similar deterioration in mental health is associated with a 3.9 percentage point decrease in the probability of entering college. Interestingly, the study also reveals that poor physical health, while negatively impacting high school completion to a degree similar to mental health, does not show a statistically significant effect on college entrance. The result suggests that while physical health is a crucial factor in early education, its impact may diminish as students transition to obtain higher education. This connection highlights a crucial area for policy makers and educators: the need for early and effective support for children with mental health issues. The implications of our findings are significant. They suggest that educational and health policies should be more interconnected, focusing not just on treating certain diagnosed mental health conditions, but also on fostering overall well-being in children. This can lead to better educational outcomes, lower economic burden of mental health, and in the long run, a more productive society.

Additionally, we recognize the need for ongoing research in this field, in particular a gender-based analysis and the impact on earnings. Understanding the long-term effects of childhood mental health issues on human capital is crucial for developing strategies that can effectively support the next generation in their educational, career, and personal development. In summary, this paper sheds light on the profound impact of childhood mental health issues on educational outcomes. As we continue to grapple with the increasing prevalence of mental health issues, research like this becomes ever more essential in guiding effective policy and practice.

Chapter 2.

Trapped in the Grind: Mental Health and Occupational Selection

2.1. Introduction

The relationship between mental health and labor market outcomes has been a topic of growing academic interest. While previous studies have examined the impact of mental health on employment status and earnings (e.g., Andersen et al., 2024; Marcotte et al., 2000; Fletcher, 2013; Shen, 2023), a separate strand of literature has explored how labor market outcomes and occupational conditions affect mental health (e.g., Charles, 2002; Flint et al., 2013; Rönnblad et al., 2019; Mandal et al., 2011; Tsai et al., 2024; Zhao, 2023). Despite this growing body of research on the bidirectional links between mental health and labor market performance, little attention has been given to how mental health specifically influences occupational outcomes. This study aims to fill this critical gap by investigating how mental and physical health influence the selection of specific occupational classifications, including high-skilled white-collar roles, physically demanding blue-collar jobs, and full-time versus part-time employment. This paper explicitly focuses on the impact of mental and physical health on occupational outcomes, rather than the reverse relationship. While labor market experiences may also influence health, such feedback effects are beyond the scope of this study. Mental and physical health are modeled as latent variables using prior indicators and treated as exogenous determinants in the occupational sorting model. Given the increasing prevalence of mental health conditions globally and their potential to shape labor market outcomes, understanding the extent to which mental and physical health dictate career paths is essential for both economic policymakers and labor market analysts.

A major limitation of the existing literature is the predominant focus on aggregate employment outcomes without a deeper examination of occupational selection. Studies such as Andersen (2015) and Germinario et al. (2022) explore the effects of mental health on employment probabilities and earnings but do not distinguish between different types of jobs individuals select into. Fletcher (2013) and Peng et al. (2013) provide evidence of long-term labor market penalties associated with adolescent depression and adult mental health disorders, but their analyses remain confined to broad employment measures rather than specific occupational classifications. Similarly, Shen (2023) and Frijters et al. (2010) highlight the significant effects of mental health on labor force participation but do not account for the heterogeneity in occupational selection. By contrast, this study is the first to examine how both mental and physical health influence occupational outcomes across two broad classifications: white-collar and full-time occupations.

This study makes several unique contributions. First, it addresses a research question that has not been explored in prior literature: how mental health conditions influence selection probabilities of white-collar and full-time occupations. Second, this study introduces a nuanced approach to grouping occupations. Instead of using industry-based classifications, common to labor economics literature, the study employs the first two digits of Standard Occupational Classification (SOC) system combined with O*NET data to create white-collar versus blue-collar definitions based on seven shared skill sets, work contexts, and knowledge requirements. A focus on occupation-specific rather than industry-based grouping follows advice from Mannetje and Kromhout (2003). The paper highlights that job roles (e.g., civil engineers, accountants) exist across multiple industries, making an occupation-based classification more flexible and broadly applicable than an industry-based classification. This classification method allows for a more refined analysis of occupational sorting and provides insights that extend beyond standard industry distinctions.

Third, this research advances the methodological approach to studying mental and physical health in labor economics. Rather than relying on self-reported single-item measures, this study constructs latent health variables using a Generalized Structural Equation Model (GSEM). Mental and physical health are modeled as latent constructs incorporating multiple observed indicators from the data. This approach reduces measurement error and better captures the multidimensional nature of health.

Fourth, this study employs a mixed-effects logistic regression model, incorporating both fixed and random effects to account for variations within and between individuals over time. This is the first application of such a model to examine the relationship between mental health and occupational sorting, providing a more robust estimation of health's impact on career selection while accounting for unobserved individual heterogeneity in occupational selection.

The analysis is based on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative U.S. dataset that follows individuals from adolescence into adulthood. This study utilizes data from Waves I, III, IV, and V, capturing 2954 individuals aged 12-18 in the baseline wave and tracking them into their 30s and 40s. The dataset is uniquely suited for this research due to its rich longitudinal coverage of mental and physical health measures alongside detailed occupational histories.

Mental and physical health are modeled as latent variables using a Generalized Structural Equation Model (GSEM). The Poor Mental Health construct includes indicators for ADHD, depression, suicidal thoughts, and self-reported unhappiness, while the Poor Physical Health construct incorporates measures of self-reported health, tobacco, alcohol, marijuana, and cocaine consumption as well as Body Mass Index (BMI). The predicted scores of these latent variables are then used in mixed-effects logistic regression models to estimate their effects on occupational selection. The regression models for the occupational classifications include lagged and differenced measures of mental and physical health, allowing for an examination of both long-term health effects and recent changes in health status. The models control for other important covariates such as age, sex, race, maternal education, marital status, and education level, with standard errors clustered at the individual level to account for repeated observations over time.

The results reveal that both mental and physical health significantly influence occupational selection probabilities. Individuals with better mental health are more likely to enter high-skilled careers. An increase in the lagged mental health score significantly increases the probability of selecting white-collar occupations, whereas lower mental health scores are associated with blue-collar job selection. Similar results hold for the choosing full-time versus part-time jobs as improvements in mental health increase probability of working full-time. Physical health also plays a critical role. Individuals with better physical health are more likely to work in professional, white-collar occupations, while those with poorer physical health are overrepresented in physically intensive, blue-collar roles such as trades and maintenance.

The heterogeneity analysis further confirms these findings. The probability of selecting white-collar occupations increases from 47.2% for individuals with poor mental health to 56.9% for those with perfect mental health. Similar patterns are observed for physical health, where those in better health are more likely to choose white-collar jobs. The analysis also shows that the probability of securing full-time employment increases from 51.9% to 68.5% when moving from poor to perfect mental health.

These results underscore the substantial role that mental and physical health play in shaping labor market outcomes. They suggest that improving mental health can facilitate upward occupational mobility, enabling individuals to select into higher-skilled, less physically demanding, and more stable careers. Policymakers should consider these findings when designing

interventions aimed at reducing occupational disparities and supporting individuals with mental health challenges in accessing better employment opportunities. Additionally, these results highlight the potential long-term economic consequences of untreated mental health conditions, as individuals with poor mental health may become trapped in lower-wage, physically demanding, or precarious jobs. Addressing these disparities through mental health support services, employer accommodations, and policy interventions could significantly enhance workforce productivity and individual well-being.

The remaining parts of the paper are structured as follows: Section 2.2 provides a detailed literature review on the impact of mental health on labor market outcomes. Section 2.3 describes the data structure and provides a comprehensive overview of the variables used in the model, along with the occupational grouping. Section 2.4 defines the GSEM and mixed-effects logistic regressions' framework. Section 2.5 outlines the obtained results. Lastly, Section 2.6 concludes the paper.

2.2. Literature Review

Fletcher (2013) investigates the long-term effects of adolescent depression on adult labor market outcomes, focusing on employment and earnings using Add Health data. The study builds on prior literature that links depression with adverse life outcomes, including diminished educational attainment and labor market performance. The analysis incorporates high school fixed effects and sibling comparisons to control for environmental and family-level confounders, alongside adjustments for co-occurring health and behavioral factors.

The study finds that adolescent depression is associated with significant reductions in both employment and earnings in adulthood. Baseline results suggest that individuals with adolescent depression experience a 7.5 percentage point decrease in employment. This effect is particularly pronounced among women, who face a 10-percentage point reduction. The findings are largely robust to the inclusion of controls for educational attainment and adult depressive symptoms, though these factors partially mediate the relationship. Sibling comparisons further support the robustness of the results, reducing the employment penalty to approximately six percentage points while highlighting that the adverse effects are concentrated among women. Fletcher concludes that adolescent depression exerts a substantial influence on labor market attachment, with the

persistence of depression and human capital deficits serving as important pathways. (Fletcher, 2013)

In terms of earnings, adolescent depression is linked to a nearly 23% reduction in adult earnings, even after accounting for school fixed effects. Adjusting for health behaviors, co-occurring conditions, and educational attainment reduces the penalty slightly to 20% and eventually to 16% when controlling for adult depressive symptoms. Interestingly, while employment penalties are more significant for women, earnings reductions are primarily concentrated among men. The study also shows that the earnings disadvantage remains robust even within sibling comparisons, further supporting the validity of the findings. Despite these robust results, Fletcher acknowledges that attributing the observed relationships entirely to causal effects remains challenging due to the potential influence of unmeasured factors. (Fletcher, 2013)

Peng, Meyerhoefer, and Zuvekas (2013) contribute to the literature on mental health and labor market outcomes by examining the causal impact of depression on employment, wages, hours worked, and absenteeism. Like Fletcher (2013), this study emphasizes the significant role of mental health in shaping economic outcomes. However, it employs a distinct methodological approach by using longitudinal data from the Medical Expenditure Panel Survey (MEPS) and estimating fixed effects and correlated random effects (CRE) models. This methodology allows the authors to address endogeneity arising from unobserved heterogeneity, such as worker productivity or health status. The use of the clinically validated Patient Health Questionnaire (PHQ-2) depression measure strengthens the reliability of the findings by linking depression directly to labor market outcomes.

The authors find a negative and statistically significant association between depression and employment. Cross-sectional estimates suggest a 17.6 percentage point reduction in employment probability for individuals with depression, consistent with prior studies like Fletcher (2013). However, the CRE model, which accounts for unobserved heterogeneity, reduces this estimate to 2.6 percentage points, indicating that earlier studies may have overstated the effect due to omitted variable bias. Unlike Fletcher's study, which highlights gender differences with stronger employment effects for women, this study does not specifically emphasize such disparities but rather underscores the methodological improvements in estimating the causal effects. (Peng et al., 2013)

Regarding wages and hours worked, the study finds minimal evidence of a robust relationship. Depression is associated with an 8.3% reduction in hourly wages in cross-sectional models, but this effect disappears when using fixed effects or CRE models. Similarly, depression does not significantly impact weekly hours worked, suggesting that these labor market dimensions are less responsive to mental health compared to employment. In contrast, Fletcher (2013) reported more substantial earnings penalties and linked them partly to human capital accumulation and persistent depression, highlighting potential differences in the datasets and methodologies used. (Peng et al., 2013)

Absenteeism emerges as a notable pathway through which depression impacts labor market outcomes. Depression increases annual work loss days by approximately 1.4 days, representing a one-third increase relative to the mean. This finding is consistent with the literature, which identifies absenteeism as a key indirect cost of mental health conditions. Interestingly, the study reveals that the cost of depression is greater for hourly paid workers, as evidenced by a 43.3% increase in work loss days for those without retirement plans compared to a 29.3% increase among salaried employees. The authors estimate the aggregate cost of workplace absenteeism due to depression in the U.S. ranges from \$0.7 to \$1.4 billion annually, highlighting the economic significance of addressing mental health issues. (Peng et al., 2013)

Halonen et al. (2018) analyze mental health outcomes, antidepressant use, sickness absence (SA) due to depression, and suicide across sex-specific occupational groups, using a large nationally representative Finnish dataset. The study employs descriptive analysis and logistic regression modeling, including dominance analysis to quantify risks associated with occupations and rank predictors like sex and occupational class.

The study reveals pronounced gender differences in mental health outcomes. Women in low-skilled occupations had higher rates of antidepressant use and SA, particularly in care work and catering services. Conversely, men in low-skilled occupations, such as building and mining, faced significantly higher suicide risks. These findings align with theories of gender-role orientations (Courtenay, 2000), suggesting that societal norms and occupational stressors shape mental health risks differently for men and women. Service professionals emerged as a shared high-risk group for both genders, though with differing trends across outcomes. (Halonen et al., 2018)

The study's dominance analysis identifies gender as the most significant predictor of mental health outcomes, explaining 80–87% of the variance for antidepressant use and SA and 65% of the variance for suicides. Occupational class was the third most important predictor of suicides but had little influence on other outcomes. Compared to Fletcher's (2013) emphasis on gendered employment penalties and Peng et al.'s (2013) causal modeling of labor market impacts, this study offers a distinctive view of how mental health risks differ across occupational and gendered lines. (Halonen et al., 2018)

Shen (2023) investigates the causal impact of mental health problems on labor supply in Canada, contributing new insights into the mechanisms mediating this relationship and introducing the concept of mental health spillover effects in workplaces. Using the 2012 Canadian Community Health Survey-Mental Health (CCHS-MH) and an instrumental variable (IV) approach that leverages family mental health history, the study addresses endogeneity concerns often associated with unobserved household or environmental factors. By estimating Two-Stage Least Squares (2SLS) models, Shen identifies the direct effects of mental health on employment and explores pathways through cognitive abilities, social relations, and spillover effects.

The study finds that worsening mental health, as measured by Kessler-6 (K6) and Kessler-10 (K10) scores, significantly reduces employment. For example, a one-point increase in the K6 score decreases employment probability by 3.4 percentage points, while poor mental health reduces employment by 26.5 percentage points. These 2SLS estimates are nearly double the magnitude of Ordinary Least Squares (OLS) estimates, highlighting the importance of addressing endogeneity. The study's findings align with earlier literature, such as Fletcher (2013), which demonstrates the adverse effects of adolescent mental health on employment, though Shen focuses specifically on the Canadian context and adult populations. (Shen, 2023)

A novel contribution of Shen's work is the examination of mediating mechanisms. Mental health problems were shown to significantly impair cognitive abilities, such as concentration and task management, and damage social relations, including interactions with strangers and maintaining friendships. These pathways suggest that diminished cognitive functioning and strained social relationships are critical channels through which mental health affects employment, a finding also supported by Peng et al. (2013) in their discussion of emotional intelligence and workplace performance. Additionally, Shen identifies a spillover effect, where an individual's

mental health problems significantly increase the probability of coworkers developing mental health issues, emphasizing the broader workplace implications of untreated mental health conditions. Shen's use of family mental health history as an instrument further strengthens the causal inference.

The study highlights significant heterogeneity in mental health impacts across demographic groups. Younger workers (<40 years) and men experience larger employment penalties, with mental health issues reducing employment probabilities by 7.6 percentage points for men compared to only 0.4 percentage points for women. This gendered finding contrasts with Halonen et al. (2018), who emphasize higher risks for women in low-skilled occupations regarding antidepressant use and sickness absence. Overall, Shen's (2023) findings emphasize the need for workplace interventions, as mental health problems not only diminish individual employment prospects but also create spillover effects that undermine collective productivity.

Frijters et.al. (2010) examines the causal impact of mental health on labor market participation using data from seven waves of the *Household, Income and Labour Dynamics in Australia (HILDA)* survey. The study employs advanced panel data models, including 2SLS, IV-Probit, and IV-FE, to address reverse causality, unobserved individual heterogeneity, and measurement error. It uses the recent death of a close friend as an instrumental variable for mental health and runs a series of regressions on both mental health (based on the *SF-36 Mental Health Component Score*) and instrumental mental health. The authors find that a one standard deviation improvement in mental health increases the probability of labor market participation by approximately 25 percentage points in their preferred IV-FE model, a substantially larger effect than estimates derived from OLS or fixed-effects models. This result highlights the attenuation bias caused by measurement error in standard approaches. The findings are consistent with prior research, such as Fletcher (2013) and Shen (2023), but report larger effects due to improved methodological rigor. Heterogeneity analyses reveal stronger effects for older individuals (21 percentage points compared to 10 for younger workers) and for women.

The study controls for physical health as a potential confounder and finds that while physical health significantly impacts participation (increasing probabilities by 7–9 percentage points), mental health exerts a more substantial influence. This research contributes to the literature by offering precise estimates of the economic burden of mental illness and highlighting the importance

of innovative methodological approaches. The findings underscore the critical need for targeted mental health interventions, particularly for older workers and women, whose participation is most sensitive to mental health improvements. (Frijters et.al., 2010)

Germinario et.al. (2022) investigates the causal effect of mental health, measured using depressive symptoms from the CES-D scale, on labor market outcomes such as employment and earnings. Using data from the National Longitudinal Study of Youth 1979 (NLSY79), it applies a nonparametric partial identification approach to address endogeneity issues stemming from omitted variable bias and reverse causality. The methodology relies on three weak assumptions: monotone treatment selection (MTS), monotone treatment response (MTR), and monotone instrumental variables (MIV). These assumptions are less restrictive than those typically required for instrumental variable (IV) or fixed-effect models, providing bounds for the population average treatment effect (ATE) rather than precise point estimates.

The results indicate that mental health affects labor market outcomes, particularly earnings. Under the strongest set of assumptions being categorized as depressed reduces employment by at most 9 percentage points (approximately 10% of the employment rate for non-depressed individuals) and earnings by up to \$6,082 annually (27% of average earnings for non-depressed individuals). These findings highlight the substantial economic burden of depression, comparable to the effects of an additional year of schooling on earnings (6–15%, according to Card, 1999). However, the results cannot exclude a zero effect at standard significance levels. When examining the severity of depressive symptoms, the study finds that moving from no or little depressive symptoms to severe symptoms reduces employment by 3–18% and earnings by 11–44%. The results suggest that the impact on the labor market is non-linear, with the most pronounced effects occurring at higher levels of mental distress. For earnings, the confidence intervals rule out null effects for transitions to severe depressive symptoms, underscoring the statistically and economically significant impact of mental health deterioration. (Germinario et.al., 2022)

The study also examines the effects by demographic subgroups. Black individuals and men appear to experience stronger negative effects of depression on employment, with estimated reductions of 4–17% and 6–36%, respectively, for transitions from no to moderate depressive symptoms. For earnings, statistically significant reductions are observed for white individuals and Hispanic individuals transitioning from no or little to severe symptoms, with effects ranging from

12–46%. These subgroup results highlight the heterogeneity in the labor market impacts of mental health, influenced by demographic and social factors. (Germinario et.al., 2022)

In addition to this growing body of literature on mental health and labor market outcomes, broader research in health economics has examined how other health risks shape economic inequality and labor allocation. For instance, Baum and Ruhm (2009) show that obesity growth disproportionately affects individuals from lower socioeconomic backgrounds, contributing to long-run health and economic inequality. Likewise, Michaud and Wiczer (2018) model the role of occupational hazard in shaping disability risk and labor market insurance, highlighting how health-related job risks influence occupational choice. Margaris and Wallenius (2024) further demonstrate that earnings inequality across education levels drives disparities in health and longevity, as individuals with higher income are more likely to invest in health-promoting behaviors. While these studies focus primarily on physical health and disability, they underscore the need to consider health-driven mechanisms in occupational outcomes, an area where mental health remains largely underexplored.

2.3. Data and Variables

The National Longitudinal Study of Adolescent to Adult Health (Add Health) was selected for this research after a thorough review of multiple data sources focusing on mental health conditions. Add Health is a school-based longitudinal survey that includes a nationally representative sample of youth in grades 7-12 in the United States, beginning in 1994-1995. The study tracks participants over 20 years through surveys. The dataset contains multiple waves of data collection, allowing researchers to follow respondents from adolescence into adulthood. It includes modules on mental health, socio-economic status, educational achievements, and comprehensive labor market outcomes offering rich content to study developmental changes and causal relationships over time.

The key reason for selecting Add Health for the purpose of this study is its extensive longitudinal metrics on mental health and employment. This makes it particularly suited for dynamic, age-specific analyses that explore the evolution of mental health issues and their impact on occupation outcomes. Data collection occurred in five waves: Wave I (1994-1995) focused on adolescents in grades 7-12, Wave II (1996) revisited the same cohort in grades 8-12, Wave III (2001-2002) tracked participants as young adults aged 18-26, Wave IV (2008-2009) surveyed

participants as adults aged 24-32, and Wave V (2016-2018) followed participants into mid-adulthood aged 33-43. For this research, data from Waves I, III, IV, and V were utilized, including 2,954 individuals in each wave, forming a panel dataset.

2.3.1. Health Latent Variables

To analyze mental and physical health, latent variables were constructed using several self-reported indicators, some of which were based on medical diagnoses. The methodology builds on that of Chapter 1 but is applied to three waves of longitudinal data rather than a cross-section. For *Mental Health*, the variables included *ADHD*, *Suicide*, *Depressed*, and *Unhappy*. ADHD was measured as a binary variable derived from participants' responses about ADHD diagnoses or medication use. Suicidal thoughts were assessed through a binary variable capturing whether participants seriously considered suicide in the past 12 months. Depression was categorized into a binary variable based on how often participants reported feeling depressed in the past week, with higher frequencies coded as one. Unhappiness was measured using a binary variable equal to 1 for participants who rarely or never enjoyed life during the past week.

Physical Health was assessed using indicators: *Poor Health*, *Tobacco*, *Alcohol*, *Marijuana*, *Poor BMI*, and *Cocaine*. Participants reporting "fair" or "poor" general health were coded as having poor health. Tobacco use was captured through a binary variable indicating regular smoking. Alcohol consumption was assessed by coding frequent use ("every day," "almost every day," or "weekly") as one. Marijuana use was categorized as one for those reporting lifetime use of three or more instances. Poor BMI was determined using calculated BMI values, coding individuals as one if they were underweight, overweight, or obese. Cocaine use was assessed using multiple survey questions, with any reported use in the past 30 days coded as one. Both mental and physical health variables were reverse-coded to represent positive health outcomes.

Table 2.1. Comparative Descriptive Statistics of health indicators

	Waves				Total
	1	3	4	5	
ADHD	0.0499 (0.218)	0.0499 (0.218)	0.0499 (0.218)	0.0499 (0.218)	0.0499 (0.218)
Suicide	0.133 (0.340)	0.0674 (0.251)	0.0610 (0.239)	0.0681 (0.252)	0.0824 (0.275)
Depressed	0.0866 (0.281)	0.0563 (0.231)	0.0563 (0.231)	0.0667 (0.250)	0.0665 (0.249)
Unhappy	0.174 (0.379)	0.164 (0.370)	0.156 (0.363)	0.247 (0.431)	0.185 (0.389)
Poor Health	0.0613 (0.240)	0.0431 (0.203)	0.0799 (0.271)	0.138 (0.345)	0.0806 (0.272)
Tobacco	0.182 (0.386)	0.256 (0.437)	0.247 (0.431)	0.193 (0.395)	0.220 (0.414)
Alcohol	0.157 (0.364)	0.462 (0.499)	0.477 (0.500)	0.172 (0.377)	0.317 (0.465)
Marijuana	0.187 (0.390)	0.170 (0.375)	0.116 (0.321)	0.147 (0.354)	0.155 (0.362)
Poor BMI	0.366 (0.482)	0.565 (0.496)	0.656 (0.475)	0.730 (0.444)	0.579 (0.494)
Cocaine	0.0104 (0.102)	0.0266 (0.161)	0.0327 (0.178)	0.0206 (0.142)	0.0226 (0.149)
Observations	2,954	2,954	2,954	2,954	11,868

Mean coefficients, standard errors in parentheses.

Table 2.1 presents descriptive statistics for key indicators used in constructing the latent mental and physical health variables across Waves 1, 3, 4, and 5 of the dataset. As all indicators are binary (coded as 0 or 1), the reported mean values represent the proportion of individuals in the sample exhibiting each condition or behavior in the corresponding wave. Several noteworthy patterns emerge. First, ADHD prevalence remains stable across all waves (approximately 5%), which may reflect the persistence of this condition over time or underreporting due to stigma or late diagnosis. In contrast, self-reported suicide attempts show a sharp decline from Wave 1 (13.3%) to subsequent waves (hovering around 6–7%), possibly suggesting recall bias in later waves or actual reductions

as individuals age. A similar downward trend is observed in depression, decreasing from 8.7% to 5.6%, before slightly rising again, hinting at cyclical or age-dependent fluctuations. Unhappiness, however, increases markedly in Wave 5, rising to 24.7%, potentially pointing to growing emotional distress in early adulthood.

Turning to physical health indicators, the most notable trend is the rapid rise in poor BMI, increasing from 36.6% in Wave 1 to 73.0% in Wave 5. This sharp upward trajectory likely reflects weight gain with age, lifestyle changes, or broader public health trends such as rising obesity. Substance use patterns also vary across waves: tobacco use peaks in Wave 3, alcohol use reaches nearly 48% in Waves 3 and 4, while marijuana use slightly declines over time. The prevalence of poor self-reported health increases steadily across waves, suggesting a deterioration in perceived physical condition with age. Cocaine use remains low but slightly increases in mid-waves.

2.3.2. Additional Variables

Additional variables used in the research include *Age*, calculated using participants' date of birth and interview date, and *Female*, coded as one for females. *Black* was included as a binary variable identifying black participants accounting for racial differences. *Mom's College* was captured as a binary variable indicating whether the participant's mother completed a college degree. *Married* was included as a binary variable indicating whether the participant was married. *Education* was measured in years, determined using established mappings from the U.S. Census Bureau and the National Center for Education Statistics (NCES) that provide detailed mappings of education levels to years of schooling for surveys like the National Household Education Surveys Program (NHES). *Full-Time* work was defined as working 35 or more hours per week, based on definitions from the U.S. Bureau of Labor Statistics (BLS).

2.3.3. Occupational Classifications Using SOC

Occupation-related variables were constructed using the Standard Occupational Classification (SOC) system, a hierarchical framework that classifies and categorizes occupations in the United States. Each SOC code consists of six digits, with the first two digits representing major occupation groups (i.e. xx-xxxx). These groups classify individuals based on the type of work performed and the required skills, education, and training, regardless of the industry of employment. For this

research, occupation classes are based on SOC Major Groups, represented by the first two digits of the SOC code. Therefore, the occupational classification variable in this study is occupation-specific rather than industry-specific. An occupation-specific classification focuses on the nature of the work performed by individuals. For example, a civil engineer (SOC Code: 17-2051) may work in industries such as construction or consulting. Similarly, an accountant (SOC Code: 13-2011) may work in industries like healthcare, education, or finance. The SOC code groups these individuals based on their occupation, not the industry.

There are 23 major occupational groups, including management, business and financial operations, healthcare, education, and construction, among others. This classification enables occupation-specific analysis that is independent of the industries in which individuals are employed.

2.3.4. Occupational Groupings Using O*NET

The 23 SOC occupational categories were further grouped into seven broader categories using National Center for O*NET Development data based on shared skills, knowledge, work contexts, and interests. The seven groupings are not included in the final model; they are used solely for descriptive analysis to provide context on the distribution of observations across different occupational categories. These groups are:

- Professional and Technical Occupations
- Healthcare and Community Services Occupations
- Education, Arts, and Media Occupations
- Service and Maintenance Occupations
- Sales, Administration, and Logistics Occupations
- Trades, Production, and Agriculture Occupations
- Military-Specific Occupations

Table 2.2.a. Occupational Categories and Their SOC Mapping

	Occupational Category	Abbreviation	SOC Major Group Classifications
1	Professional and Technical Occupations	Prof/Tech	11- Management Occupations 13- Business and Financial Operations Occupations 15- Computer and mathematical occupations 17- Architecture and Engineering Occupations 19- Life, Physical, and Social Science Occupations 23- Legal Occupations
2	Healthcare and Community Services Occupations	Health/Comm	21- Community and Social Service Occupations 29- Healthcare Practitioners and Technical Occupations 31- Healthcare Support Occupations
3	Education, Arts, and Media Occupations	Edu/Arts	25- Education, Training, and Library Occupations 27- Arts, Design, Entertainment, Sports, and Media Occupations
4	Service and Maintenance Occupations	Service/Maint	33- Protective Service Occupations 35- Food Preparation and Serving Related Occupations 37- Building and Grounds Cleaning and Maintenance Occupations 39- Personal Care and Service Occupations
5	Sales, Administration, and Logistics Occupations	Sales/Admin	41- Sales and Related Occupations 43- Office and Administrative Support Occupations 53- Transportation and Material Moving Occupations
6	Trades, Production, and Agriculture Occupations	Trades/Prod	45- Farming, Fishing, and Forestry Occupations 47- Construction and Extraction Occupations 49- Installation, Maintenance, and Repair Occupations 51- Production Occupations
7	Military-Specific Occupations	Military	55- Military specific occupation

Tables 2.2.a and 2.2.b provide an overview of how detailed SOC occupational categories were aggregated into broader occupational groupings, along with the underlying interests and skill profiles that define each category. The first category, Professional and Technical Occupations, includes Management Occupations (11), Business and Financial Operations Occupations (13), Computer and Mathematical Occupations (15), Architecture and Engineering Occupations (17), Life, Physical, and Social Science Occupations (19), and Legal Occupations (23). These occupations share several key characteristics. The roles within this grouping have a significant overlap in skills, including strong analytical abilities, critical thinking, and leadership capabilities. Additionally, the knowledge areas associated with these occupations, such as business management, mathematics, engineering, and law, often necessitate extensive academic preparation. The work contexts for these roles frequently involve office settings, research environments, or collaborative project management, with tasks often performed within specialized teams. Furthermore, the interests associated with these occupations align predominantly with Investigative interests, which emphasize thinking and research, as well as Enterprising interests, which focus on leadership and decision-making, as outlined in O*NET. This grouping highlights the common foundational elements, the interconnected requirements, and work environments that unite these professions.

The second category, *Healthcare and Community Services Occupations*, encompasses Healthcare Practitioners and Technical Occupations (29), Healthcare Support Occupations (31), and Community and Social Service Occupations (21). These occupations share several important characteristics that justify their grouping. The roles within this category share a strong emphasis on interpersonal abilities, caregiving, and technical healthcare expertise. The knowledge areas required for these occupations include medicine, therapy, public health, and social work. The work context for these roles frequently involves direct interaction with patients or clients, often taking place in clinical, community-based, or home settings. Additionally, the interests associated with these occupations typically align with Social interests, which emphasize helping and counseling, as well as Realistic interests, which focus on hands-on work, as identified by O*NET. This grouping reflects the focus on providing care and support to individuals and communities, as well as the practical and human-centered nature of the work.

Table 2.2.b. Interest Types and Skill Characteristics Across Occupational Categories

	Occupational Category	Interests	Skills
1	Professional and Technical Occupations	• Investigative (thinking, research) • Enterprising (leading, decision-making)	Analytical, critical thinking, and leadership skills are common.
2	Healthcare and Community Services Occupations	• Social (helping, counseling) • Realistic (hands-on work)	Focus on interpersonal, caregiving, and technical healthcare skills.
3	Education, Arts, and Media Occupations	• Artistic (creativity, innovation) • Social (teaching, helping)	Emphasis on creativity, communication, and subject-matter expertise.
4	Service and Maintenance Occupations	• Realistic (practical, hands-on) • Social (helping, serving)	Require interpersonal and technical skills focused on service delivery or facility upkeep.
5	Sales, Administration, and Logistics Occupations	• Enterprising (sales, leadership) • Conventional (organization, attention to detail)	Organization, customer service, or logistics management skills.
6	Trades, Production, and Agriculture Occupations	• Realistic (practical, mechanical) • Conventional (structured, repetitive tasks)	Emphasize physical, manual, or mechanical skills.

The third category, Education, Arts, and Media Occupations, includes Education, Training, and Library Occupations (25) as well as Arts, Design, Entertainment, Sports, and Media Occupations (27). These occupations are grouped together due to several shared characteristics regarding their nature and focus. The roles in this category jointly require skills in creativity, communication, and subject-matter expertise. The knowledge areas associated with these occupations span arts, education, language, communication, and multimedia production. The work environments often include classrooms, studios, theaters, and other spaces where interpersonal interactions and artistic or educational output are central. Additionally, the interests associated with these occupations strongly align with Artistic interests, which focus on creativity and innovation, as well as Social interests, which emphasize teaching and helping others, as outlined by O*NET. This grouping highlights the shared commitment of these professions to fostering creativity, learning, and meaningful human connection in a variety of settings.

The fourth category, Service and Maintenance Occupations, comprises Protective Service Occupations (33), Food Preparation and Serving Related Occupations (35), Building and Grounds Cleaning and Maintenance Occupations (37), and Personal Care and Service Occupations (39). These occupations are grouped together based on several shared characteristics reflecting their focus and scope. The roles within this category require a combination of interpersonal and technical skills, with focus on service delivery or facility upkeep. The knowledge areas associated with these occupations include basic knowledge in safety, food services, hygiene or personal care, which are essential to the functions performed in these roles. The work settings often involve physical labor or direct, face-to-face customer interactions, highlighting their hands-on and customer-focused nature. Additionally, the interests associated with these occupations generally align with Realistic interests, which emphasize practical tasks, as well as Social interests, which focus on helping and serving others, as identified by O*NET. This grouping underlines the shared emphasis on practical work, service-oriented tasks, maintaining essential facilities, and providing care.

The fifth category, Sales, Administration, and Logistics Occupations, includes Sales and Related Occupations (41), Office and Administrative Support Occupations (43), and Transportation and Material Moving Occupations (53). These occupations are grouped together due to shared characteristics and required skill sets along with operational focus. The roles in this category exhibit an overlap in skills, particularly in organization, customer service, and logistics

management. The knowledge areas essential for these occupations include marketing, customer service, transportation systems, and clerical tasks, reflecting the broad range of activities within this grouping. The work contexts for these occupations vary widely, encompassing offices, stores, vehicles, and warehouses, depending on the specific role. Additionally, the interests associated with these occupations tend to align with Enterprising interests, which focus on sales and leadership, as well as Conventional interests, which emphasize organization and attention to detail, as identified by O*NET. This grouping is justified due to shared emphasis on coordination, customer engagement, and the management of goods, services, and administrative processes.

The sixth category, Trades, Production, and Agriculture Occupations, includes Farming, Fishing, and Forestry Occupations (45), Construction and Extraction Occupations (47), Installation, Maintenance, and Repair Occupations (49), and Production Occupations (51). These occupations are grouped together based on shared characteristics such as their hands-on, technical, and practical nature. The roles within this category emphasize physical, manual, or mechanical skills, which are central to their operations. The knowledge areas required for these occupations include agriculture, machinery, construction techniques, and production processes. The work settings for these occupations are often outdoors or in industrial settings, where hands-on tasks and the use of tools are a primary focus. Additionally, the interests associated with these professions align strongly with Realistic interests, which emphasize practical and mechanical work, as well as Conventional interests, which focus on structured and repetitive tasks, as outlined by O*NET. This grouping reflects the shared focus on practical labor, mechanical proficiency, and technical expertise across these fields.

The final category consists solely of Military-Specific Occupations (55). This category is treated separately from the others due to its unique characteristics and demands. According to O*NET, military roles encompass a wide range of specialized skills, knowledge areas, and work contexts that are distinct from those in other occupations. These roles often involve mission-specific training, leadership under high-pressure conditions, and unique physical and logistical requirements that are not typically shared with occupations in other categories. Given these distinctions, it is most appropriate to consider military on its own, reflecting its specialized and multidimensional nature. Overall, these broader groupings, utilizing O*NET guidelines, allow for a more cohesive understanding of occupational distribution in the data.

Table 2.3. Comparative Descriptive Statistics of Occupation Categories

	Occupation Categories							
	Prof/ Tech	Health/ Comm	Edu/ Arts	Service/ Maint	Sales/ Admin	Trades /Prod	Military	Total
Age	31.40 (5.808)	30.88 (5.889)	30.66 (5.716)	28.53 (6.343)	29.76 (6.554)	29.60 (6.093)	28.66 (6.880)	30.16 (6.208)
Female	0.526 (0.499)	0.838 (0.369)	0.748 (0.434)	0.571 (0.495)	0.630 (0.483)	0.161 (0.368)	0.114 (0.320)	0.577 (0.494)
Black	0.185 (0.388)	0.201 (0.401)	0.190 (0.393)	0.194 (0.396)	0.206 (0.404)	0.152 (0.359)	0.157 (0.367)	0.190 (0.393)
Mom's College	0.419 (0.494)	0.324 (0.468)	0.439 (0.497)	0.238 (0.426)	0.270 (0.444)	0.162 (0.369)	0.343 (0.478)	0.310 (0.463)
Married	0.494 (0.500)	0.479 (0.500)	0.469 (0.499)	0.293 (0.455)	0.383 (0.486)	0.420 (0.494)	0.471 (0.503)	0.422 (0.494)
Education (<i>years</i>)	15.67 (2.305)	15.41 (2.598)	16.37 (2.317)	13.55 (1.894)	14.02 (1.832)	12.89 (1.654)	14.30 (2.516)	14.61 (2.392)
Full-Time	0.781 (0.414)	0.657 (0.475)	0.638 (0.481)	0.516 (0.500)	0.606 (0.489)	0.765 (0.424)	0.686 (0.468)	0.662 (0.473)
Mental Health (<i>lag</i>)	0.871 (0.190)	0.843 (0.228)	0.873 (0.197)	0.818 (0.226)	0.836 (0.223)	0.834 (0.200)	0.874 (0.175)	0.846 (0.212)
Physical Health (<i>lag</i>)	0.813 (0.196)	0.829 (0.190)	0.838 (0.197)	0.778 (0.227)	0.808 (0.207)	0.749 (0.222)	0.851 (0.164)	0.804 (0.208)
Observations	1,724	1,090	825	1,126	2,084	982	70	7,901

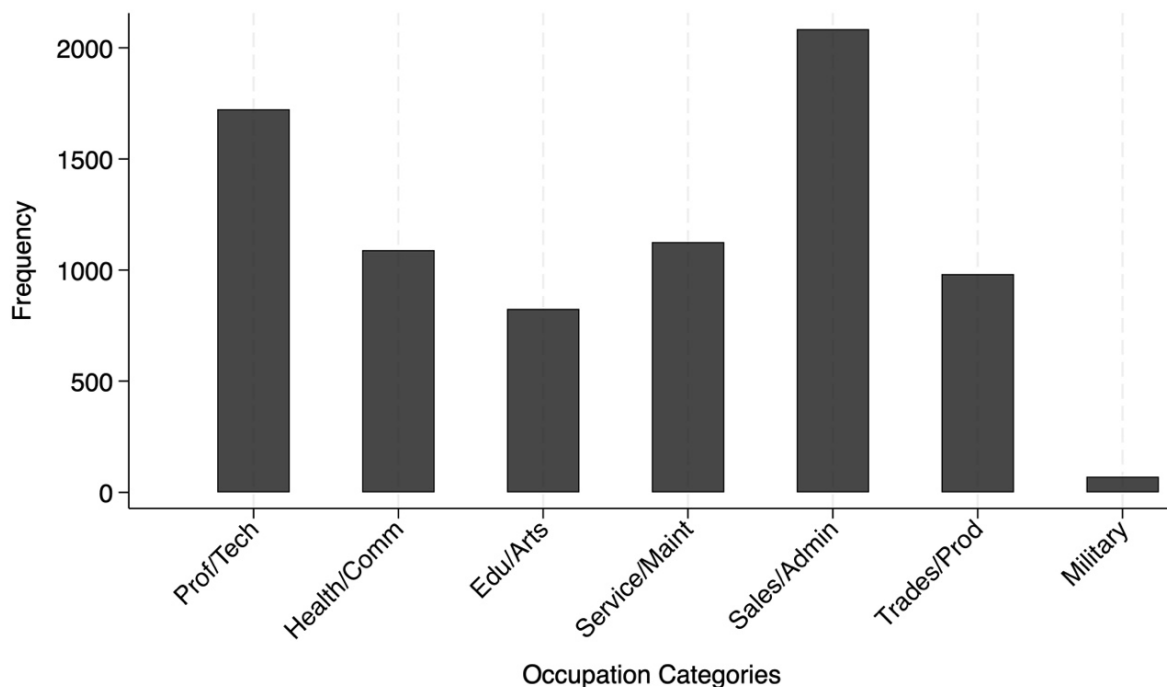
Mean coefficients, standard errors in parentheses.

Table 2.3 provides a comparative snapshot of individual characteristics across occupational categories. Notably, Education, Arts, and Media occupations are associated with the highest average years of education (16.37), while Trades and Production roles report the lowest (12.89). Female representation is highest in Healthcare and Community Services (83.8%) and lowest in Military and Trades (11.4% and 16.1%, respectively), reflecting well-documented gender sorting across sectors. Professional and Technical jobs show the highest maternal education rates (41.9%) and the highest share of full-time employment (78.1%), suggesting stronger intergenerational educational advantages and labor market stability. Individuals in Service and Maintenance roles are the youngest on average (28.5 years) and least likely to be married, while those in Professional

occupations tend to be older and more likely to be married. Mental and physical health scores are relatively high across all categories, but slightly lower in Service and Maintenance, Sales, Administration, and Logistics, and Trades, Production, and Agriculture occupations, indicating potential health-related disadvantages in these sectors.

Figure 2.1 presents the frequency distribution of individuals across the seven occupational categories used in the analysis. The largest share of the sample is concentrated in Sales, Administration and Logistics roles, followed closely by Professional and Technical occupations. Service and Maintenance occupations, along with Healthcare and Community Services, represent mid-sized segments of the labor force in this dataset. Meanwhile, Trades, Production and Agriculture, as well as Education, Arts and Media, show comparatively lower frequencies. Military-specific occupations are the least represented category by a substantial margin. This distribution highlights the heterogeneity in occupational sorting and provides context for the relative prevalence of each category in the subsequent regression analysis.

Figure 2.1. Distribution Across the Seven Occupation Categories



2.3.5. White-Collar Occupations

Finally, to analyze occupational differences through mixed-effects regressions, roles were categorized into white-collar and blue-collar groups. The *White-Collar* Occupations category encompasses roles that typically involve professional, managerial, or administrative work. These occupations are characterized by a focus on cognitive skills, intellectual tasks, and minimal physical labor. They often require higher levels of education and advanced expertise in specific fields. Occupations in this group include the following:

- Management Occupations (11)
- Business and Financial Operations Occupations (13)
- Computer and Mathematical Occupations (15)
- Architecture and Engineering Occupations (17)
- Life, Physical, and Social Science Occupations (19)
- Community and Social Service Occupations (21)
- Legal Occupations (23)
- Education, Training, and Library Occupations (25)
- Arts, Design, Entertainment, Sports, and Media Occupations (27)
- Healthcare Practitioners and Technical Occupations (29)
- Sales and Related Occupations (41)
- Office and Administrative Support Occupations (43)

The grouping is based on several shared characteristics. The work context for these occupations is primarily office-based or revolves around intellectual tasks such as management, teaching, research, or technical problem-solving. The skills and knowledge required for these roles include specialized expertise in fields like law, education, and science, as well as soft skills such as communication, analysis, and decision-making. These occupations also align strongly with Investigative, Enterprising, and Social interests, as defined by O*NET. Additionally, these roles involve minimal physical exertion compared to blue-collar occupations, further distinguishing them as white-collar jobs.

The *Blue-Collar* Occupations category comprises roles associated with manual labor, skilled trades, and hands-on activities. These occupations typically require vocational training, practical skills, and significant physical effort, distinguishing them from white-collar jobs that emphasize intellectual tasks. Occupations in this group include:

- Healthcare Support Occupations (31)
- Protective Service Occupations (33)
- Food Preparation and Serving Related Occupations (35)
- Building and Grounds Cleaning and Maintenance Occupations (37)
- Personal Care and Service Occupations (39)
- Farming, Fishing, and Forestry Occupations (45)
- Construction and Extraction Occupations (47)
- Installation, Maintenance, and Repair Occupations (49)
- Production Occupations (51)
- Transportation and Material Moving Occupations (53)

These occupations share several key characteristics that justify their grouping. The work context for blue-collar roles is typically non-office-based and often occurs in settings such as factories, farms, construction sites, maintenance workshops, or other physical environments. The skills and knowledge required for these jobs are practical and technical, involving activities such as machinery operation, building trades, or other forms of hands-on work. These roles strongly align with Realistic and Conventional interests, as defined by O*NET, emphasizing structured, hands-on tasks and practical problem-solving. Additionally, most blue-collar roles involve significant physical exertion or labor-intensive tasks, further distinguishing them from white-collar occupations. This grouping reflects the shared focus on manual work, technical expertise, and physical activity across a diverse range of industries. Overall, white-collar occupations typically involve office settings, require cognitive skills, and focus on intellectual work with minimal physical labor, whereas blue-collar occupations are associated with manual labor and hands-on activities, often requiring physical effort and technical skills.

Table 2.4. Comparative Descriptive Statistics of Key Variables Across Waves

	Waves			Total
	3	4	5	
Age	22.28 (1.806)	28.89 (1.772)	37.18 (1.923)	30.16 (6.208)
Married	0.183 (0.386)	0.421 (0.494)	0.598 (0.490)	0.422 (0.494)
Education (<i>years</i>)	13.48 (1.885)	14.77 (2.286)	15.27 (2.531)	14.61 (2.392)
Full-Time	0.668 (0.471)	0.574 (0.495)	0.746 (0.435)	0.662 (0.473)
White-Collar	0.567 (0.496)	0.625 (0.484)	0.694 (0.461)	0.635 (0.482)
Mental Health (<i>lag</i>)	0.830 (0.236)	0.847 (0.204)	0.857 (0.202)	0.846 (0.212)
Physical Health (<i>lag</i>)	0.829 (0.218)	0.788 (0.212)	0.802 (0.193)	0.804 (0.208)
Observations	2,104	2,909	2,888	7,901

Mean coefficients, standard errors in parentheses.

Table 2.4 presents descriptive statistics for key study variables across Waves 3, 4, and 5 restricted to the working sub-sample. As expected, average age increases across waves, reflecting the longitudinal nature of the data. Notably, the proportion of married individuals more than triples from Wave 3 (18.3%) to Wave 5 (59.8%), indicating a significant shift in relationship status over time. Educational attainment also rises, with the average years of education increasing from 13.48 to 15.27. Full-time employment rates dip slightly in Wave 4 before increasing again in Wave 5, while the share of individuals in white-collar occupations rises steadily, suggesting upward occupational mobility. In terms of health, both mental and physical health indicators show relatively high and stable levels across waves.

2.4. Methodology

This study employs a Generalized Structural Equation Model (GSEM) to construct latent variables representing mental and physical health, followed by a mixed-effects logistic model to examine their impact on selecting into specific occupational classifications. The details of each stage are outlined in the subsections below.

2.4.1. Measurement System for Latent Variables

Following the framework established by Cunha and Heckman (2008) and Chapter 1 of this dissertation, a Generalized Structural Equation Model is applied to create latent variables for mental and physical health using a factor analysis approach. The reasoning for this choice of methodology is that mental and physical health are complex, multidimensional phenomena that cannot be fully captured by a single observed variable. Relying solely on self-reported health status or the presence of a single condition often leads to measurement error, as such approaches may fail to account for underlying health variations. By using latent variables, this study integrates multiple indicators to more accurately represent overall mental and physical health, reducing potential biases and improving the robustness of the analysis. The first latent factor, Poor Mental Health, is identified using binary indicators for ADHD, depression, unhappiness, and suicidal thoughts that were explained in the previous section. These indicators are modeled through a logistic regression equation through a GSEM framework, where the probability of each mental health indicator is linked to the latent variable, Poor Mental Health, via factor loadings. Specifically, equation 2.1 expresses the log-odds of experiencing each of these conditions as a function of the underlying mental health status.

$$\log \left(\frac{P(Y_{i,m}=1)}{1-P(Y_{i,m}=1)} \right) = \beta_{0,m} + \beta_{1,m} \tilde{M}_i \quad (2.1)$$

, where $Y_{i,m}$ represents the m^{th} binary indicator for the i^{th} observation, $\beta_{0,m}$ is the intercept for the m^{th} binary indicator, $\beta_{1,m}$ is the factor loading of the latent variable, Poor Mental Health, on the m^{th} indicator, $\tilde{M}_i$ represents the latent variable Poor Mental Health for the i^{th} observation, and $m = \{1,2,3,4\} = \{\text{ADHD, Depressed, Unhappy, Suicide}\}$.

Similarly, the second latent factor, Poor Physical Health, is determined through binary indicators reflecting self-reported health, alcohol, marijuana, tobacco, and cocaine use, as well as poor BMI. Like the mental health model, this latent variable is estimated using logistic regressions, where the probability of each physical health determinant is linked to the Poor Physical Health latent variable through a GSEM model. The corresponding equation is:

$$\log \left(\frac{P(Y_{i,p}=1)}{1-P(Y_{i,p}=1)} \right) = \beta_{0,p} + \beta_{1,p} \tilde{P}_i \quad (2.2)$$

, where $Y_{i,p}$ signifies the p^{th} binary indicator for the i^{th} observation, $\beta_{0,p}$ is the intercept for the p^{th} binary indicator, $\beta_{1,p}$ is the factor loading of the latent variable, *Poor Physical Health*, on the p^{th} indicator, $\tilde{P}_i$ denotes the latent variable *Poor Physical Health* for the i^{th} observation, and $p = \{1,2,3,4,5,6\} = \{\text{Poor Health, Tobacco, Alcohol, Marijuana, Poor BMI, Cocaine}\}$.

To ease interpretation, these scores are normalized between zero and one and are reversed. The reversed scores are defined as $M_i = 1 - \tilde{M}_i$ and $P_i = 1 - \tilde{P}_i$, such that higher values of M_i and P_i now indicate better mental and physical health, respectively.

2.4.2. Mixed-Effects Logistic Model for Occupational Sorting

Drawing from Baayen et al. (2008) and Tedjawirja et al. (2022) a mixed-effects logistic model is employed to examine the relationship between the latent mental health variable and probability of choosing certain occupations. The primary outcome variables of interest in this study are occupational classifications: White-Collar and Full-Time employment, which is modeled using a series of mixed-effects logistic regressions. The log odds of an individual selecting a particular occupation class relative to not choosing that category is modeled through the logit function, incorporating both fixed and random effects. The fixed-effects component includes key independent variables such as mental and physical health status, as well as demographic and socioeconomic controls, including age, squared age (to capture nonlinear age effects), sex, race, maternal education, marital status, and changes in educational achievement. The random-effects component introduces a grouping variable based on individuals' ID to account for within-group correlations and between-group variability, allowing for unobserved heterogeneity across individuals. For example, it allows for individual-level differences in the baseline likelihood of

being in each occupation classification. The logit functions used to estimate the effects of mental and physical health on occupational classifications follow the equations below:

$$\text{logit}\left(P(C_{i,t} = 1)\right) = \beta_0 + \beta_1 M_{i,t-1} + \beta_2 \Delta M_{i,t} + \sum_{k=3}^K \beta_k X_{k,i,t} + b_i + \varepsilon_{i,t} \quad (2.3)$$

$$\text{logit}\left(P(C_{i,t} = 1)\right) = \gamma_0 + \gamma_1 P_{i,t-1} + \gamma_2 \Delta P_{i,t} + \sum_{k=3}^K \gamma_k X_{k,i,t} + b_i + \varepsilon_{i,t} \quad (2.4)$$

where $C = \{1,2\} = \{\text{“Full-Time”, “White-Collar”}\}$, denoting the two major occupation classifications predicted in this study; $\text{logit}(p)$ is the logit function, $\log\left(\frac{p}{1-p}\right)$, that maps probabilities. $P(C_{i,t} = 1)$ is the probability of the binary outcome $C_{i,t}$ for observation i in period t (the grouping here refers to the same individual observed over time).

The coefficients β_0 and γ_0 are the fixed intercepts. The term $M_{i,t-1}$ in Eq.3 represents the lagged mental health of individual i in period t , and β_1 is its coefficient. This means it captures the mental health score from the previous period, $t - 1$, allowing for an analysis of how past mental health impacts current outcomes. The term $\Delta M_{i,t}$ with the coefficient β_2 represents the effect of the change in mental health between the current period and the previous one (t and $t - 1$), meaning it is calculated as the difference. This term measures how an individual's mental health has evolved over time. $\gamma_1 P_{i,t-1}$ and $\gamma_2 \Delta P_{i,t}$ in Eq.4 follow a similar interpretation but for physical health. Each $X_{k,i,t}$ is the k -th covariate (predictor) for observation i in period t . β_k or γ_k is the fixed-effect coefficient for the k -th covariate. Since the data is structured as a panel with repeated observations for the same individual over time, grouping is done using a random effects approach to account for unobserved heterogeneity. This allows for individual-specific characteristics that do not change over time to be considered, ensuring that variations in mental health are modeled appropriately. Hence, b_i is the Random Effect specific to observation i , assumed to follow a normal distribution: $b_i \sim N(0, \sigma_b^2)$. $\varepsilon_{i,t}$ is the residual error term that captures within-individual variation or measurement errors $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$. The log odds of choosing each of the two occupation classifications, white-collar vs. blue-collar, and full-time vs. part-time, is modelled separately as a binary outcome variable.

The methodologic justification for a mixed-effects logistic model with random intercepts is the presence of a binary outcome as well as the fact that the data contains repeated measurements with

a hypothesis that there is unobserved heterogeneity in individuals' differing mental and physical health levels, making it necessary to account for both within-group correlation as well as between-group variability. Furthermore, the effects of mental and physical health are modeled separately in the mixed-effects logistic regression framework. Specifically, the model is estimated twice: once to examine the probability of selecting each occupational class as a function of mental health while controlling for other socioeconomic indicators, and another time to analyze the probability of selecting each occupational class based on physical health using the same set of control variables.

The reasoning for this approach is grounded in the need to separate the effects of mental and physical health on occupational sorting. A single regression model incorporating both health dimensions yielded poor results, potentially due to multicollinearity and overlapping effects. To address this, two separate models were estimated, one for physical health and another for mental health, allowing for a clearer interpretation of their respective impacts. This separation provides complementary insights, while recognizing that physical health may be more relevant for physically demanding jobs, whereas mental health conditions may be more detrimental in cognitive and white-collar occupations. A key consideration in this methodology is that the two predictions, from the physical health model and from the mental health model, do not suggest independent odd ratios, but they represent hypothetical scenarios. Each model is estimated separately: one includes mental health while excluding physical health, and the other includes physical health while excluding mental health. This specification avoids potential multicollinearity and allows each health dimension's effect to be interpreted in isolation, holding other covariates constant. This approach provides clear policy insights by disentangling the distinct effects of mental and physical health, guiding interventions in workforce health policies.

Lastly, the model also includes a variance-covariance specification where standard errors are clustered at the individual level to ensure robust statistical inference. This approach adjusts for potential within-group correlations, ensuring that the standard errors are robust and not underestimated. In other words, this accounts for the possibility that observations of the same individual over time may be correlated.

2.4.3. Estimation Approach

The estimation of the mixed-effects logistic regression models follows a maximum likelihood estimation (MLE) approach, incorporating both fixed effects and individual-specific random effects to account for unobserved heterogeneity. Given the binary nature of the occupational sorting variable in each model, the likelihood function is constructed based on the logistic regression framework with a random intercept. For each occupational class, the probability of individual i in group j (individual i over time) choosing that occupation group is modeled as a function of their lagged health status, the change in health status, and a set of covariates, while accounting for individual-level random effects. The presence of random effects implies that the likelihood function takes the form of a mixed-effects model, requiring integration over the distribution of the random effects. The likelihood contributions of an individual i in period t for the models with mental health, $M_{i,t}$, and physical health, $P_{i,t}$, are given by:

$$L_{i,t} = P(C_{i,t} = 1 | M_{i,t}, X_{i,t}, b_i)^{C_{i,t}} (1 - P(C_{i,t} = 1 | M_{i,t}, X_{i,t}, b_i))^{1-C_{i,t}} \quad (2.5)$$

$$L_{i,t} = P(C_{i,t} = 1 | P_{i,t}, X_{i,t}, b_i)^{C_{i,t}} (1 - P(C_{i,t} = 1 | P_{i,t}, X_{i,t}, b_i))^{1-C_{i,t}} \quad (2.6)$$

Since b_i is unobserved, the model is estimated using the marginal likelihood:

$$L_i = \int \prod_t L_{i,t} f(b_i) db_i \quad (2.7)$$

where $f(b_i)$ is the probability density function of the normally distributed random effects. This integral does not have a closed-form solution and is approximated using numerical integration methods such as adaptive quadrature. The overall log-likelihood function, which is maximized across all individuals, is:

$$\ln(L) = \sum_{i=1}^I \ln \left(\int \prod_t L_{i,t} f(b_i) db_i \right) \quad (2.8)$$

After estimation, average marginal effects (AME) are computed to convert log odds to probabilities and to quantify how changes in health status and other covariates influence the probability of choosing a given occupation classification. These effects provide an interpretable

measure of the relationship between health and selection into different occupational classes and are presented in the following section.

2.5. Results

This section presents the empirical findings in four parts. First, I describe the measurement system for the two latent variables, mental and physical health, estimated using a Generalized Structural Equation Model (GSEM). This step validates the construction of the health measures used throughout the analysis. Second, I report the results from the mixed-effects logistic regression models that estimate the impact of mental and physical health on the likelihood of entering the two key occupational classifications. Third, I present the predicted marginal probabilities to illustrate how occupational selections vary across levels of mental and physical health, offering policy-relevant interpretations. Finally, I provide post-estimation diagnostic tests to assess the robustness and validity of the model results.

2.5.1. Measurement System

The generalized structural equation model (GSEM) results provide estimates for the measurement system of two latent variables: Poor Mental Health and Poor Physical Health. As previously explained, the Poor Mental Health latent variable is constructed based on four observed indicators: ADHD, Depressed, Unhappy, and Suicide. The estimated parameters in Panel A of Table 2.5.a indicate that all constant terms are negative and statistically significant, suggesting that in the absence of poor mental health, the likelihood of exhibiting these indicators is relatively low. For ease of interpretation, only the average marginal effects from Panel B will be discussed, as the raw coefficients are in log odds ratios and are not directly interpretable. The factor loadings for Poor Mental Health are positive and statistically significant across all indicators, confirming that an increase in the latent construct is associated with a higher probability of experiencing these mental health issues. The average marginal effects indicate that a one standard deviation increase in Poor Mental Health leads to an increase in the probability of reporting symptoms of Unhappiness by 18.5 percentage points, followed by Suicide, 8.25 percentage points, Depressed, 6.71 percentage points, and ADHD, 4.99 percentage points. In marginal effect terms and comparing to baseline probabilities, these results suggest that poor mental health is most strongly associated with unhappiness.

Table 2.5.a. Measurement System - Mental Health

	ADHD	Depressed	Unhappy	Suicide
Panel A: Estimated parameters				
Constant	-3.015*** (0.048)	-6.052*** (0.426)	-2.298*** (0.074)	-3.252*** (0.079)
Poor Mental Health	0.206*** (0.035)	1.904*** (0.221)	1	0.815*** (0.058)
Panel B: Average Marginal Effects of Factors (AME)				
Poor Mental Health AME	0.0499*** (0.002)	0.0671*** (0.002)	0.185*** (0.004)	0.0825*** (0.003)
Observations	11868	11868	11868	11868

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

The measurement system for Poor Physical Health is based on six observed indicators: Poor Health, Tobacco Use, Alcohol Use, Marijuana Use, Poor BMI, and Cocaine Use. The estimated parameters in Panel A of Table 2.5.b show variability in the constant terms across indicators, with most being negative and statistically significant, except for Poor BMI, which has a positive and significant constant term, 0.320. The factor loadings for Poor Physical Health in Panel B are all positive and statistically significant. The average marginal effects indicate that poor BMI is the strongest determinant of poor physical health, increasing the probability of having poor physical health by 57.9 percentage points. This is followed by Cocaine Use, 36.5 percentage points, and Alcohol Use, 31.7 percentage points. In contrast, Poor Health exhibits the smallest marginal effect, 8.07 percentage points, suggesting that while poor physical health significantly influences substance use behaviors, its association with self-reported poor health is weaker. These findings suggest that the Poor Physical Health latent variable is primarily driven by behavioral indicators such as substance use rather than self-reported health conditions.

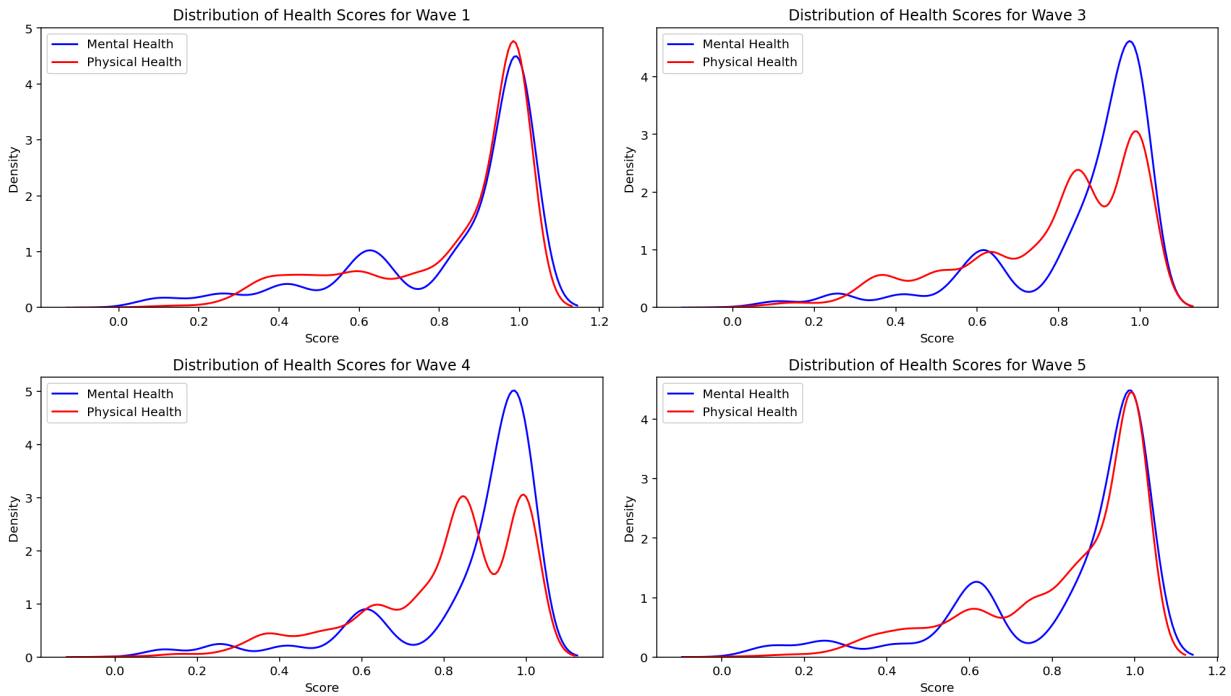
Table 2.5.b. Measurement System - Physical Health

	Poor Health	Tobacco	Alcohol	Marijuana	Poor BMI	Cocaine
Panel A: Estimated parameters						
Constant	-2.549*** (0.041)	-1.708*** (0.044)	-0.866*** (0.024)	-3.095*** (0.147)	0.320*** (0.019)	-5.615*** (0.227)
Poor Physical Health	0.214*** (0.027)	0.564*** (0.055)	0.314*** (0.027)	1	-0.0318** (0.011)	0.856*** (0.088)
Panel B: Average Marginal Effects of Factors (AME)						
Poor Physical Health AME	0.0807*** (0.003)	0.219*** (0.004)	0.317*** (0.004)	0.155*** (0.003)	0.579*** (0.005)	0.365*** (0.008)
Observations	11868	11868	11868	11868	11868	11868

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

The Poor Physical and Mental Health scores are predicted through a Maximum Likelihood Estimation (MLE) process. The scores are then normalized between zero and one and reversed so that higher values represent healthier individuals. Figure 2.2 illustrates the kernel density distributions of the normalized latent factor scores for mental and physical health across Waves 1, 3, 4, and 5. All scores are scaled between 0 and 1, with higher values indicating better health. Across all waves, both mental and physical health distributions are right-skewed, with the majority of individuals reporting relatively high levels of health. However, distinct differences between the evolution of the two health dimensions over time are observable. In Wave 1, mental and physical health scores closely overlap, both peaking near the upper bound. By Wave 3, the distributions begin to diverge more noticeably, with mental health scores becoming more polarized; a larger share of individuals cluster near the maximum, while a secondary peak appears around 0.6. In contrast, physical health remains more evenly distributed with a broader spread. In Wave 4, physical health shows a bimodal pattern, suggesting increased heterogeneity in individuals' physical conditions, while mental health maintains a sharp peak around 0.9. By Wave 5, both distributions converge slightly, yet mental health remains more concentrated at higher values, whereas physical health retains a more dispersed shape.

Figure 2.2.



Figures 2.3.a and 2.3.b display the distributions of the normalized latent mental and physical health scores across the two occupational classifications. In Figure 2.3.a, white-collar workers tend to have higher mental and physical health scores on average compared to blue-collar workers. The distribution for white-collar workers peaks further to the right, particularly in the mental health graph, indicating a greater concentration of individuals with higher scores. In contrast, the distributions for blue-collar workers are flatter and more dispersed, suggesting lower average health levels. Figure 2.3.b reveals a similar pattern when comparing full-time and part-time workers, with full-time workers showing higher average scores in both health dimensions. These patterns support the empirical findings that better mental and physical health are associated with choosing more stable, full-time, and cognitively demanding occupations.

Figure 2.3.a.

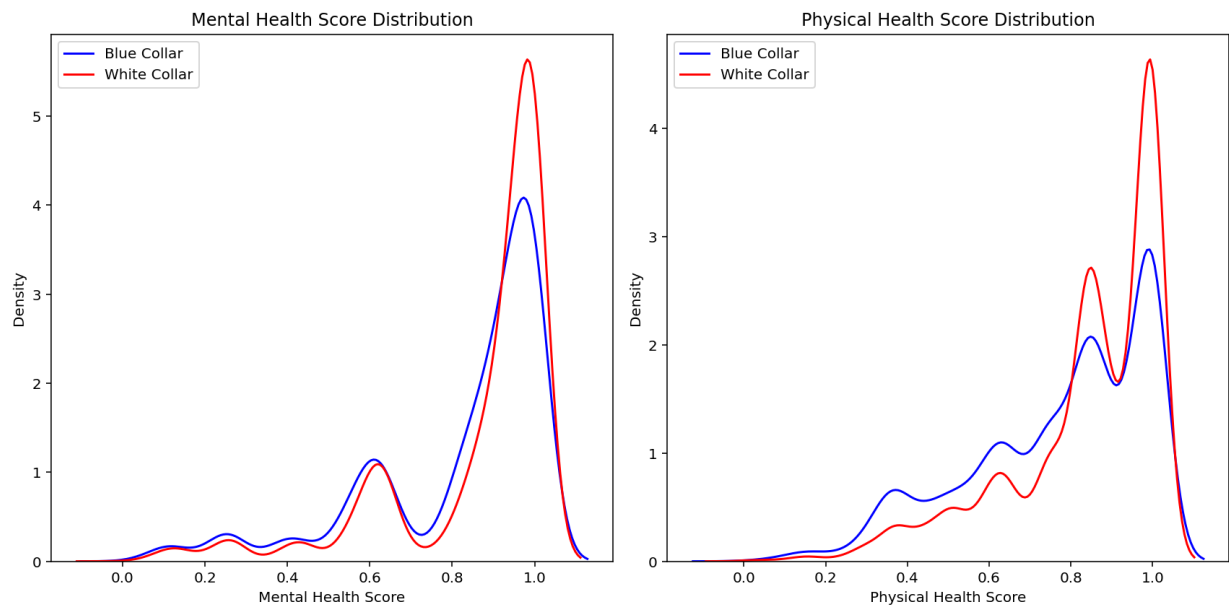
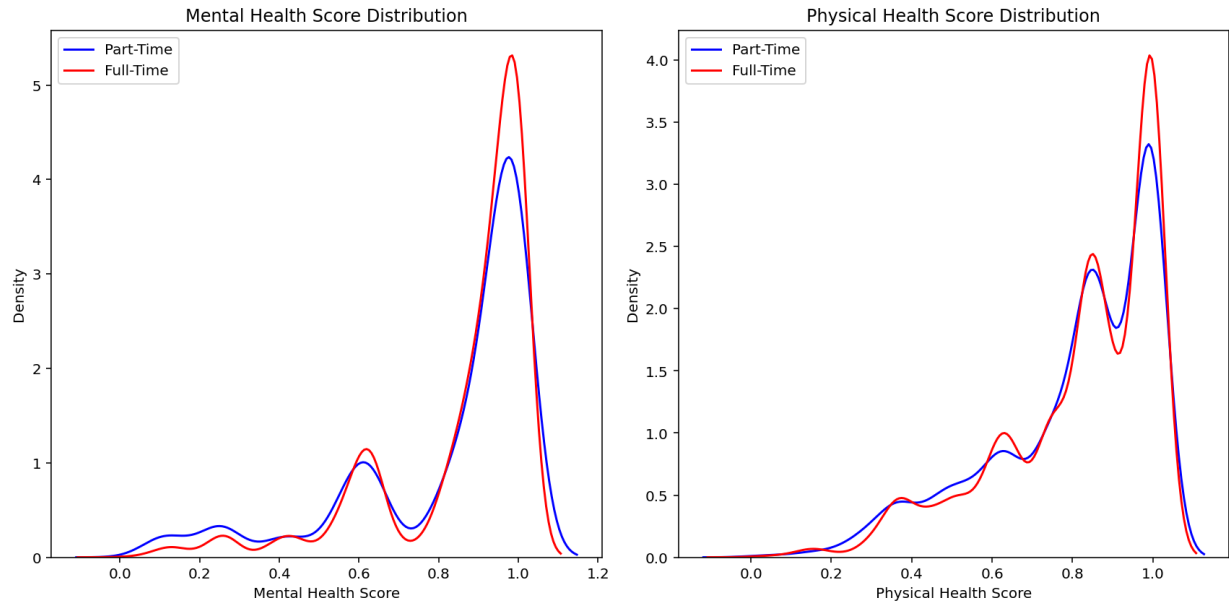


Figure 2.3.b.



2.5.2. Occupational Selection

The results from the mixed-effects logistic regression models are portrayed in Table 2.6 and provide a detailed assessment of how mental and physical health influence occupational selection

across full-time and white-collar occupation classifications. Focusing on lagged and differenced mental health, the average marginal effect estimates demonstrate significant and varying effects on occupational selection.

The analysis of full-time versus part-time employment portrayed in the first column of Table 2.6 highlights the crucial role of mental health in securing full-time jobs. Lagged mental health is strongly positive (0.158, $p < 0.001$), meaning that individuals with better mental health are 15.8 percentage points more likely to work full-time. Differenced mental health also has a significant positive effect (0.173, $p < 0.001$), implying that even recent improvements in mental health increase the likelihood of moving toward full-time employment by 17.3 percentage points. Physical health, while not significant in its lagged form (0.0388, $p = 0.08$), has a positive and significant effect when differenced (0.138, $p < 0.001$), suggesting that health improvements facilitate full-time employment. Women are significantly less likely to work full-time, reflecting gender disparities in labor market participation. Neither race nor maternal education significantly affects full-time employment likelihood.

For white-collar versus blue-collar occupations outlined in the second column of Table 2.6, the effects of mental health are even more pronounced. Lagged mental health has a strong positive effect (0.184, $p < 0.001$), indicating that individuals with better mental health are 18.4 percentage points more likely to work in white-collar jobs. Differenced mental health is also significant (0.140, $p < 0.001$), suggesting that as mental health improves, individuals are 14 percentage points more likely to move into white-collar roles. Physical health also plays a crucial role, with lagged physical health (0.265, $p < 0.001$) and differenced physical health (0.187, $p < 0.001$) significantly increasing the probability of selecting white-collar jobs. These findings indicate that both mental and physical health are key determinants of upward occupational mobility. Women are significantly more likely to work in white-collar occupations (0.203, $p < 0.001$). Black individuals are significantly less likely to be in white-collar jobs (-0.0497, $p < 0.01$), suggesting potential systemic barriers in career advancement due to possible racial discrimination, poverty, and lower exposure to high-quality education.

Table 2.6. Occupational Selection Probabilities – Mixed-Effects Logistic Regression

	Full-Time		White-Collar	
	<i>M</i> -Model	<i>P</i> -Model	<i>M</i> -Model	<i>P</i> -Model
Mental health (<i>lag</i>)	0.158*** (0.0327)	-	0.184*** (0.0333)	-
Mental Health (<i>diff</i>)	0.173*** (0.0263)	-	0.140*** (0.0238)	-
Physical Health (<i>lag</i>)	-	0.0388 (0.0338)	-	0.265*** (0.0333)
Physical Health (<i>diff</i>)	-	0.138*** (0.0307)	-	0.187*** (0.0282)
Age	-0.0403*** (0.0104)	-0.0419*** (0.0104)	0.0551*** (0.0096)	0.0610*** (0.0097)
Age (<i>sq</i>)	0.0008*** (0.0002)	0.0008*** (0.0002)	-0.0007*** (0.0002)	-0.0008*** (0.0002)
Female	-0.147*** (0.0112)	-0.151*** (0.0114)	0.203*** (0.0122)	0.189*** (0.0124)
Black	0.0140 (0.0147)	0.0154 (0.0149)	-0.0380* (0.0166)	-0.0497** (0.0166)
Mom's College	-0.0135 (0.0123)	-0.0121 (0.0123)	0.170*** (0.0138)	0.171*** (0.0137)
Married	0.0099 (0.0117)	0.0151 (0.0120)	0.0459*** (0.0115)	0.0368** (0.0115)
Education (<i>diff, years</i>)	-0.0077* (0.0034)	-0.0070 (0.0034)	0.0259*** (0.0036)	0.0256*** (0.0035)
Observations	7,901	7,901	7,901	7,901

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Marital status has a positive effect, with married individuals more likely to be employed in white-collar occupations. This may reflect that married individuals place higher value on job characteristics such as stability, benefits, or long-term security, which are often associated with white-collar work. Alternatively, it is possible that individuals who are more likely to attain stable, white-collar employment are also more likely to marry, reflecting a selection effect rather than a direct causal relationship.

2.5.3. Heterogeneity Analysis

The heterogeneity analyses, depicted in Tables 2.7.a and 2.7.b, performed on specific levels of predicted mental and physical health scores (i.e. 0, 0.5, and 1 indicating poor, moderate, and perfect health) further support these conclusions. These tables provide the variation of the effects of mental and physical health across full-time and white-collar classifications. The heterogeneity analysis of full-time versus part-time employment shows that both mental and physical health significantly increase the likelihood of working full-time. Individuals with poor mental health have a 51.9% probability of full-time employment, increasing to 60.4% for moderate mental health and 68.5% for perfect mental health. This represents a 16.6 percentage point increase in the likelihood of full-time employment when moving from poor to perfect mental health. A similar pattern is observed for physical health, where full-time employment probability increases from 62.9% for poor physical health to 64.9% for moderate physical health and 66.8% for perfect physical health. This reflects a 3.9 percentage point increase from poor to perfect physical health. These results suggest that better mental and physical health enable individuals to maintain full-time employment, possibly due to increased resilience and capacity to manage work demands. More importantly, the results provide empirical evidence that the effect of mental health on the likelihood of full-time employment is over 4 times greater than that of physical health.

For white-collar versus blue-collar occupations, the results are particularly noticeable. Individuals with poor mental health have a 47.2% probability of working in white-collar jobs, compared to 56.9% for those with moderate mental health and 66.2% for those with perfect mental health. This corresponds to a 19.0 percentage point increase in the likelihood of white-collar employment when moving from poor to perfect mental health. Similarly, individuals with poor physical health have a 41.0% probability of white-collar employment, increasing to 55.1% for moderate physical health and 68.6% for perfect physical health. This implies a 27.6 percentage point increase from poor to perfect physical health. These findings highlight the significant role that both mental and physical health play in upward occupational mobility, with better health increasing the likelihood of securing higher-status, less labor-intensive jobs.

Table 2.7.a. Heterogeneity of the Effects of Mental Health

	Full-Time	White-Collar
0: Poor Mental Health	0.519*** (0.0312)	0.472*** (0.0307)
0.5: Moderate Mental Health	0.604*** (0.0136)	0.569*** (0.0138)
1: Perfect Mental Health	0.685*** (0.00714)	0.662*** (0.00805)

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7.b. Heterogeneity of the Effects of Physical Health

	Full-Time	White-Collar
0: Poor Physical Health	0.629*** (0.0291)	0.410*** (0.0288)
0.5: Moderate Physical Health	0.649*** (0.0122)	0.551*** (0.0125)
1: Perfect Physical Health	0.668*** (0.00833)	0.686*** (0.00900)

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, the heterogeneity analysis underscores the central role of mental and physical health in occupational selection. While better health increases the likelihood of securing high-skilled, white-collar, and full-time jobs, poor health is associated with higher probabilities of working in physically demanding, lower-skilled, or unstable occupations. Improvements in health over time facilitate selecting into more desirable jobs, emphasizing the importance of health policies in supporting upward occupational mobility. Sex, race, and socioeconomic background further shape these patterns, with women being underrepresented in physically demanding roles, Black individuals facing barriers in white-collar employment, and higher maternal education consistently associated with better occupational prospects. Additionally, age follows a nonlinear relationship in many categories, where younger individuals may initially enter physically demanding or lower-skilled jobs but shift toward higher-status roles as they gain experience and additional years of schooling, though in some physically intensive occupations, older workers are less likely to remain

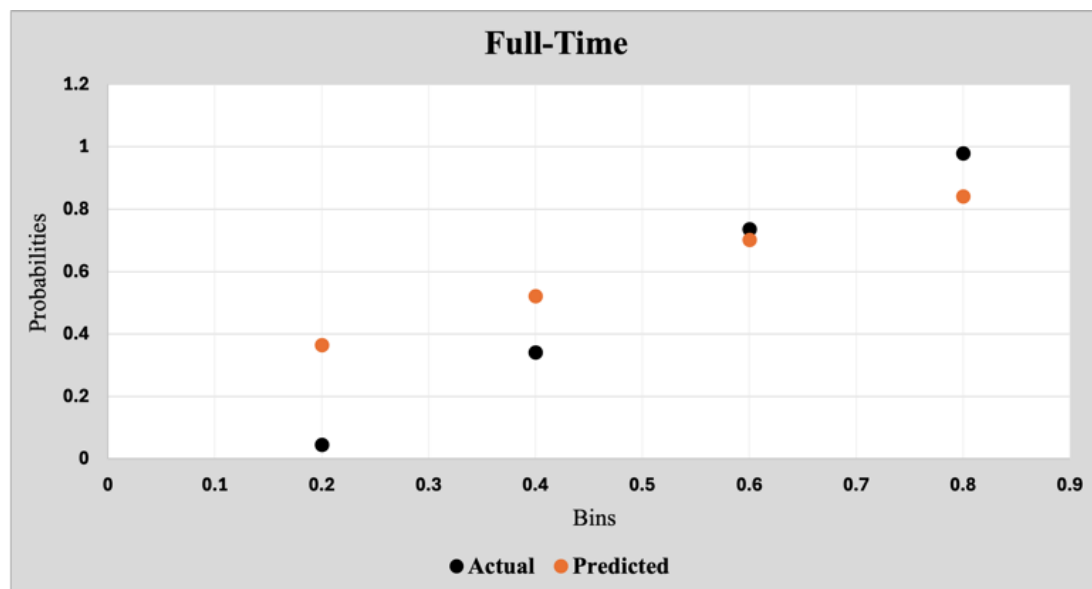
employed due to declining physical capacity. These findings highlight the interplay of health, demographic, and socioeconomic factors in shaping career trajectories.

2.5.4. Postestimation

2.5.4.1. Binned Residuals

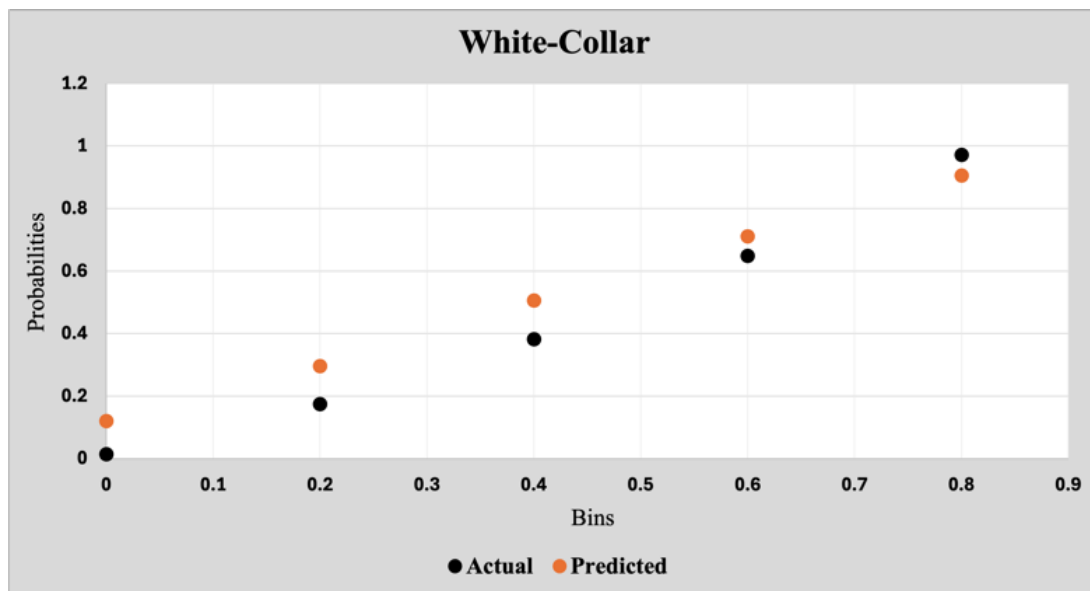
Binned residual analysis is a diagnostic tool used to evaluate how well a model predicts observed outcomes. In this process, the predicted probabilities from the model are divided into intervals, or 'bins', so that we can systematically compare the average predicted probability within each bin to the average observed probability in that bin. The use of mean probability is particularly appropriate for binary data, where the outcome is either 0 or 1, because it reflects the expected probability of success within a given range of predicted values. When we take the mean of the actual values within each bin, we are essentially computing the proportion of cases where the outcome is 1 within that probability range. The goal is to assess model predictive power, ensuring that predicted probabilities align with actual outcomes. If a model is successful at predicting the outcome and is well-specified, the predicted values should closely match the observed values across the probability spectrum.

Figure 2.4.a. Binned Residuals



The binned residual plots are presented in Figure 2.4.a and 2.4.b, and they provide insight into how well the model predicts occupational selection across the two major classifications. According to Figure 2.4.a, the plot for full-time employment shows a satisfactory alignment between predicted and actual probabilities. The analysis of the white-collar class in Figure 2.4.b shows a much better performance. There is only slight discrepancy in the low and mid-range bins, while the model performs even better at the higher probability levels. The model in general seems to predict white-collar occupation choices more accurately compared to the full-time class.

Figure 2.4.b. Binned Residuals

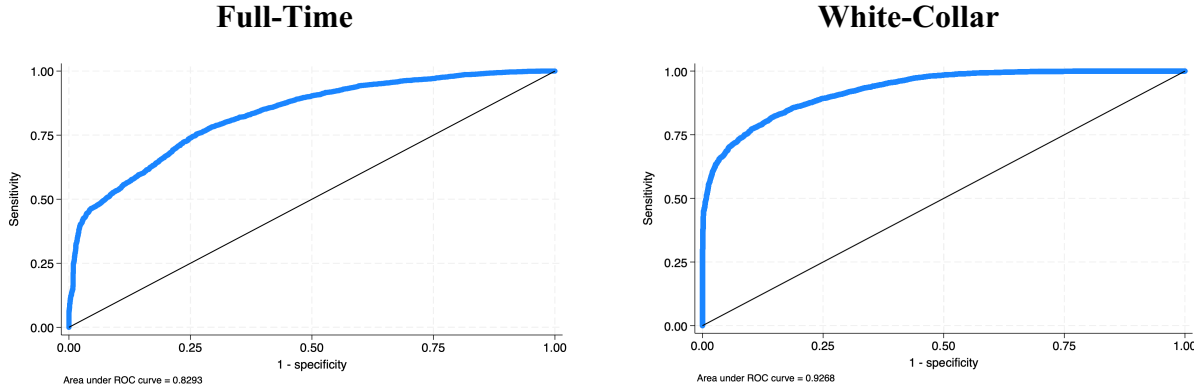


2.5.4.2. Receiver Operating Characteristic Curves

ROC (Receiver Operating Characteristic) curves are used to evaluate the performance of a classification model by plotting the trade-off between sensitivity (true positive rate) and specificity (false positive rate). The area under the ROC curve (AUC) provides a single measure of model performance, with values closer to 1 indicating a better model that discriminates well between the two outcome categories. The ROC plots for the mixed-effects logistic models are provided in Figure 2.5. They indicate that the classification models perform well, with AUC values demonstrating strong predictive ability. Both AUC values are above 0.82, suggesting near-perfect discrimination between categories. The ROC curves that rise steeply and approach the upper-left corner quickly show that the model effectively distinguishes between individuals in different

occupational categories, a pattern that is apparent for the white-collar classification with an ROC value of 0.93. Overall, the ROC analysis confirms that the models perform well.

Figure 2.5. Receiver Operating Characteristic Curves



2.5.4.3. Intraclass Correlation Coefficient (ICC)

The random effects analysis using the Intraclass Correlation Coefficient (ICC) assesses how much of the variation in occupational selection is due to individual differences rather than residual factors or external influences. By incorporating a random intercept, the model captures unobserved heterogeneity, acknowledging that individuals have unique baseline probabilities of selecting specific occupation classes. Higher ICC values indicate that individual characteristics play a major role in determining occupational outcomes, while lower values suggest a greater influence from time-varying or external factors. ICC in logistic models follows the following equation:

$$ICC = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_\epsilon^2}$$

, where σ_b^2 is the variance of the random intercept (individual-level variance) and σ_ϵ^2 is the fixed residual variance in mixed-effects logistic regression models, equal to $\frac{\pi^2}{3}$.

The results show variation across occupational classifications. For example, white-collar occupations have ICC values of approximately 50%, suggesting that individual differences play a dominant role in shaping these occupational selections. In contrast, full-time occupations have a lower ICC, meaning that their variation is more influenced by external circumstances and other time-varying covariates rather than stable individual characteristics.

The variance of the random intercept further supports these findings. Lower variance in full-time employment suggests a more homogenous baseline likelihood across individuals. The variance-covariance matrix confirms that clustering effects at the individual level are statistically significant, reinforcing the need for random effects modeling. Overall, the results highlight that selection into white-collar and full-time occupations are shaped not only by observable predictors but also by individual-specific tendencies that persist over time. The variation in ICC values across occupational classes confirms that while some choices are largely driven by stable personal factors, others are more influenced by external, time-varying elements. This justifies the multilevel modeling approach, ensuring that both within-individual and between-individual variations are appropriately accounted for in understanding occupational selection.

2.6. Conclusion

This study contributes to the understanding of how mental and physical health influence occupational selection across two major classifications, white-collar versus blue-collar and full-time versus part-time occupations, an area that has remained largely unexplored in economics. While previous research has examined the impact of mental health on employment and earnings, this study uniquely addresses how health conditions shape occupational sorting across occupational classifications that are not merely industry-based but are formed according to certain job characteristics. By employing a novel occupational grouping framework using a combination of SOC and O*NET data and advanced econometric techniques, the findings provide compelling evidence that both mental and physical health play a fundamental role in determining career prospects.

The results indicate that individuals with better mental health are significantly more likely to enter high-skilled, white-collar occupations, while those experiencing mental health challenges are disproportionately found in lower-skilled, physically demanding, blue-collar job categories. Similarly, physical health emerges as a critical factor in career selection, with healthier individuals more likely to work in white-collar occupations requiring cognitive skills, whereas those with poor physical health are overrepresented in physically intensive, blue-collar roles. These findings underscore the importance of health status as a determinant of labor market inequality beyond merely employment probabilities or earnings.

A key methodological advancement of this study is the use of latent variables to measure mental and physical health, reducing measurement error and capturing the multidimensional nature of these constructs. This approach allows for a more progressive analysis of how different aspects of health contribute to occupational sorting. Furthermore, by employing a mixed-effects logistic regression model with both fixed and random effects to model occupational selection variations, the study accounts for both individual heterogeneity and time-variant changes, ensuring a robust estimation of health's impact on occupational outcomes.

Beyond the core findings, the heterogeneity analysis highlights important patterns in occupational selection based on varying health levels. The probability of working in white-collar professions increases substantially with better mental health, whereas individuals with poor health are more likely to be in precarious, lower-wage jobs. These trends remain consistent across various demographic groups, suggesting that the relationship between health and career outcomes is not driven by specific subpopulations. Moreover, the role of sex, race, and socioeconomic background further shapes occupational outcomes, highlighting the significance of systemic factors besides health that restrict upward career mobility.

The robustness of the results was confirmed through multiple post-diagnostic tests, including binned residuals plots and ROC curves, which validated the predictive accuracy of the models and ensured the model is well-specified. These diagnostic checks provide additional confidence in the validity of the conclusions drawn from this research.

These findings carry substantial policy implications. Mental and physical health interventions should be integrated into workforce development programs, ensuring that individuals with health challenges receive the necessary support to access higher-quality jobs. Employers and policymakers must also recognize the long-term economic impact of untreated mental health conditions, as individuals struggling with poor mental health may become trapped in lower-paying, physically demanding roles with limited upward career mobility. Expanding workplace accommodations, mental health support services, and targeted training programs can mitigate these disparities and create a more inclusive labor market.

While this study provides robust evidence of the causal relationship between mental health and occupational selection by leveraging panel data, lagged effects, and mixed-effects logistic

regressions, future research could further explore the specific mechanisms driving these relationships. Structural models, such as dynamic job search models or matching models, could provide a deeper understanding of how mental health influences labor market transitions and associated earnings. Additionally, causal inference methods (e.g. dynamic treatment effect models) could help identify the pathways through which mental health affects occupational selection such as cognitive ability, self-esteem, and productivity. Exploring long-term career outcomes through overlapping generations (OLG) models could also shed light on how mental health shocks in early life shape occupational mobility and lifetime earnings potential.

Overall, this research advances our understanding of the critical role of mental and physical health in shaping labor market outcomes. By recognizing that occupational path is not solely driven by skills, education, or economic factors but also by underlying health conditions, this study provides a foundation for future work that bridges labor economics and public health. Addressing these disparities requires an integrated approach that combines labor policies, health interventions, and education reforms to ensure that individuals, regardless of their health status, can access meaningful and sustainable employment opportunities.

Chapter 3.

Mental Health and Productivity Over Time: A Mixed-Effects Modelling Approach

3.1. Introduction

The interplay between individual health status, both physical and mental, and labor market productivity has become a central theme in modern economic research. The foundation of this relationship is rooted deeply in human capital theory, a concept initially proposed by Grossman (1972), which argues that health is a critical component of human capital that directly influences labor productivity. Healthier individuals tend to work more regularly, experience fewer job disruptions, and have higher labor force participation and earnings potential. Currie and Madrian (1999) emphasize that poor health significantly reduces the capacity to work and shapes job choice, hours, and wages, highlighting the critical role of health in determining labor market outcomes. Empirical investigations spanning various contexts and methodologies have consistently corroborated this theoretical stance, highlighting the significant productivity costs associated with poor health (Bloom & Canning, 2000). In particular, Schultz and Edington (2007) systematically review evidence linking a wide range of health risks, such as obesity, physical inactivity, and chronic conditions like arthritis, to presenteeism, emphasizing that on-the-job productivity losses often exceed direct medical costs.

Within the expansive literature on health and labor economics, attention has progressively shifted toward examining mental health as a distinct yet equally impactful dimension of overall well-being. Mental health disorders such as depression, anxiety, and stress-related illnesses have emerged prominently as critical determinants of reduced productivity and labor market engagement (Chatterji et al., 2007). For example, Knudsen et al. (2013) document that common mental disorders substantially increase the likelihood of long-term sickness absence, thus imposing significant economic burdens not only on individuals and firms but also on public health systems and social safety nets. Similarly, Bubonya et al. (2017), using Australian longitudinal data, demonstrate that poor mental health substantially elevates rates of presenteeism and absenteeism, thus amplifying productivity losses. These studies underscore the intricate channels through which mental health influences workplace outcomes, thus broadening the scope for targeted policy interventions.

Despite substantial progress, existing research predominantly focuses either on physical health outcomes or provides limited analyses regarding the measurement challenges and dynamic nature

of mental health impacts on productivity. For instance, previous research often relied on self-reported productivity measures or simple binary indicators of health status, which likely underestimate or obscure the true productivity effects due to measurement errors or biases inherent in self-reporting (Goetzel et al., 2004). These approaches, while valuable, would limit our understanding of how health trajectories influence productivity changes across the life course. Addressing these limitations is critical for accurately quantifying the economic implications of health interventions and informing efficient allocation of resources.

This dissertation explicitly addresses these critical gaps by employing advanced econometric methodologies that substantially improve upon existing approaches to measuring and modeling the relationship between health, particularly mental health, and workplace productivity. Utilizing the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative and longitudinal dataset, the present analysis offers three distinctive contributions. Firstly, it leverages Generalized Structural Equation Modeling (GSEM) to construct robust latent variables for both mental and physical health. This latent variable approach allows for a comprehensive integration of multiple indicators, reducing measurement errors and capturing the underlying dimensions of health more accurately than single-item measures. Specifically, latent mental health is measured through indicators such as self-reported depression, unhappiness, suicidal thoughts, and ADHD diagnoses. Likewise, latent physical health integrates general health measures, body mass index (BMI), and substance use indicators, including alcohol, tobacco, marijuana, and cocaine use. This rigorous and detailed modeling approach substantially enhances construct validity and facilitates precise estimation of health-productivity relationships.

Secondly, this study applies the same latent variable framework to construct an internally consistent and multidimensional measure of productivity that moves beyond simplistic or narrow measures based solely on earnings or hours worked. The latent productivity score is modeled using three key observed indicators: job satisfaction (measured as a binary outcome), weekly work hours (continuous), and the natural logarithm of weekly income (continuous). By integrating subjective job satisfaction, alongside objective labor market outcomes, the latent construct captures not only economic productivity but also the individual's sense of workplace engagement and contentment. The GSEM approach allows for simultaneous estimation of the relationships among these indicators while accounting for their differing distributions and measurement characteristics. This

latent productivity variable is normalized to ensure interpretability and comparability across individuals, and it serves as a central outcome in the mixed-effects regression analysis, offering a more holistic and statistically robust measure of workplace functioning than conventional productivity metrics.

Third, the study employs mixed-effects regression models, effectively accommodating the longitudinal structure of the Add Health data. While the modeling approach itself is well-established, its application to examine the impact of health on productivity in this context represents a distinct contribution. This modeling framework incorporates individual-specific random intercepts alongside fixed-effects estimators to robustly control for both observed and unobserved heterogeneity, thus addressing a common limitation in cross-sectional or simpler longitudinal analyses. By explicitly modeling temporal dynamics, these mixed-effects estimators yield insights into the causal pathways linking changes in health status over time to corresponding changes in productivity, thus contributing to the existing body of economic literature by providing clearer policy-relevant implications.

The empirical results of this rigorous analysis reveal compelling evidence of the productivity impacts attributable specifically to mental health, as well as physical health. Lagged mental health significantly predicts higher productivity outcomes, with an increase from poor to good mental health (i.e., from zero to one on the normalized scale) corresponding to a 0.0251 increase in latent productivity and a 0.0201 increase in calculated productivity, both measured on a scale from zero to one. These findings underscore that mental health improvements enhance labor market productivity. Similarly, physical health exhibits a strong predictive relationship with calculated productivity, although its effect on the latent productivity score is comparatively smaller. Beyond health metrics alone, demographic variables such as sex, race, and education reveal significant differential impacts on productivity.

From a broader economic perspective, these findings hold considerable significance for both policy and organizational practice. They suggest that investments targeting improvements in mental health can yield productivity gains, thereby enhancing economic growth and reducing the broader socioeconomic costs associated with mental illness. For policymakers, the results indicate a clear benefit to integrating robust mental health support mechanisms into labor and health policy frameworks. Organizationally, employers can directly benefit from investing in comprehensive

mental health initiatives, such as workplace wellness programs, mental health training, counseling services, and supportive work environments, to maximize employee productivity and minimize the costly consequences of mental health.

In summary, this dissertation contributes to the economic literature in three fundamental ways: firstly, by employing advanced latent-variable modeling to accurately measure mental and physical health dimensions and productivity; secondly, by utilizing robust longitudinal econometric techniques to examine dynamic changes in productivity associated with changes in mental health while incorporating both fixed and random effects; and thirdly, by clearly quantifying and distinguishing the economic impacts of mental health from physical health on productivity, thus providing precise evidence for implementation of targeted policies. Collectively, these contributions represent significant methodological and empirical advancements, enhancing the capacity of future economic research to analyze and interpret complex health-productivity relationships.

This dissertation is organized as follows. Section 3.2 reviews the existing literature on the relationship between health and labor market outcomes, with a particular focus on health and workplace productivity. Section 3.3 describes the data and variable construction, including the indicators of latent health and productivity measures. Section 3.4 details the empirical methodology, including the Generalized Structural Equation Modeling framework for both health and productivity as well as mixed-effects regression specifications. Section 3.5 presents the main results and robustness checks, with particular attention to the distinct effects of mental and physical health. Finally, Section 3.6 concludes by summarizing the findings, discussing policy implications, and outlining directions for future research.

3.2. Literature Review

Mental health plays a critical role in shaping labor market outcomes, influencing both employment probabilities and workplace productivity. A growing body of literature has established that poor mental health reduces labor force participation and employment probabilities, and a few have examined its impact on productivity losses through absenteeism and presenteeism. This section reviews key studies that examine the intersection of mental health and labor market performance. The literature spans diverse methodologies and geographic contexts, offering insights

into how mental health influences employment probabilities, earnings, and workplace productivity, as well as how policy interventions and social support systems may mitigate these effects.

A study by Bubonya et al. (2017) investigates the relationship between mental health and workplace productivity using a conditional fixed-effects logit model. The authors focus on absenteeism and presenteeism using data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Although policies often aim to reduce healthcare costs and incentivize employment, much of the economic burden arises from decreased workplace productivity among individuals with mental health challenges. A significant contribution of the research is its examination of how job characteristics, such as control, security, stress, and complexity, moderate the effects of mental health on productivity. Additionally, the study explores gender differences, shedding light on how men and women experience and respond to workplace conditions when facing mental health issues.

The results show a clear association between poor mental health and diminished workplace productivity. Workers experiencing poor mental health are significantly more likely to report presenteeism, meaning reduced productivity while at work, and absenteeism, meaning higher absence rates. For example, men with poor mental health are over six times more likely to experience presenteeism compared to women. The study also finds that job characteristics also play a critical role in shaping these outcomes. Greater job control, security, and complexity are associated with lower presenteeism rates, while job stress is linked to increased presenteeism. However, the mitigating effects of positive job characteristics are more pronounced for workers in good mental health than for those with mental health issues, highlighting that job conditions alone may not fully counteract the productivity challenges posed by mental illness. In terms of absenteeism, authors suggest that poor mental health increases absence rates for both men and women. Men benefit from increased job control, which reduces their absenteeism, while women experience heightened absenteeism with greater job stress. Interestingly, job security is associated with higher absenteeism rates, potentially reflecting greater access to sick leave entitlements. Gender differences are evident in how mental health interacts with job conditions: women's absenteeism is higher with increased job stress and lower control when they have mental health issues, while men with mental health problems experience reduced absenteeism due to higher job control. (Bubonya et al., 2017)

Another paper by Andersen (2015) evaluates the labor market impacts of mental health parity mandates, which require health insurance plans to provide coverage for mental health treatment. Using data from the 1997–2001 National Health Interview Survey (NHIS) linked to the 1998–2003 Medical Expenditure Panel Survey (MEPS), it examines outcomes such as employment, employer-provided insurance coverage, wages, hours worked, and earnings, with a specific focus on how these effects vary by levels of mental distress. The methodology includes probit and Heckman selection models to address potential endogeneity and sample selection bias. The analysis accounts for covariance within states, uses state and year fixed effects, and calculates average marginal effects to estimate the impact of the mandates. Interaction terms are employed to capture heterogeneity in the effects by mental distress levels.

The study reveals that mental health parity mandates significantly increase employer-provided insurance coverage for individuals with moderate mental distress, with relative increases ranging from 4.6% to 8.3%. These mandates eliminate disparities in insurance offer rates for distressed individuals compared to their non-distressed counterparts. In terms of employment, a marginally significant increase of 16 percentage points in the probability of employment was observed for severely distressed individuals; however, this result may be unreliable due to the small sample size (135 observations) for severely distressed individuals in mandate-adopting states. The results also suggest that parity mandates lead to significant gains in wages and hours worked for moderately distressed workers, with log annual earnings increasing by approximately 8.8% to 12.5% and weekly hours worked rising by 8.9% to 11.0%. These findings indicate that mandates improve labor market outcomes for individuals whose mental health status previously hindered their economic potential. For non-distressed individuals, however, there were no significant changes in wages or hours worked, suggesting that the mandates' effects are concentrated among those most likely to benefit from improved mental health care access. Importantly, the study also highlights that the effects are largely confined to smaller firms with fewer than 200 employees, as these firms are less likely to self-insure and are therefore more directly affected by mandates. (Andersen, 2015)

Additionally results suggest that family members of moderately distressed individuals increased their labor supply significantly after parity mandates were implemented. While the change in their wages was not statistically significant, their weekly hours worked rose by approximately 12%, suggesting a labor supply response driven by reduced household distress and

improved mental health resources. These findings align with broader labor market dynamics, indicating that parity mandates result in an outward shift in labor demand for moderately distressed individuals, likely driven by productivity improvements enabled by better access to mental health care. Overall, this study demonstrates that mental health parity mandates enhance social welfare by addressing disparities in labor market outcomes for a vulnerable population. The author concludes that by improving access to mental health care, these policies contribute to increased productivity and labor market participation, particularly for moderately distressed workers and their families. (Andersen, 2015)

Another study by Currie and Stabile (2009) investigates the long-term effects of childhood mental health problems on human capital development, emphasizing academic outcomes and educational attainment. Using data from the Canadian National Longitudinal Survey of Children and Youth (NLSCY) and the American National Longitudinal Survey of Youth (NLSY), the study examines the impact of three major types of mental health disorders, ADHD, anxiety and depression, and conduct disorders, alongside a general behavior problem index. Their analysis incorporates sibling fixed effects models to address confounding factors, such as family background and socio-economic status, which are often correlated with both mental health conditions and educational outcomes.

The study finds that childhood behavior problems have significant and lasting effects on future human capital outcomes. ADHD is consistently associated with grade repetition and lower test scores across both datasets, with effects comparable in magnitude to large differences in family income or maternal education. For example, a one-unit increase in hyperactivity scores reduced standardized math scores by 4–7% of a standard deviation in both countries. Conduct disorders negatively impacted grade repetition and test scores in the U.S., while in Canada, they reduced school attendance among 16–19 year-olds but had weaker effects on other outcomes. Anxiety and depression increased grade repetition but did not significantly affect test scores, suggesting that these disorders operate through mechanisms other than cognitive performance. Importantly, the study concludes that the effects of early mental health problems on cognitive achievements are substantial and persist even when controlling for current mental health status. (Currie and Stabile, 2009)

The authors also utilize sibling fixed effects approach further strengthens causal inferences by controlling for unobserved familial factors. However, they acknowledge that their fixed-effects models may not fully capture the mitigating effects of higher income or maternal education, as interactions between mental health conditions and socio-economic factors were largely insignificant. (Currie and Stabile, 2009)

Currie and Stabile's findings underscore the importance of early intervention for children with mental health conditions, as these issues significantly shape educational trajectories and cognitive outcomes. Their research contributes to a growing literature demonstrating that investments in childhood mental health can yield substantial benefits for human capital development, with implications for both educational policy and broader socio-economic inequality.

Another research by Lu et al. (2009) investigates the relationship between mental health and labor market outcomes in China, providing empirical evidence on how psychological well-being influences employment probability and earnings. Using data from the China Health Surveillance Baseline 2001 Survey, which includes a diverse sample of 5,053 individuals across nine provinces, the authors assess the impact of mental health on labor force participation and income. To address endogeneity concerns, related to mental health status and labor market outcomes, they employ an instrumental variable (IV) approach using a community-level mental health index as an exogenous predictor of individual mental health. Additionally, they apply propensity score matching to verify the robustness of their findings.

The study constructs a mental health index based on self-reported responses to eight survey questions reflecting symptoms of depression and anxiety. Individuals scoring below 24 on the index are categorized as having poor mental health, while those scoring above 32 are classified as having good mental health. Labor market outcomes are measured by employment status and log annual earnings. The empirical strategy follows a two-part model: a logistic regression for employment probability and an ordinary least squares (OLS) regression for conditional earnings.

Aligned with findings of Bubonya et al. (2017), Lu et al.'s findings reveal a significant relationship between mental health and labor market performance. Without accounting for endogeneity, a one-unit increase in the mental health index raises the likelihood of employment by 8.6 percentage points for men and 6.9 percentage points for women, while increasing earnings by

2.0% and 1.8%, respectively. After applying IV estimation, the effects remain significant: good mental health increases employment log likelihood by 11.9 percentage points for men and 17.1 percentage points for women. However, while the positive correlation between mental health and income persists, the IV estimates for earnings lose statistical significance, suggesting that mental health plays a stronger role in determining labor force participation than earning levels. Sensitivity tests and propensity score matching confirm these patterns.

To quantify the broader economic implications, the authors simulate labor market outcomes under two scenarios: one where individuals have an average mental health index of 31.85 (close to good mental health) and another where it declines to 23.85 (poor mental health). The probability of employment drops from 85.1% to 61.4% for men and from 78.7% to 41.1% for women, while annual income falls by 38.5% for men and 32.6% for women. These effects are particularly pronounced for women, who experience a larger relative decline in employment likelihood, underscoring the gender-based heterogeneity of mental health impacts on labor outcomes. (Lu et al., 2009)

Overall, Lu et al.'s study contributes to the growing body of evidence on the economic costs of mental illness, emphasizing the need for targeted policy interventions in China. Their findings suggest that improving mental health services and integrating mental health considerations into labor policies could enhance workforce participation and reduce income disparities, particularly among vulnerable populations such as women.

A study by Vaalavuo (2021) examines the labor market consequences of breast cancer among Finnish women, with a particular focus on the heterogeneous effects across different socioeconomic groups and the mediating role of mental health. The paper is among the few economics studies that have analyzed how health effects vary by prior earnings levels or accounted for the role of mental health problems in shaping economic trajectories post-diagnosis. Leveraging Finland's comprehensive register data covering the entire population from 2000 to 2016, the study provides a quasi-experimental approach to estimating the causal effects of breast cancer on employment, earnings, and psychiatric diagnoses. By adopting a difference-in-differences methodology with individual fixed effects, Vaalavuo compares women diagnosed with breast cancer between 2004 and 2009 (treatment group) to those diagnosed between 2010 and 2015 (control group), effectively avoiding an important source of unobserved heterogeneity.

The findings indicate that breast cancer leads to a statistically significant decline in earnings, though the impact on employment is relatively modest. On average, annual earnings decrease by 5.1% following diagnosis, and this effect remains largely unchanged (4.7%) even after controlling for psychiatric diagnoses. This suggests that while mental health deteriorates following a cancer diagnosis, evidenced by a 2.7 percentage-point increase in psychiatric diagnoses, severe mental health problems do not fully explain the earnings decline. The employment effect is relatively small, with breast cancer survivors being just 1 percentage point less likely to be employed five years post-diagnosis, suggesting that the labor market effects manifest primarily through earnings rather than job loss. Notably, those with weaker labor market attachment before diagnosis, such as those in the lowest income quintiles, experience significantly steeper declines in earnings, with drops of 13.4% in the bottom quintile compared to smaller declines in higher quintiles. Additionally, cancer survivors are less likely to transition to self-employment or move from private to public sector employment, suggesting that serious illness reduces job mobility and career progression opportunities. (Vaalavuo, 2021)

A key contribution of Vaalavuo (2021) is its analysis of the role of Finland's social security system in mitigating income losses. While earnings decline, the impact on total personal income, including social transfers such as sickness benefits, is substantially smaller, at around 2.6%. This suggests that Finland's welfare system provides an effective buffer against income shocks due to illness, although it does not fully compensate for lost earnings, particularly for those in lower income groups (Vaalavuo, 2021). These results contrast with findings from other countries with weaker social safety nets, such as the United States, where Moran et al. (2011) report that female cancer survivors experience a 7-8 percentage-point drop in employment. Similarly, Jeon (2017) finds a 10% decline in earnings for Canadian cancer survivors, indicating that the labor market effects of illness are more severe in contexts with less comprehensive social support.

Vaalavuo's findings complement studies on health and labor market outcomes by also incorporating the effect of physical health. In particular, the study compares to Lu et al. (2009), who examine the impact of mental health on employment and earnings in China. While both studies find a strong link between health status and labor market outcomes, Lu et al. highlight the significant employment penalties associated with poor mental health, whereas Vaalavuo finds that employment effects for breast cancer survivors are minimal, with earnings reductions occurring

mainly through other mechanisms. One possible explanation for this difference is that breast cancer, unlike mental illness, is more likely to trigger social support mechanisms such as employer accommodations or sickness benefits, which may help individuals remain employed despite income losses. Additionally, Lu et al. find that mental health has a stronger effect on labor market participation for women than for men, a gendered dynamic that Vaalavuo's study does not directly address but aligns with her findings that women in lower income brackets experience greater financial hardship following illness.

Another interesting comparison can be drawn with Andersen (2015), who examines the labor market effects of mental health parity mandates in the U.S. Andersen finds that improving access to mental health treatment increases employment and earnings among moderately distressed workers, suggesting that targeted policy interventions can mitigate the economic burden of illness. Similarly, Vaalavuo's findings suggest that Finland's welfare system partially cushions the income shock associated with breast cancer. This highlights the importance of proactive labor market policies, not just social transfers, to support individuals suffering from major mental or physical health conditions.

Vaalavuo (2021) also suggests that while social security systems can reduce financial distress, they do not fully prevent labor market inequalities from widening. The findings suggest that additional policy measures, such as workplace accommodations, mental health support, and targeted employment programs may be needed to prevent long-term economic disadvantages for illness survivors, particularly those in lower socioeconomic groups.

Lastly, McDaid et al. (2024) provide a systematic review of the economic costs associated with mental disorders in South Asia, addressing a significant gap in the literature by consolidating findings across multiple studies. The paper compiles and analyzes data from 72 studies, with a focus on productivity losses, healthcare expenditures, and broader socioeconomic impacts. The authors note that most prior global reviews of the economic burden of mental health have included little to no data from South Asia, making this study particularly valuable for understanding the financial consequences of mental illness in low and middle-income country (LMIC) settings.

The review covers studies from several South Asian countries, with India and Pakistan dominating the sample. The methodological approaches of the studies vary, including cost of

illness studies, observational analyses, economic evaluations, and randomized controlled trials (RCTs), where control groups did not receive active interventions. Across these studies, the economic burden of mental disorders is found to be substantial, with productivity losses accounting for the majority of costs, typically exceeding 70% of total costs in cases of major depressive disorder, schizophrenia, and bipolar disorder. For example, in India, productivity losses constituted 73% of total depression-related costs at three months and 76% at twelve months (Patel et al., 2017; Weobong et al., 2017). In Pakistan, hospital outpatients with depression incurred 77% of their total costs through lost work productivity rather than direct healthcare expenses (Malik and Khan, 2016). This pattern suggests that the primary economic consequence of mental illness in South Asia is not direct medical spending, but rather forgone labor income and the additional burden placed on informal caregivers.

The findings from McDaid et al. (2024) expand upon several key themes in the economics literature on mental health and labor markets. Their review supports the conclusion of Lu et al. (2009), who demonstrated that poor mental health significantly reduces employment probabilities and earnings in China. However, while Lu et al. find that employment probabilities fall sharply with deteriorating mental health, McDaid et al. present a broader perspective in which productivity losses, rather than outright job loss, drive most economic costs. This suggests that in the South Asian context, where informal employment is prevalent, workers may continue to participate in the labor market but at reduced productivity levels, a pattern consistent with Bubonya et al. (2017), who find presenteeism to be a major driver of lost productivity among Australian workers with mental health conditions.

Overall, McDaid et al. (2024) make a critical contribution to the literature on the economic costs of mental health, particularly in LMICs. Their findings reinforce the argument that poor mental health is not only a public health crisis but also a significant economic burden that reduces labor supply, productivity, and household financial stability. The study provides compelling evidence for increased investment in mental health services in South Asia, emphasizing that failure to address these issues has far-reaching economic consequences. Furthermore, by highlighting the role of productivity losses, the review offers important insights that are relevant to the current study's focus on the impact of mental health on workplace productivity.

3.3. Data and Variables

This section provides a detailed description of the data sources, variable construction, and key measures used in the empirical analysis. It is organized into four subsections. Subsection 3.3.1 introduces the dataset, offering an overview of the National Longitudinal Study of Adolescent to Adult Health (Add Health) and its relevance to the study's objectives. Subsection 3.3.2 explains how productivity is measured, including both a latent construct and a wage measure based on income and hours worked. Subsection 3.3.3 outlines the main explanatory variables, including latent measures of mental and physical health, along with the sociodemographic controls incorporated into the models. Finally, Subsection 3.3.4 presents descriptive statistics that summarize key differences across productivity groups and provide preliminary insights into the relationship between health and workplace productivity. Together, these components establish the empirical foundation for the subsequent analysis.

3.3.1. Overview of the Dataset

This dissertation utilizes data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative panel study that follows a cohort of U.S. youth from adolescence into adulthood. Initially launched in 1994–1995, Add Health collected data across five waves. This study focuses on Waves III (2001–2002), IV (2008–2009), and V (2016–2018), encompassing respondents aged 18–43. The dataset offers a robust framework to examine dynamic associations between mental health and workplace productivity over time, capturing transitions in education, labor market engagement, and physical and mental well-being. The longitudinal design enables the modeling of time-varying outcomes and covariates for a panel of 2,954 individuals observed across three waves.

A noteworthy advantage of using Add Health is the breadth of psychological, behavioral, and occupational data it offers, along with repeated measures from the same individuals across multiple life stages. This richness allows for a more dynamic assessment of how early-life and adult health interact to shape long-term economic productivity. Moreover, the inclusion of biomarkers, mental health assessments, and retrospective job history across waves provides a multidimensional view of respondents' well-being and labor market outcomes.

3.3.2. Productivity Measures

In this study, productivity is measured using two approaches to ensure the robustness of the results across different specifications. First, productivity is constructed as a latent variable using a set of observed indicators from the data. Second, it is computed directly based on weekly income and weekly working hours. A detailed description of both measures is provided below.

- **Latent Productivity (*PL*)**

A central feature of the study that distinguishes its methodology from the existing literature is the estimation of individual productivity as a latent construct, *Productivity (PL)*. Given the multifaceted nature of productivity, which cannot be directly observed, the analysis uses a Generalized Structural Equation Modeling framework to define Productivity based on three observed indicators: *Job Satisfaction*, *weekly Hours Worked*, and *weekly Income(ln)*. Job satisfaction is modelled as a binary indicator. The variable is based on responses to the survey question: 'How satisfied are you with this job, as a whole?' Participants who answered, 'extremely satisfied' or 'somewhat satisfied' were coded as 1, while all other responses were coded as 0." Weekly hours worked and log weekly income are both continuous variables.

The decision to model productivity as a latent construct is motivated by limitations in existing literature, where productivity is often narrowly proxied by income alone. This approach allows for integration of both objective labor market behaviors and subjective assessments, reflecting a more comprehensive representation of workplace performance.

The weekly hours of work required considerable preprocessing due to missingness and inconsistencies in the raw data. To address this, multiple imputation was performed using predictive mean matching (PMM). First, the extent and pattern of missingness was examined. The raw variable, weekly hours worked, was registered for imputation, while a set of relevant covariates, including demographic characteristics (e.g., age, sex, race), socioeconomic indicators (e.g., education, parental education, marital status, income), and health measures (e.g., latent mental and physical health scores) were registered as regular predictors. I used predictive mean matching with one nearest neighbor and generated 10 imputations. This method ensures that missing values in weekly hours of work are replaced with observed values from respondents with

similar covariate profiles, preserving the original data distribution. Finally, a unified variable imputed weekly *Hours Worked* was created by combining the observed and imputed values across all datasets, which is then used in subsequent analyses. Furthermore, respondents' annual income was transformed into weekly income to align with hours worked. The natural logarithm of weekly income, *Income(ln)*, was then created to capture the nonlinear relationship between income and other factors and is used both as an indicator in the latent productivity model and as a component in the wage measure productivity measure.

The inclusion of job satisfaction in the latent construct for productivity in the current study is motivated by empirical evidence linking employee happiness to improved labor productivity. This relationship is supported by Bellet et al. (2019), who find that workers' happiness significantly enhances sales performance through increased efficiency and schedule adherence. This latent structure for productivity allows for the estimation of a single underlying productivity construct, that captures an individual's labor market engagement and subjective job experience. The predicted latent scores from this model are saved as a productivity factor score and normalized between zero and one, and used as the dependent variable, *Productivity (PL)*, in subsequent mixed-effects models examining the role of mental and physical health on productivity. These models will be discussed in detail under Section 4, Methodology.

▪ **Wage-Measure of Productivity (PC)**

This productivity measure is a non-latent measure of productivity calculated by dividing weekly Income by weekly Hours Worked. This measure and its log-transformed version were used to create a final productivity scale that was normalized between zero and one. The final variable is stored as *Productivity (PC)*.

While the latent productivity score offers a theoretically grounded construct, including the wage measure of productivity allows for validation against a more conventional economic proxy. Comparing both measures across models also helps assess the robustness of health-productivity relationships and offers practical relevance for policy translation.

3.3.3. Explanatory Variables

- **Mental and Physical Health**

The core explanatory variables in this study are two latent constructs: *Mental Health* and *Physical Health*. These variables were developed and described in detail in Chapter 2; therefore, only a summary is provided here for context. As detailed in Chapter 2, latent constructs for Mental Health and Physical Health were created using multiple self-reported indicators, some based on medical diagnoses. The mental health construct includes variables such as ADHD diagnosis, suicidal attempts, depressive symptoms, and self-reported unhappiness. The physical health construct incorporates measures of general health, substance use (tobacco, alcohol, marijuana, cocaine), and BMI. All indicators were coded as binary variables and reverse-coded to reflect better health outcomes. Both Mental Health and Physical Health variables are normalized as continuous scores between zero and one.

- **Sociodemographic Controls**

The models also incorporate a set of demographic and socioeconomic control variables to adjust for individual-level heterogeneity and potential confounding. These variables, except for one, are also explained in detail in Chapter 2 and only a summary is provided here. These controls account for demographic and educational characteristics that may influence productivity. Specifically, the model includes *Age* and age squared (*Age (sq)*) to capture nonlinear patterns, binary indicators for sex (*Female*), race (*Black*), and marital status (*Married*), as well as measures of educational attainment, both years of schooling completed (*Education*) and maternal college education (*Mom's College*). Additionally, variable *At School* is included as a binary indicator identifying current school enrollment.

Finally, another key explanatory variable is *Occupation*. This study controls for occupation using a categorical variable consisting of seven distinct categories based on O*NET classifications. These occupational groupings, explained in detail in Chapter 2, reflect shared skills, knowledge areas, work contexts, and interests. They include: (1) Professional and Technical, (2) Healthcare and Community Services, (3) Education, Arts, and Media, (4) Service and Maintenance, (5) Sales, Administration, and Logistics, (6) Trades, Production, and Agriculture, and (7) Military-Specific

occupations. Grouping occupations this way allows for a more interpretable analysis of occupational effects while maintaining consistency with the classification framework used earlier in the dissertation.

All covariates were selected based on theoretical relevance and their empirical role in shaping labor market outcomes. They are included in the mixed-effects models to isolate the specific effect of mental and physical health on productivity net of observable demographic and background characteristics. These variables are measured consistently across waves to capture both time-varying and time-invariant characteristics that may influence productivity. This allows the estimation of within-individual changes over time and accounts for temporal dynamics in labor market status, education, and health behaviors. The use of time-varying controls increases the model's sensitivity to life-course changes that influence productivity trajectories.

In summary, this study integrates a rich panel dataset, a carefully constructed latent productivity framework, a calculated productivity measure based on weekly earnings and weekly hours of work, and well-defined measures of mental and physical health to investigate how psychological well-being shapes workplace productivity over the life course. Through extensive data cleaning, multiple imputation, and transformation procedures, the final analytic sample is well-suited for longitudinal analysis.

3.3.4. Descriptive Statistics

Table 3.1.a presents descriptive statistics comparing respondents in the low and high productivity groups, based on the normalized latent *Productivity (PL)*. On average, individuals in the high productivity group are older (mean age = 31.31) compared to those in the low productivity group (mean age = 27.53), consistent with the idea that productivity tends to increase with age and accumulated labor market experience. The proportion of female respondents is notably higher in the low productivity group (65.6%) than in the high productivity group (50.2%), suggesting potential gender disparities in measured productivity. Race also appears to play a role in shaping productivity outcomes, as 17.2% of highly productive individuals are *Black*, compared to 22.3% in the low productivity group, suggesting possible racial differences in labor market performance and access to higher-productivity jobs. A higher percentage of respondents in the high productivity group are married (47.5% vs. 31.7%), and they also report slightly higher levels of educational

attainment (approximately 15 years vs. 14 years). Interestingly, the difference in maternal college education is minimal between the two groups. Regarding mental health, the high productivity group has slightly better lagged mental health scores (mean = 0.857) than the low productivity group (mean = 0.830), while physical health scores are relatively similar across both groups.

Table 3.1.a. Descriptive Statistics, Socioeconomic Comparison Across Productivity Levels

	Low Productivity	High Productivity	Total
Age	27.53 (6.198)	31.31 (6.085)	29.40 (6.426)
Female	0.656 (0.475)	0.502 (0.500)	0.580 (0.494)
Black	0.223 (0.416)	0.172 (0.377)	0.198 (0.398)
Mom's College	0.313 (0.464)	0.317 (0.465)	0.315 (0.464)
Married	0.317 (0.465)	0.475 (0.499)	0.395 (0.489)
Education (<i>years</i>)	14.10 (2.213)	14.87 (2.516)	14.48 (2.398)
Mental Health (<i>lag</i>)	0.830 (0.230)	0.857 (0.199)	0.844 (0.216)
Physical Health (<i>lag</i>)	0.813 (0.212)	0.801 (0.204)	0.807 (0.208)
Observations	4,485	4,377	8,862

Mean coefficients, standard errors in parentheses.

Table 3.1.b provides further detail by examining employment status and occupational distribution across productivity groups. All individuals in the high productivity group are employed full-time, whereas only 24.3% of those in the low productivity group are *Full-Time* workers, reinforcing the link between full-time employment and higher productivity scores. Furthermore,

66.6% of workers in the high-productivity group are employed in *White-Collar* occupations, compared to 59.6% of individuals in the low-productivity group.

Table 3.1.b. Descriptive Statistics, Occupation Based Comparison Across Productivity Levels

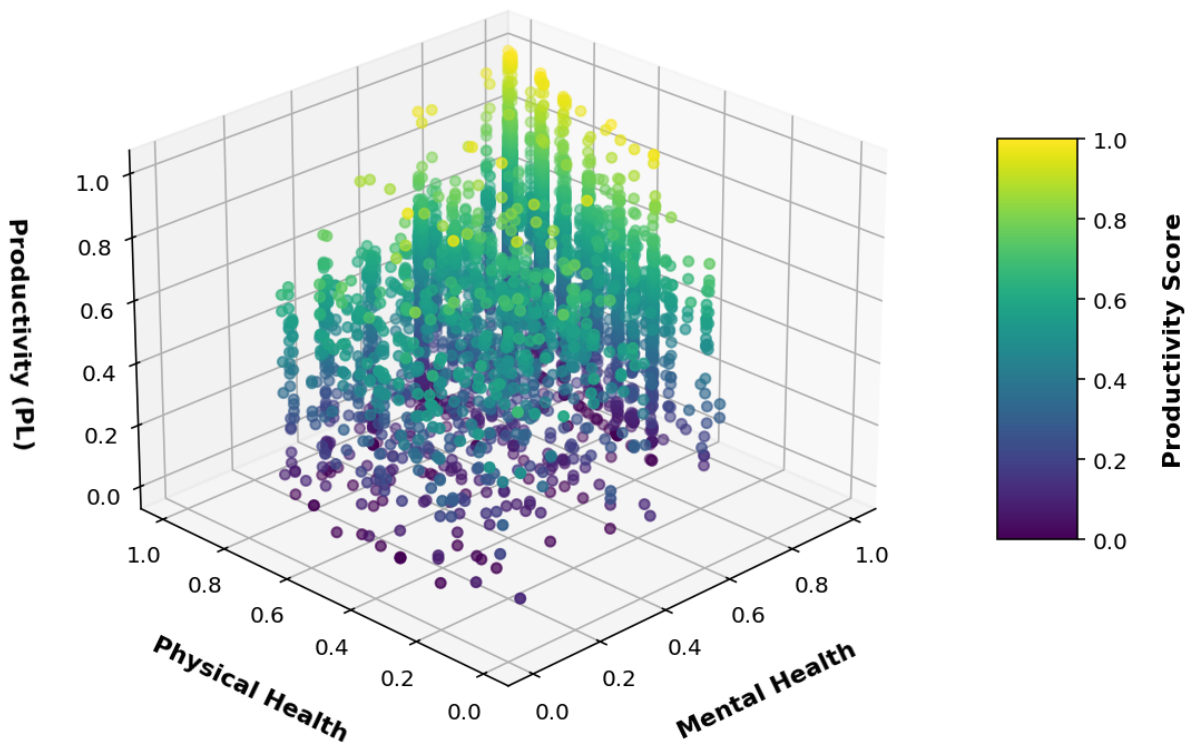
	Low Productivity	High Productivity	Total
Full-Time	0.243 (0.429)	1.000 (0.0214)	0.662 (0.473)
White-Collar	0.596 (0.491)	0.666 (0.472)	0.635 (0.482)
Prof/Tech	0.142 (0.350)	0.279 (0.449)	0.218 (0.413)
Health/Comm	0.139 (0.346)	0.137 (0.344)	0.138 (0.345)
Edu/Arts	0.104 (0.306)	0.104 (0.306)	0.104 (0.306)
Service/Maint	0.203 (0.402)	0.0939 (0.292)	0.143 (0.350)
Sales/Admin	0.306 (0.461)	0.230 (0.421)	0.264 (0.441)
Trades/Prod	0.0985 (0.298)	0.145 (0.352)	0.124 (0.330)
Military	0.00624 (0.0788)	0.0110 (0.104)	0.00886 (0.0937)
Observations	3,524	4,377	7,901

Mean coefficients, standard errors in parentheses.

In terms of occupational breakdown, professional and technical roles (*Prof/Tech*) are more prevalent in the high productivity group (27.9%) compared to the low productivity group (14.2%). Conversely, service and maintenance occupations (*Service/Maint*) are disproportionately represented in the low productivity group (20.3%) relative to the high productivity group (9.4%). Sales, administrative, and logistics roles are also more common among the low productivity group. The occupational distribution illustrates that respondents in high productivity roles are more

concentrated in white-collar and skill-intensive fields, while those in lower productivity brackets are more likely to be employed in service-oriented or manual labor occupations.

Figure 3.1.a. Latent Productivity, Mental, and Physical Health



To complement these statistics, Figure 3.1.a presents a three-dimensional scatterplot illustrating the relationship between latent productivity scores, *Productivity (PL)*, Mental Health, and Physical Health. The color gradient reflects the predicted productivity score, normalized between zero and one. The figure shows a clear upward pattern in productivity scores as both health indicators increase, with the highest density of high-productivity observations occurring near the corner of the graph where both mental health and physical health scores are close to one. This visual reinforces the idea that optimal productivity tends to occur when both dimensions of health are simultaneously high.

Figure 3.1.b. Wage Measure of Productivity, Mental, and Physical Health

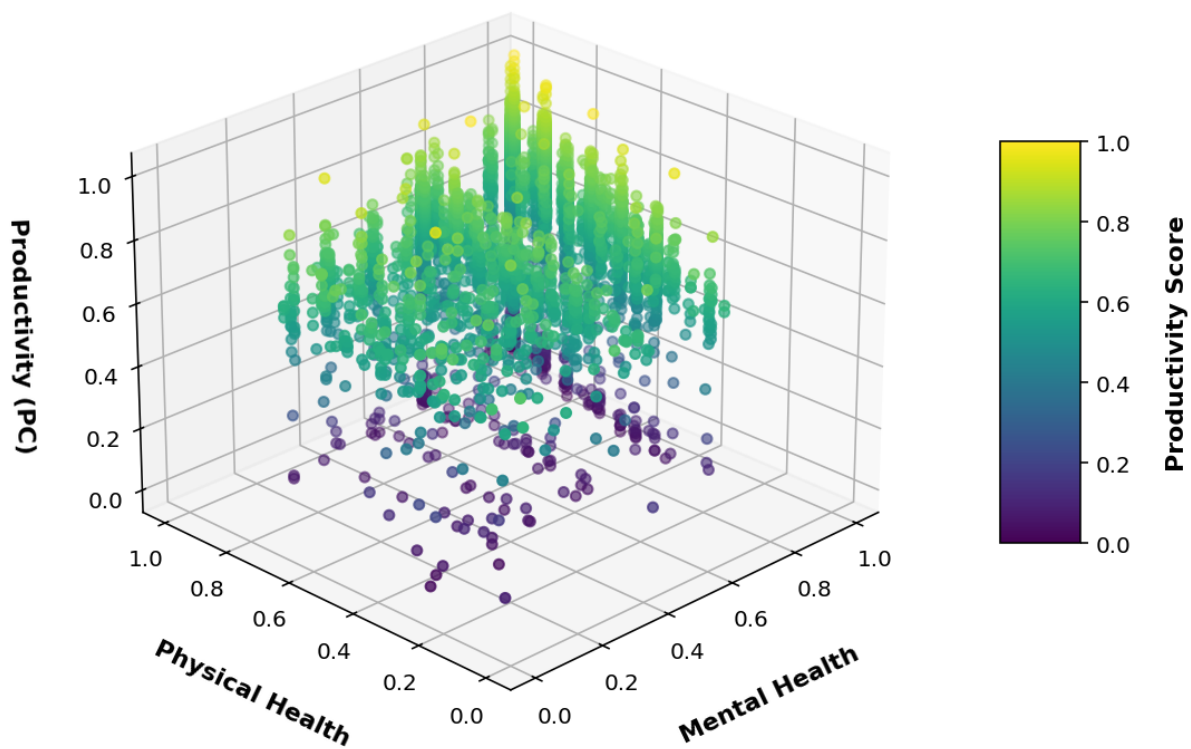


Figure 3.1.b plots the wage measure of *Productivity (PC)* against *Mental Health* and *Physical Health*. The pattern is similar to Figure 3.1.a but appears slightly more diffuse. This suggests that while higher health scores still correlate with greater productivity, the relationship may be less tightly defined when using calculated earnings per hour instead of the latent construct. This difference highlights the conceptual advantage of the latent measure in capturing the multidimensional aspects of productivity.

Figures 3.2.a and 3.2.b further investigate the bivariate relationships between health scores and productivity by plotting smoothed curves. In Figure 3.2.a, the red and blue lines show how latent productivity scores change with increasing mental and physical health, respectively. Both curves exhibit a clear upward trend, indicating that better health corresponds to greater productivity, though mental health shows a more linear and steady increase.

Figure 3.2.a. Smoothed Relationship Between Health and Productivity (PL)

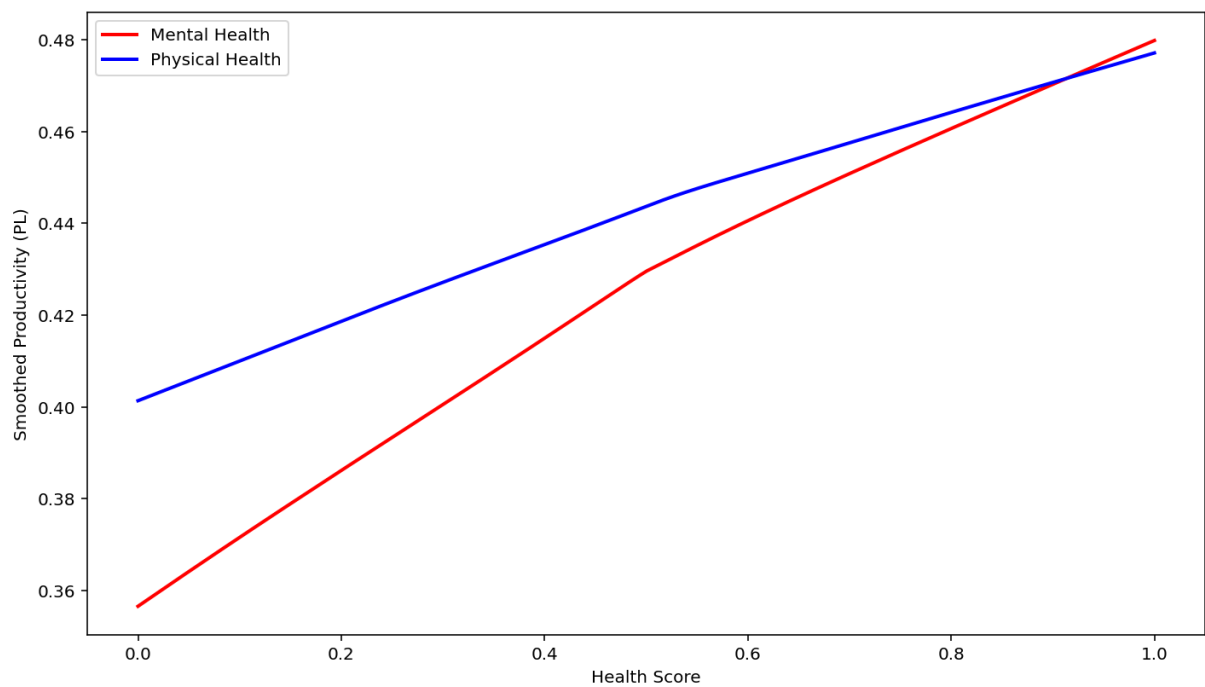


Figure 3.2.b. Smoothed Relationship Between Health and Productivity (PC)

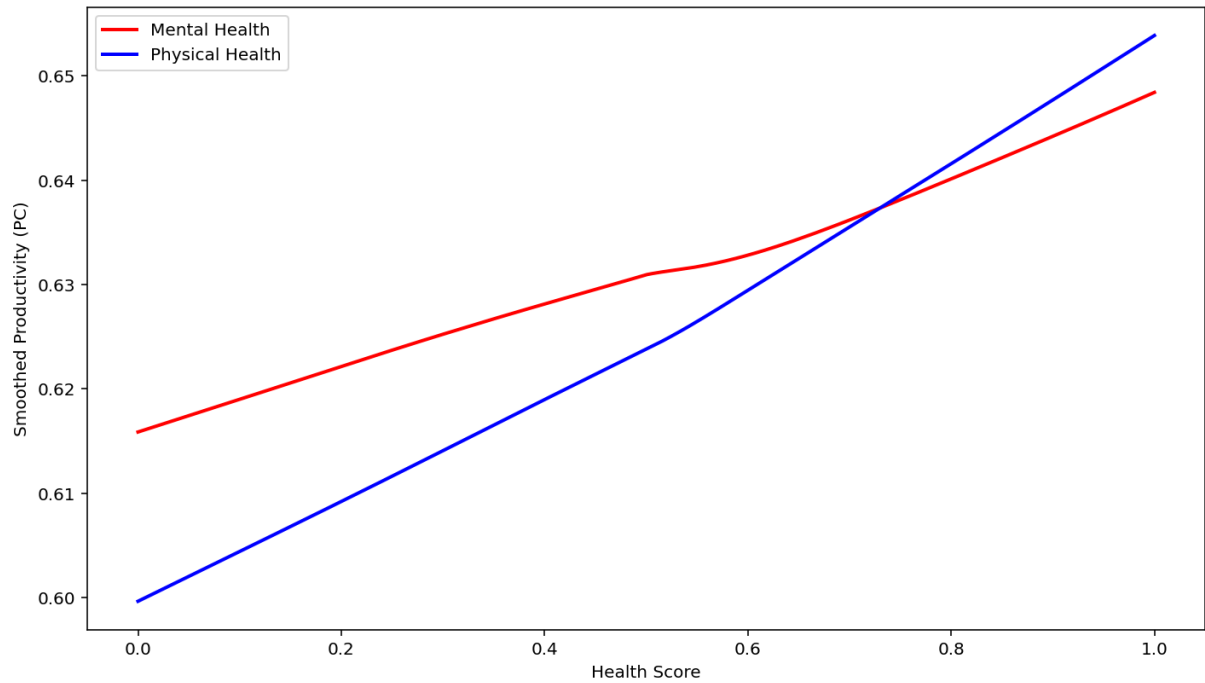


Figure 3.2.b presents the same analysis using log-transformed wage measure of productivity. Here, physical and mental health have a strong and mostly monotonic positive association with productivity, however, the relationship is stronger for physical health as supported by the steeper slope of the blue curve. Collectively, Figures 3.1.a–3.2.b provide visual evidence of the central hypothesis that both mental and physical health are important predictors of productivity, though mental health may play a more robust role based on the latent measure of productivity.

3.4. Methodology

The empirical analysis in this chapter unfolds in two main modeling stages. The first stage constructs a latent productivity variable using a Generalized Structural Equation Modeling (GSEM) framework based on three observed indicators. The second stage evaluates the impact of mental and physical health, estimated in Chapter 2, on both the latent productivity score and the natural log of the wage measure of productivity. This is accomplished by using mixed-effects regression models applied to three waves of the Add Health dataset. Each productivity outcome, latent and calculated, is analyzed in separate models to ensure robustness. Mental and physical health are included in separate specifications due to their high correlation, which raises concerns of multicollinearity if entered simultaneously.

The longitudinal design of the Add Health dataset enables the identification of both within and between-individual effects over time, making mixed-effects models particularly suitable for assessing temporal dynamics in productivity associated with health changes.

3.4.1. Construction of Latent Productivity

The factor analysis approach used to construct all latent variables in the current study follows the methodology of Cunha and Heckman (2008). Building on this framework, a latent productivity score is estimated through a GSEM system using three observed indicators: job satisfaction, weekly work hours, and weekly income. This approach is to ensure all key dimensions of productivity, in particular job satisfaction, are captured rather than relying merely on earnings data. The measurement model is specified as follows:

$$\text{logit} \left(P(\text{Job Satisfaction}_i = 1) \right) = \alpha_1 + \lambda_1(PL)_i \quad (3.1)$$

$$Hours\ Worked_i = \alpha_2 + \lambda_2(PL)_i + \varepsilon_{2i} \quad (3.2)$$

$$\ln(Income_i) = \alpha_3 + \lambda_3(PL)_i + \varepsilon_{3i} \quad (3.3)$$

Where α is the constant term and λ is the factor loading of each indicator. For *Job Satisfaction* a logit link is used as it is a binary indicator, for weekly *Hours Worked* and weekly *Income(ln)*, a Gaussian distribution with identity link is used as they are continuous indicators. Predicted latent productivity scores are extracted and normalized using min-max scaling to ensure comparability across individuals.

This normalized score serves as the dependent variable in the latent productivity regression models and is interpreted as a relative position on the productivity scale ranging from 0 (least productive) to 1 (most productive). Because it incorporates both objective measures (earnings and hours worked) and subjective assessment (satisfaction), this construct provides a holistic indicator of workplace functioning. Additionally, the latent variable approach helps to capture the unobservable component of productivity that might otherwise be obscured by reporting errors or inconsistencies in the survey responses, especially in self-reported work hours and income.

3.4.2. Construction of Latent Health Variables

Prior to examining the effect of health on productivity, latent scores for *Mental Health*, M , and *Physical Health*, P , were constructed in Chapter 2 using GSEM. These latent constructs were estimated from multiple binary indicators reflecting self-reported diagnoses and health-related behaviors. Mental health is represented as a latent trait reflected in indicators namely, *Depressed*, *Unhappy*, *Suicide*, and *ADHD*, while physical health is inferred from *Poor Health*, *Poor BMI*, and substance use patterns including *Tobacco*, *Alcohol*, *Marijuana*, and *Cocaine*. The GSEM framework allows for modeling the relationship between each latent trait and its corresponding observed indicators through a logit link, while accounting for measurement error and unobserved heterogeneity. The general form of the measurement equations is:

$$\log \left(\frac{P(Y_{i,m} = 1)}{1 - P(Y_{i,m} = 1)} \right) = \alpha_m + \lambda_m \tilde{M}_i \quad (3.4)$$

$$\log \left(\frac{P(Y_{i,p} = 1)}{1 - P(Y_{i,p} = 1)} \right) = \alpha_p + \lambda_p \tilde{P}_i \quad (3.5)$$

where $Y_{i,m}$ and $Y_{i,p}$ are the m^{th} and p^{th} indicators for mental and physical health of the i^{th} individual respectively; λ_m and λ_p refer to the factor loadings of the indicators, and $\tilde{M}_i$ and $\tilde{P}_i$ are the Mental Health and Physical health latent constructs.

To ease interpretation, these scores are normalized between zero and one and are reversed. The reversed scores are defined as $M_i = 1 - \tilde{M}_i$ and $P_i = 1 - \tilde{P}_i$, such that higher values of M_i and P_i now indicate better mental and physical health, respectively.

The scores were estimated independently for each wave, allowing for temporal variation in mental and physical health to be captured across the life course. All factor scores were reverse-coded and normalized between zero and one, with higher values reflecting better health. The latent structure is particularly important in panel studies such as Add Health, where respondents' interpretations of subjective health items may vary across time or context. The GSEM approach mitigates such inconsistencies by anchoring the health scores in multiple observed indicators that are conceptually and empirically grounded.

3.4.3. Mixed-Effects Regression Model

The relationship between mental and physical health and productivity is estimated through mixed-effects models, which incorporate both fixed effects for observed covariates and random intercepts at the individual level. One of the earliest applications of mixed-effects models in labor economics dates back to Abowd and Kramarz (1999), where they addressed econometric challenges in the analysis of longitudinal linked employer–employee data and highlighted the advantages of using such models in labor economics. The use of mixed-effects modelling in the current study accounts for the repeated-measures structure of the data and controls for time-invariant individual heterogeneity. The general model can be written as:

$$PL_{i,t} = \beta_0 + \beta_1 M_{i,t-1} + \beta_2 X_{i,t} + u_i + \epsilon_{i,t} \quad (3.6)$$

$$PL_{i,t} = \gamma_0 + \gamma_1 P_{i,t-1} + \gamma_2 X_{i,t} + u_i + \epsilon_{i,t} \quad (3.7)$$

$$PC_{i,t} = \theta_0 + \theta_1 M_{i,t-1} + \theta_2 X_{i,t} + u_i + \epsilon_{i,t} \quad (3.8)$$

$$PC_{i,t} = \vartheta_0 + \vartheta_1 P_{i,t-1} + \vartheta_2 X_{i,t} + u_i + \epsilon_{i,t} \quad (3.9)$$

Here, $PL_{i,t}$ and $PC_{i,t}$ represent the latent and calculated productivity scores for individual i in wave t respectively; β_1 and γ_1 are the coefficients of Mental and Physical Health in the latent model, where θ_1 and ϑ_1 represent these coefficients in the wage measure productivity model; $X_{i,t}$ is a vector of control variables including *Age*, *Age (sq)*, *Female*, *Black*, *Married*, *Education (years)*, *Mom's College*, and currently *At School*, as well as occupation categories; u_i denotes the individual-specific random intercept, and $\epsilon_{i,t}$ is the idiosyncratic error term.

This modeling framework is designed to handle the longitudinal structure of the data while accounting for both observed and unobserved heterogeneity. The random intercept absorbs all unobserved time-invariant individual-specific characteristics, thus controlling for potential omitted variable bias due to stable traits. The inclusion of wave-specific fixed effects and time-varying covariates also allows the model to account for dynamic changes across the life course.

3.4.4. Estimation of Predicted Productivity

The mixed-effects model is estimated by maximizing the restricted log-likelihood function under the REML framework, which is defined as:

$$l_{REML}(\varphi) = -\frac{1}{2} \left[(n - p) \log(2\pi) + \log|V| + \log|X^T V^{-1} X| + (y - X\hat{\beta})^T V^{-1} (y - X\hat{\beta}) \right] \quad (3.10)$$

where $\hat{\beta} = (X^T V^{-1} X)^{-1} X^T V^{-1} y$ obtained by minimizing the generalized squared distance between the observed outcomes and their predicted values; n is the number of observations, p is the number of fixed-effects, V is the entire variance-covariance matrix of the outcome variable y ; X is the design matrix for fixed effects that contains all the fixed-effect covariates, and y contains all the actual values of the dependent variable you are trying to model; and φ represents all model parameters including variance components. The REML method improves the estimation of variance parameters by adjusting for the degrees of freedom used in estimating fixed effects.

In summary, this multi-stage methodological structure provides several advantages. Using latent variables accounts for measurement error by aggregating multiple health and productivity indicators, thereby improving construct validity. Separate estimation of mental and physical health effects addresses multicollinearity and allows for interpretation of distinct channels. Finally, the mixed-effects framework is well-suited for longitudinal data, capturing individual-specific

unobserved heterogeneity and making full use of repeated observations in the dataset. Together, these features support a rigorous examination of the health-productivity relationship.

3.5. Results

This section presents the empirical results from the mixed-effects models designed to evaluate the impact of mental and physical health on workplace productivity. The analysis is organized into three main parts. The first subsection presents the results of the measurement system for the latent productivity construct, which is derived using a GSEM approach. This model includes three observed indicators to estimate a continuous latent productivity score. The estimated factor loadings and marginal effects of each indicator will be discussed in detail. The second part examines the association between mental health and the latent productivity score derived from the structural equation modeling framework, followed by a parallel model that assesses the role of physical health in relation to the same latent productivity measure. The subsection then shifts to the wage measure productivity outcome, specifically, the natural logarithm of productivity, estimated separately for mental and physical health to ensure robustness and allow comparison across different productivity constructs. The third part reports post-estimation marginal analysis to explain the heterogeneity of the effect of mental and physical health on productivity across the health gradient. This approach presents predicted productivity levels at three representative values of the health indicators (0, 0.5, and 1), thereby illustrating how incremental improvements in mental and physical health are associated with corresponding gains in both latent and calculated productivity. This exercise offers insight into the potential productivity benefits of improving mental health at the population level. Each subsection reports the results and provides interpretations of key coefficients to explain the strength, direction, and statistical significance of health-related effects on productivity.

3.5.1. Latent Productivity Measurement

The measurement model for the latent productivity construct is estimated using a GSEM approach and incorporates three observed indicators: *Job Satisfaction* (binary), *Hours Worked* per week (continuous), and the weekly natural logarithm of *Income* (continuous). Given that job satisfaction is binary, a logistic link is applied for this indicator, while identity links are used for the continuous outcomes. Panel A of Table 3.2 presents the estimated factor loadings and

intercepts. All three indicators load significantly onto the latent productivity factor, suggesting strong construct validity. The loading for job satisfaction is normalized to 1 to scale the latent factor, while the loadings for hours worked (14.08, $p < 0.001$) and log income (0.774, $p < 0.001$) are statistically significant and positive, indicating that higher latent productivity is strongly associated with increased hours worked and higher earnings.

Panel B reports the average marginal effect (AME) of the latent productivity variable on job satisfaction. The AME of 0.675 ($p < 0.001$) implies that a one standard deviation increase in latent productivity is associated with a 67.5 percentage point increase in the predicted probability of reporting high job satisfaction, holding all other variables constant. The AMEs for the continuous indicators are not reported because, in linear models, they are numerically equivalent to the raw coefficients. For the continuous outcomes, a one standard deviation increase in latent productivity is associated with an increase of 14.08 hours worked per week and a 0.774 increase in logged income. While these effects are not directly comparable in magnitude due to differing units and scale, the results suggest that latent productivity is positively and substantially associated with all three outcomes. These findings support the internal validity of the latent productivity construct and offer empirical justification for its multidimensional structure.

Table 3.2. Measurement System - Latent Productivity (*PL*)

	Job Satisfaction	Hours Worked	Income (<i>ln</i>)
Panel A: Estimated parameters			
Constant	0.891*** (0.0298)	32.04*** (0.185)	5.708*** (0.0199)
Productivity (<i>PL</i>)	1	14.08*** (0.951)	0.774*** (0.0338)
Panel B: Average Marginal Effects of Factors (AME)			
Productivity (<i>PL</i>) AME	0.675*** (0.0050)	-	-
Observations	8,862	8,862	8,862

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, AME: Average marginal effects of a one standard deviation increase of each factor, holding other variables fixed.

These findings not only support the theoretical foundations of the model. By incorporating both subjective (job satisfaction) and objective (hours and income) indicators, the latent productivity construct captures a more holistic measure of an individual's workplace contribution. Importantly, the statistically significant loading of hours worked, in particular, suggests that time-based labor market engagement remains a crucial component of productivity in this context. Furthermore, the magnitude of the average marginal effect (AME) on job satisfaction underscores the model's strong explanatory power in linking unobserved productivity levels with affective workplace outcomes. This result suggests that higher latent productivity is not merely about economic performance but is also intimately connected with workers' psychological engagement and overall work fulfillment. This multidimensionality is essential in understanding real-world productivity variations that are not fully captured by traditional economic metrics.

3.5.2. Effects of Health on Productivity

Tables 3.3.a and 3.3.b in this section present the regression outputs for both latent *Productivity (PL)* and wage measure of *Productivity (PC)*. Table 3.3.a presents estimates from two mixed-effects linear regression models that examine how lagged mental and physical health predict variation in the latent productivity score, which is a continuous variable normalized between zero and one. The table also includes the coefficients of a range of demographic, educational, and occupational controls. Lagged mental health exhibits a positive and statistically significant association with latent productivity (0.0251, $p < 0.001$), indicating that individuals with better prior mental health are more likely to score higher on the latent productivity scale. Similarly, lagged physical health is also positively associated with latent productivity (0.0151, $p < 0.05$), although the effect size is 1.66 times smaller than that of mental health. This suggests that while both dimensions of health are relevant, mental health appears to exert a comparatively stronger influence on the latent productivity construct.

Table 3.3.a. Productivity (PL) and Health – Mixed-Effects Regression

	Latent Productivity (PL)	
	M-Model	P-Model
Mental health (<i>lag</i>)	0.0251*** (0.0061)	-
Physical Health (<i>lag</i>)	-	0.0151* (0.0065)
Age	0.0319*** (0.0022)	0.0324*** (0.00227)
Age (<i>sq</i>)	-0.0005*** (0.0001)	-0.0005*** (0.0001)
Female	-0.0439*** (0.0031)	-0.0448*** (0.0031)
Black	-0.0117** (0.0037)	-0.0124*** (0.0037)
Mom's College	-0.0049 (0.0033)	-0.0048 (0.0033)
Married	0.0055 (0.0028)	0.0057* (0.0028)
Education (<i>years</i>)	0.0036*** (0.0007)	0.0038*** (0.0007)
At School	-0.0618*** (0.0034)	-0.0616*** (0.0034)
Prof/Tech	Baseline	Baseline
Health/Comm	-0.0246*** (0.0045)	-0.0251*** (0.0045)
Edu/Arts	-0.0265*** (0.0049)	-0.0265*** (0.0049)
Service/Maint	-0.0544*** (0.0045)	-0.0545*** (0.0045)
Sales/Admin	-0.0344*** (0.0038)	-0.0347*** (0.0038)
Trades/Prod	-0.0064 (0.0050)	-0.0062 (0.0050)
Military	0.0301* (0.0137)	0.0299* (0.0137)
Constant	-0.242*** (0.0344)	-0.242*** (0.0354)
Observations	7,901	7,901

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Among the covariates, age has a nonlinear effect on productivity: the positive coefficient on age (0.0319, $p < 0.001$) coupled with a negative coefficient on age squared (-0.0005 , $p < 0.001$) suggests diminishing productivity gains as individuals grow older. Female respondents exhibit significantly lower latent productivity scores (-0.0439 , $p < 0.001$), as do Black participants (-0.0117 , $p < 0.01$), even after controlling for education and employment status. Lastly, being currently enrolled in school is negatively associated with productivity (-0.0618 , $p < 0.001$), likely reflecting reduced labor market participation while pursuing education. The estimated coefficients for all sociodemographic indicators remain highly consistent in the model incorporating physical health, as presented in the second column of Table 3.3.a.

Regarding occupational differences, all categories except military and trades/production show significantly lower productivity relative to the baseline group (professional/technical occupations), with the strongest negative association observed among service and maintenance workers (-0.0544 , $p < 0.001$). The occupational patterns also reveal insights into labor segmentation and health inequality. The significantly negative coefficients for service/maintenance and sales/admin roles relative to professional/technical occupations may reflect structural differences in job quality and exposure to stressors. This highlights the need to interpret health-productivity relationships within the broader context of occupational environments. Marital status and maternal education do not appear to significantly predict latent productivity. Education in years has a slight positive effect (0.0036 , $p < 0.001$) on productivity.

Table 3.3.b provides parallel estimates using the natural logarithm of wage measure of productivity as the outcome variable. The results remain broadly consistent with those in Table 3.a. Lagged mental health is again positively associated with productivity (0.0201 , $p < 0.01$), though the magnitude is slightly smaller than in the latent model. Lagged physical health shows a significant and positive effect as well (0.0271 , $p < 0.001$). The difference in female coefficients between the latent and wage measure models is noteworthy. In the latent model, which incorporates satisfaction, women appear to experience a larger productivity penalty (-0.0439), which may reflect broader gender disparities in workplace engagement, expectations, or even satisfaction reporting biases. In contrast, the wage measure model, based strictly on hours and earnings, shows a smaller penalty (-0.0237), suggesting that the latent productivity measure may capture gender-related aspects of workplace performance, such as satisfaction or engagement, not fully reflected

Table 3.3.b. Productivity (PC) and Health – Mixed-Effects Regression

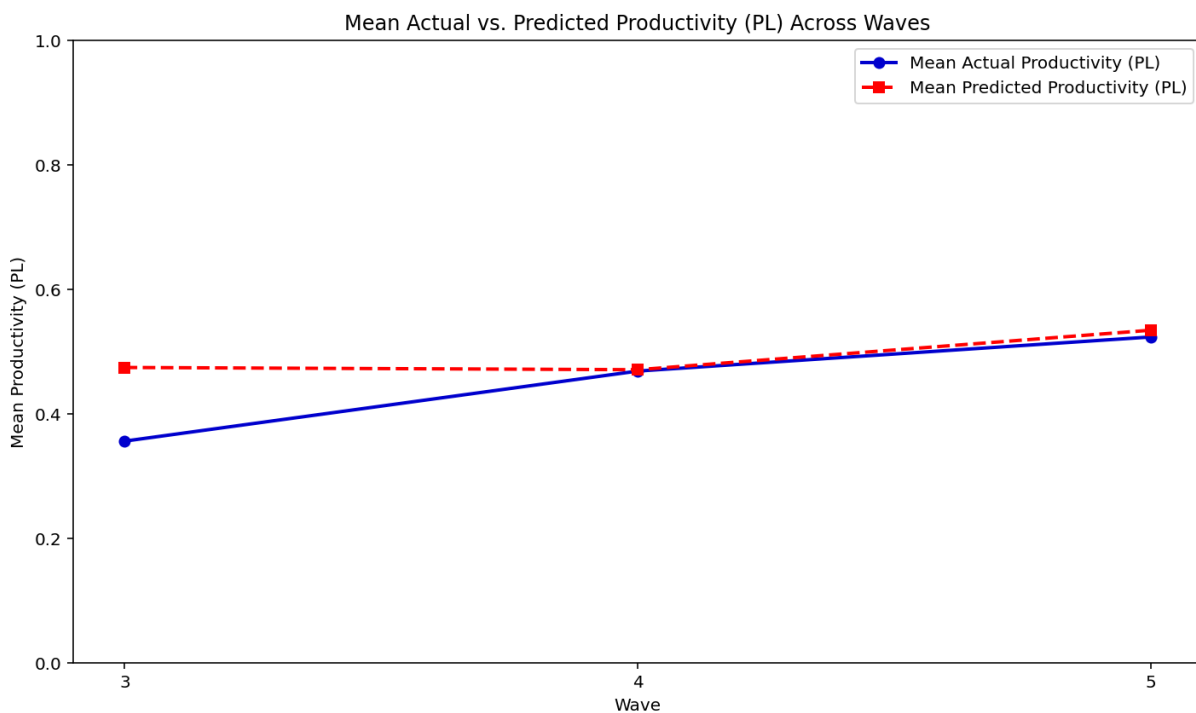
	Wage Measure of Productivity (PC)	
	M-Model	P-Model
Mental health (<i>lag</i>)	0.0201** (0.0074)	-
Physical Health (<i>lag</i>)	-	0.0271*** (0.0078)
Age	0.0587*** (0.0029)	0.0601*** (0.0029)
Age (<i>sq</i>)	-0.0009*** (0.0001)	-0.0009*** (0.0001)
Female	-0.0226*** (0.0035)	-0.0237*** (0.0035)
Black	-0.0277*** (0.0041)	-0.0294*** (0.0041)
Mom's College	0.0068 (0.0036)	0.0072* (0.0036)
Married	0.0203*** (0.0034)	0.0197*** (0.0034)
Education (<i>years</i>)	0.0083*** (0.0008)	0.0082*** (0.0008)
At School	0.0039 (0.0042)	0.0036 (0.0042)
Prof/Tech	Baseline	Baseline
Health/Comm	-0.0150** (0.0054)	-0.0155** (0.0054)
Edu/Arts	-0.0312*** (0.0059)	-0.0314*** (0.0059)
Service/Maint	-0.0291*** (0.0055)	-0.0289*** (0.0055)
Sales/Admin	-0.0207*** (0.0046)	-0.0209*** (0.0046)
Trades/Prod	-0.0239*** (0.0060)	-0.0233*** (0.0060)
Military	0.0214 (0.0167)	0.0205 (0.0167)
Constant	-0.435*** (0.0441)	-0.460*** (0.0453)
Observations	7,901	7,901

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in traditional income and working hours measures of productivity. On the other hand, the coefficient for Black respondents becomes more negative in the wage measure model (-0.0277) compared to the latent model (-0.0117). Despite these differences in magnitude, the direction and statistical significance of the effects are consistent across specifications.

Additionally, years of education continues to have a modest positive impact on the wage measure of productivity (0.0083 , $p < 0.001$), and marital status becomes significant (0.0203 , $p < 0.001$). Interestingly, current enrollment in school is not significantly associated with wage measure productivity, possibly because this measure reflects hourly productivity (i.e., income divided by hours worked), which may remain stable even if total hours are reduced due to school attendance.

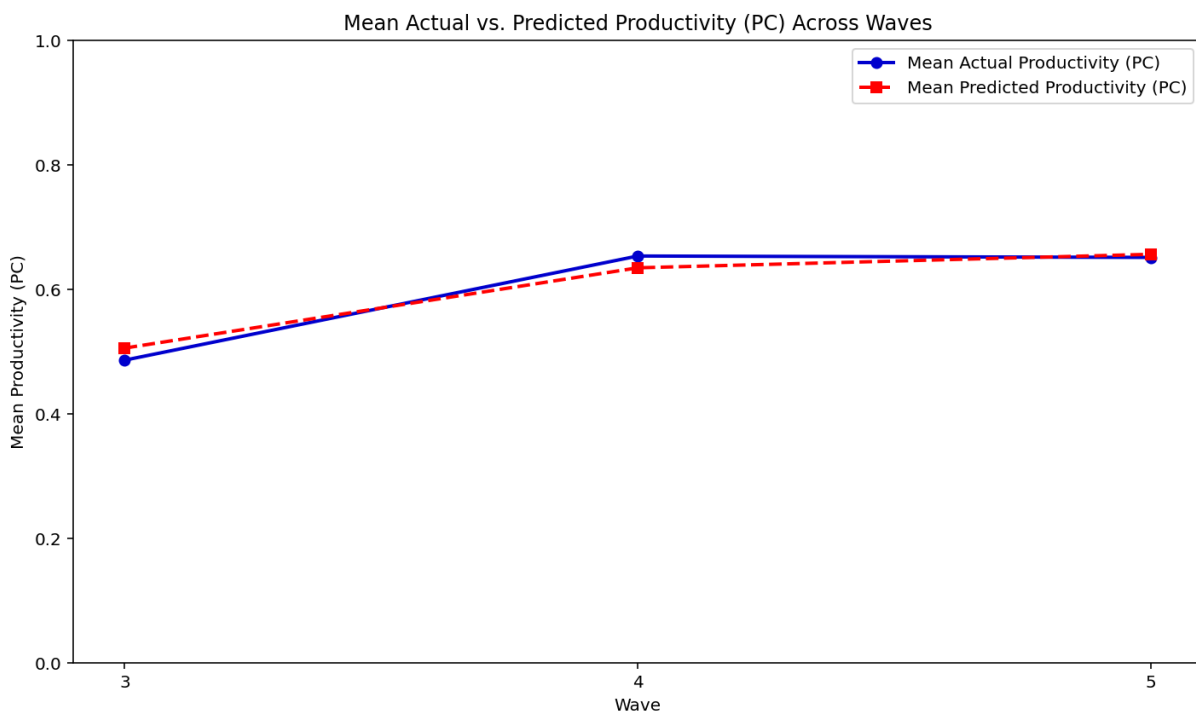
Figure 3.3.a.



Figures 3.3.a and 3.3.b assess the predictive power and construct validity of the mixed effects models. Figure 3.3.a illustrates the trend of mean actual versus predicted latent productivity scores across Waves 3, 4, and 5. The actual latent *Productivity (PL)* increases steadily from approximately 0.35 in Wave 3 to about 0.51 in Wave 5, while the predicted values remain slightly higher, ranging from about 0.49 to 0.52. The observed alignment in Wave 4 and convergence in Wave 5 highlight

the model's accuracy in capturing productivity dynamics over time. Figure 3.3.b presents a similar plot for wage measure of *Productivity (PC)*. Here, both actual and predicted values show a more parallel increase, rising from around 0.49 in Wave 3 to nearly 0.67 in Wave 5. The tighter fit between predicted and actual values across waves in this model suggests that the calculated productivity specification may be more responsive to underlying health changes, possibly due to its direct reliance on observable economic behaviors such as income and hours worked. Together, these figures demonstrate that the regression models perform well in tracking productivity trajectories and confirm robustness of the estimated effects.

Figure 3.3.b.



These findings provide strong evidence that both mental and physical health contribute meaningfully to workplace productivity, with mental health exhibiting a somewhat stronger predictive role in the latent model. This is consistent with the literature highlighting the multi-dimensional nature of productivity loss due to poor health. In particular, these results resonate with Lu et al. (2009), who found that physical and mental health significantly influence labor market outcomes, especially in terms of hours worked and participation. Furthermore, the observed gender disparities and educational influences align with findings from Bubonya et al. (2017), who also

identified mental health-related productivity penalties to be heterogeneous across socio-demographic groups and job types.

3.5.3. Heterogeneity of the Effects of Health on Productivity

To complement the regression results presented earlier, Table 3.4 reports the predicted productivity scores at three values of mental and physical health (0 = poor, 0.5 = moderate, and 1 = perfect), using post-estimation margins analysis. This approach provides a more intuitive interpretation of how health status is associated with productivity by estimating the expected value of productivity at representative health levels, while holding other covariates constant.

Table 3.4.a shows the results for mental health. For the latent productivity score, individuals with poor mental health are predicted to score 0.474, which increases to 0.486 at moderate mental health, and to 0.499 at perfect mental health. This corresponds to an increase of 1.2 percentage points from poor to moderate mental health, 1.3 percentage points from moderate to perfect mental health, and 2.5 percentage points from poor to perfect mental health. A similar pattern emerges for calculated productivity: predicted values increase from 0.591 to 0.601 and 0.611 across the three mental health levels. These changes represent increases of 1.0 percentage point from poor to moderate mental health, 1.0 percentage point from moderate to perfect mental health, and 2.0 percentage points from poor to perfect mental health. All estimated values are statistically significant at the 0.1% level.

Table 3.4.a. Heterogeneity of the Effects of Mental Health on Productivity

	Latent Productivity (<i>PL</i>)	<i>Wage</i> Productivity (<i>PC</i>)
0: Poor Mental Health (<i>lag</i>)	0.474*** (0.0053)	0.591*** (0.0064)
0.5: Moderate Mental Health (<i>lag</i>)	0.486*** (0.0025)	0.601*** (0.0030)
1: Perfect Mental Health (<i>lag</i>)	0.499*** (0.0017)	0.611*** (0.0019)

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4.b presents the analogous results for physical health. The predicted latent productivity score rises from 0.483 under poor physical health to 0.490 for moderate health and to 0.498 under

perfect health. This reflects an increase of 0.7 percentage points from poor to moderate health, 0.8 percentage points from moderate to perfect health, and 1.5 percentage points from poor to perfect health. For wage measure of productivity, the predicted scores increase from 0.586 to 0.600 and 0.613, again showing a clear positive gradient. These increases correspond to 1.4 percentage points from poor to moderate health, 1.3 percentage points from moderate to perfect health, and 2.7 percentage points from poor to perfect physical health. All effects are statistically significant at the 0.1% level.

Table 3.4.b. Heterogeneity of the Effects of Physical Health on Productivity

	Latent Productivity (<i>PL</i>)	Wage Productivity (<i>PC</i>)
0: Poor Physical Health (<i>lag</i>)	0.483*** (0.0054)	0.586*** (0.0064)
0.5: Moderate Physical Health (<i>lag</i>)	0.490*** (0.0024)	0.600*** (0.0028)
1: Perfect Physical Health (<i>lag</i>)	0.498*** (0.0019)	0.613*** (0.0022)

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These results reinforce the earlier regression findings in two important ways. First, they confirm that both mental and physical health are positively associated with productivity outcomes in a statistically significant manner. Second, they suggest that the productivity gains associated with mental health are somewhat larger when assessed through the latent construct, while the calculated productivity measure yields slightly higher gains in productivity with improvements in physical health. These patterns align with the existing literature such as Bubonya et al. (2017), who found that improvements in mental health are associated with reductions in presenteeism and enhanced workplace productivity.

Another notable observation is that these results suggest that conventional productivity measures, such as income per hour, may underestimate the impact of mental health on workplace performance while simultaneously amplifying the perceived effect of physical health, relative to more comprehensive latent constructs that incorporate both objective and subjective dimensions of productivity, such as job satisfaction. However, an important implication of the analysis is the consistency in the direction and significance of coefficients across both latent and wage measure

productivity models. While the latent productivity construct incorporates both objective labor market indicators and subjective components such as job satisfaction, the wage measure is derived solely from observed economic behavior, namely income and hours worked. The fact that both measures yield statistically significant associations with lagged mental and physical health supports the validity of the estimated effects.

This robustness across model specifications implies that health improvements, regardless of whether they target psychological or physical domains, can produce measurable gains in productivity under alternative specifications. The joint application of latent variable modeling and conventional output-based productivity measures, combined with mixed-effects estimation, reinforces the causal plausibility of the identified relationships. These findings contribute to the literature by providing empirical evidence for the role of health as a determinant of labor productivity and offer relevant insights for policy design aimed at enhancing workforce efficiency through targeted health interventions.

3.6. Conclusion

This dissertation has provided comprehensive evidence that both mental and physical health significantly influence workplace productivity, highlighting health's critical role in labor economics and broader economic policy. By employing rigorous econometric methodologies, notably Generalized Structural Equation Modeling (GSEM) for latent variable estimation and mixed-effects regression models, the analysis robustly quantified how variations in health, particularly mental health, translate directly into measurable differences in workplace productivity. Such an analytical approach overcomes substantial limitations observed in prior research, including measurement errors associated with self-reported health indicators and the lack of longitudinal data to capture temporal dynamics. As such, the results generated by this study constitute a valuable advancement in our empirical understanding of the health-productivity interplay.

Central among the findings is the clear, positive, and statistically significant relationship between mental health improvements and increased productivity, with robust evidence presented across two distinct productivity constructs, latent and wage-based measures. Specifically, the analysis established that improved mental health status is associated with a meaningful rise in

productivity scores, where even incremental improvements in mental health translate into observable and statistically significant productivity gains.

From a policy perspective, these results hold profound implications. The evident productivity gains from enhanced mental health indicate a compelling economic rationale for increased investments in mental health services, both within organizational contexts and broader public policy frameworks. For employers, the findings suggest clear benefits from prioritizing workplace mental health interventions, such as employee assistance programs, mental health awareness training, stress management initiatives, and fostering psychologically supportive work environments. Such investments, as evidenced by the present analysis, are likely to yield tangible returns in the form of improved workforce productivity, reduced absenteeism, and lower presenteeism. More broadly, public policy initiatives aimed at expanding mental health care access, reducing stigma around mental health conditions, and improving early diagnosis and intervention are supported by the robust empirical findings presented herein, demonstrating their economic as well as social merit.

This dissertation also contributes methodologically to existing economic literature. The innovative combination of latent variable construction and mixed-effects regression models demonstrates substantial strengths in addressing measurement error, unobserved heterogeneity, dynamic changes in productivity and health over time, and within-between variations in productivity due to unobserved factors. These methodological advancements enhance the precision and reliability of estimates regarding the health-productivity relationship and can serve as a valuable framework for future researchers investigating similar complex, longitudinal phenomena in economics. Furthermore, the explicit distinction between mental and physical health outcomes enables a clearer interpretation of distinct policy implications for different dimensions of health, allowing targeted, evidence-based interventions.

Nonetheless, despite these significant contributions, several limitations merit acknowledgment. While the longitudinal nature of the Add Health dataset provides notable advantages, future research could benefit from incorporating experimental or quasi-experimental designs that further strengthen causal inference, particularly through randomized interventions or instrumental variable methodologies explicitly designed to address potential endogeneity concerns.

Looking forward, several promising avenues for future research emerge clearly from this dissertation. A particularly compelling direction involves the development and application of structural microeconomic models that explicitly incorporate individual expectations and behavioral responses related to health investments and labor supply decisions. Structural models, by identifying the deep parameters that describe preferences and constraints, allow for the analysis of counterfactual policies and the uncovering of mechanisms that underpin observed behavior (Low & Meghir, 2017). Similarly, Blundell (2017) discusses the advantages of structural models in providing counterfactual predictions and uncovering the mechanisms that underpin observed behavior. These structural approaches can deepen our understanding of individual decision-making processes around health investments and labor supply responses, further refining policy implications and contributing to a more effective public policy landscape.

Moreover, future research could further disentangle the heterogeneous impacts of mental health interventions across different demographic and socioeconomic subgroups. Understanding precisely how mental health improvements translate into productivity gains among vulnerable populations, such as lower-income individuals, minority groups, or workers in precarious occupations, could provide deeper insights into potential policy mechanisms to address labor market inequalities and enhance social welfare. This line of research would build upon findings that highlight how health-related economic outcomes often differ markedly across demographic groups, suggesting targeted interventions as potentially powerful tools for reducing disparities and improving overall economic equity. In conclusion, by systematically quantifying the economic benefits of mental and physical health improvements through rigorous longitudinal and latent variable analyses, this dissertation has provided clear evidence for health's pivotal role in shaping labor market productivity. These findings justify increased policy and organizational investments in mental health interventions, suggesting significant economic returns from improving workers' mental health. The methodological and empirical contributions offered in this study not only enhance our understanding of the health-productivity relationship but also lay a strong foundation for future scholarly efforts aimed at deepening and refining this critical area of economic research.

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Appendices for Chapter 1

Appendix A. Data and Variables

Figure A.1. Schooling Decision (Mentally ill)

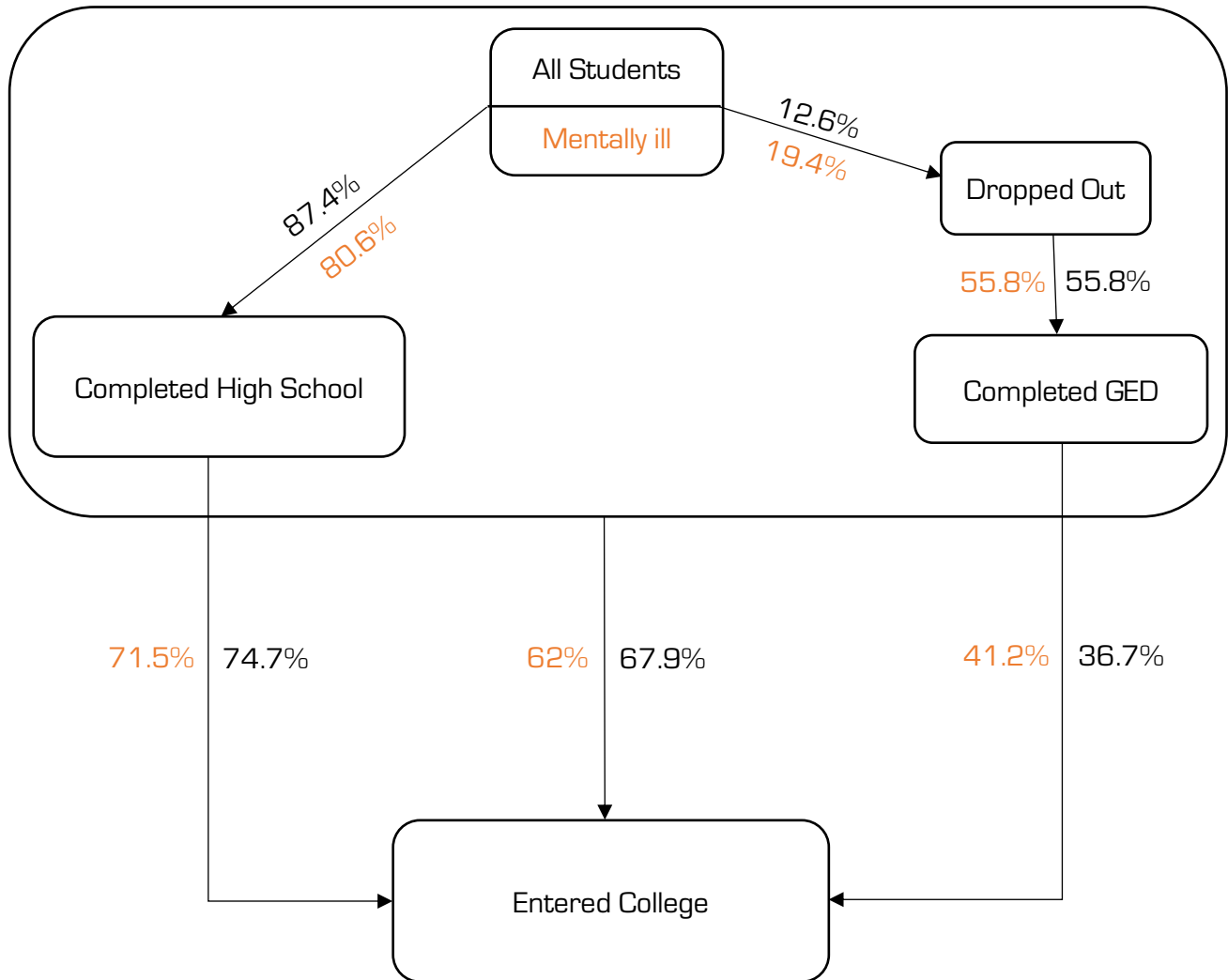
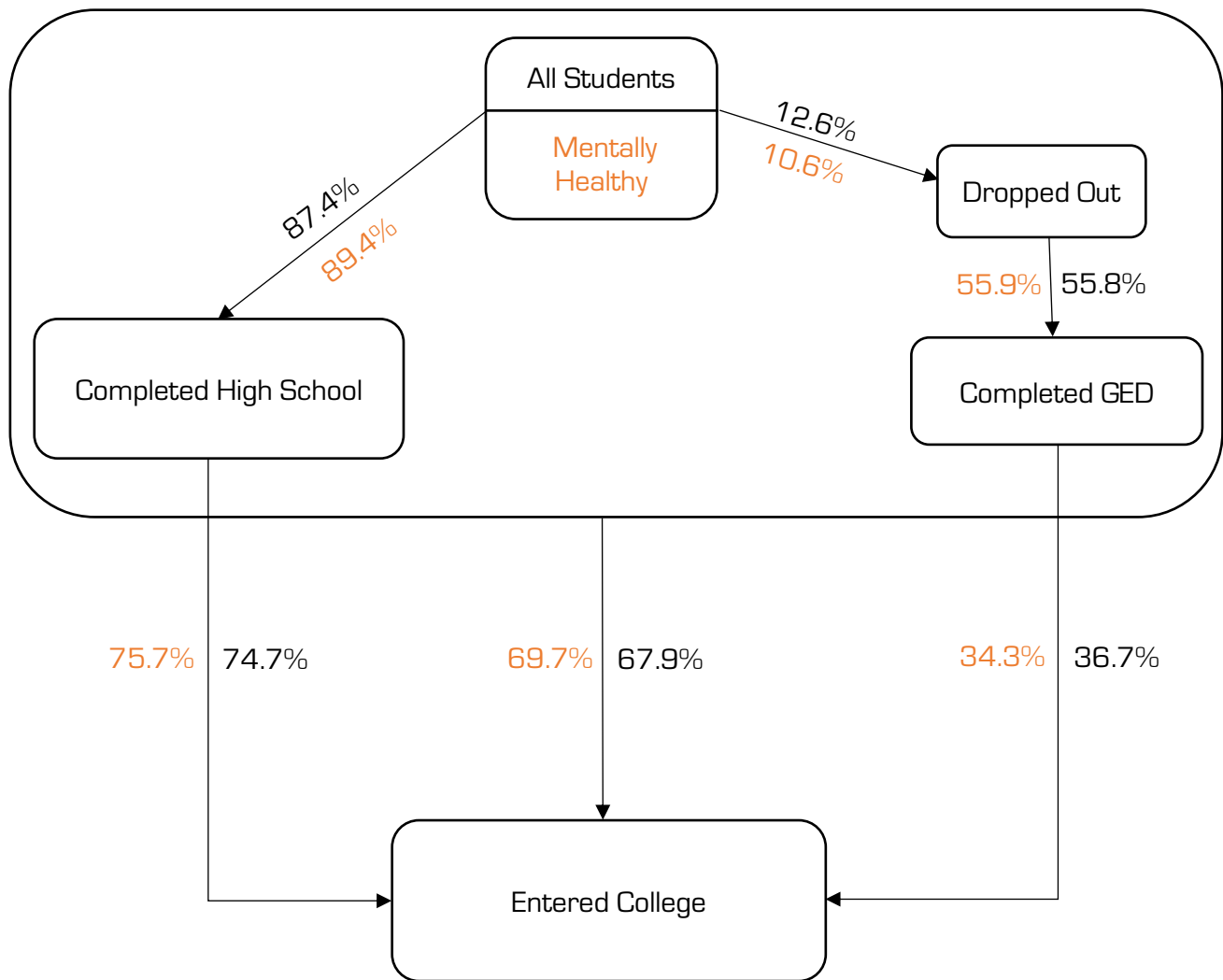


Figure A.2. Schooling Decision (Mentally Healthy)



Appendix B. Model Equations

The $Y_{i,m}, Y_{i,p}, Y_{i,a}, Y_{i,Senior Student}$, and $V_{i,b}$ are $n \times 1$ vectors of observed characteristics, $m, p, a, Senior Student$, and b of individual i associated with latent variables M, P, A, B (*Poor Mental Health, Poor Physical Health, Activity, and Ability*). The detailed expressions for the measurement system take the following form:

$$\log \left(\frac{P(Y_{i,ADHD} = 1)}{1 - P(Y_{i,ADHD} = 1)} \right) = \beta_{0,ADHD} + \beta_{1,ADHD} M_i$$

$$\log \left(\frac{P(Y_{i,Depressed} = 1)}{1 - P(Y_{i,Depressed} = 1)} \right) = \beta_{0,Depressed} + \beta_{1,Depressed} M_i$$

$$\log \left(\frac{P(Y_{i,Fearful} = 1)}{1 - P(Y_{i,Fearful} = 1)} \right) = \beta_{0,Fearful} + \beta_{1,Fearful} M_i$$

$$\log \left(\frac{P(Y_{i,Unhappy} = 1)}{1 - P(Y_{i,Unhappy} = 1)} \right) = \beta_{0,Unhappy} + \beta_{1,Unhappy} M_i$$

$$\log \left(\frac{P(Y_{i,Suicide} = 1)}{1 - P(Y_{i,Suicide} = 1)} \right) = \beta_{0,Suicide} + \beta_{1,Suicide} M_i$$

$$\log \left(\frac{P(Y_{i,Poor Health} = 1)}{1 - P(Y_{i,Poor Health} = 1)} \right) = \beta_{0,Poor Health} + \beta_{1,Poor Health} P_i$$

$$\log \left(\frac{P(Y_{i,Tobacco} = 1)}{1 - P(Y_{i,Tobacco} = 1)} \right) = \beta_{0,Tobacco} + \beta_{1,Tobacco} P_i$$

$$\log \left(\frac{P(Y_{i,Alcohol} = 1)}{1 - P(Y_{i,Alcohol} = 1)} \right) = \beta_{0,Alcohol} + \beta_{1,Alcohol} P_i$$

$$\log \left(\frac{P(Y_{i,Marijuana} = 1)}{1 - P(Y_{i,Marijuana} = 1)} \right) = \beta_{0,Marijuana} + \beta_{1,Marijuana} P_i$$

$$\log \left(\frac{P(Y_{i,Poor BMI} = 1)}{1 - P(Y_{i,Poor BMI} = 1)} \right) = \beta_{0,Poor BMI} + \beta_{1,Poor BMI} P_i$$

$$\log \left(\frac{P(Y_{i,Bicycle} = 1)}{1 - P(Y_{i,Bicycle} = 1)} \right) = \beta_{0,Bicycle} + \beta_{1,Bicycle} A_i$$

$$\log \left(\frac{P(Y_{i,Sport} = 1)}{1 - P(Y_{i,Sport} = 1)} \right) = \beta_{0,Sport} + \beta_{1,Sport} A_i$$

$$\log \left(\frac{P(Y_{i,Exercise} = 1)}{1 - P(Y_{i,Exercise} = 1)} \right) = \beta_{0,Exercise} + \beta_{1,Exercise} A_i$$

$$V_{i,English\ Score} = \lambda_{0,English\ Score} + \lambda_{1,English\ Score} B_i + \epsilon_{i,English\ Score}$$

$$V_{i,Math\ Score} = \lambda_{0,Math\ Score} + \lambda_{1,Math\ Score} B_i + \epsilon_{i,Math\ Score}$$

$$V_{i,History\ Score} = \lambda_{0,History\ Score} + \lambda_{1,History\ Score} B_i + \epsilon_{i,History\ Score}$$

$$V_{i,Science\ Score} = \lambda_{0,Science\ Score} + \lambda_{1,Science\ Score} B_i + \epsilon_{i,Science\ Score}$$

$$\log \left(\frac{P(Y_{i,Senior\ Student} = 1)}{1 - P(Y_{i,Senior\ Student} = 1)} \right) = \beta_{0,Senior\ Student} + \beta_{1,Senior\ Student} B_i$$

It is essential to note that each of the latent factors is determined by an exclusive set of observed indicators.

Appendix C. Results

Table C.1: Two-Step Estimation - Logistic regression

Variables	High School Coefficients	College Coefficients
Poor Mental Health	0.777*** (0.042)	0.786*** (0.035)
Poor Physical Health	0.733*** (0.028)	1.029 (0.033)
Activity	0.706** (0.101)	1.730*** (0.185)
Ability	2.785*** (0.319)	3.292*** (0.312)
Female	1.423*** (0.160)	1.846*** (0.152)
Age	1.423*** (0.052)	1.238*** (0.032)
Mom's College	2.960*** (0.459)	4.535*** (0.484)
Black	0.611*** (0.079)	0.756*** (0.072)
Family Income (<i>ln</i>)	1.023* (0.012)	1.015* (0.009)
Constant	0.026*** (0.015)	0.039*** (0.017)
<i>N</i>	3959	3959

Note: Standard errors in parentheses based on 100 bootstrap replications of the entire estimation process, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.2: High School Information Criterion

Model	N	$ll(\text{null})$	$ll(\text{model})$	df	AIC	BIC
1 st step	3,959	.	- 47847.18	56	95806.36	96158.25

Model	N	$ll(\text{null})$	$ll(\text{model})$	df	AIC	BIC
2 nd step	3,959	-1497.703	-1168.957	10	2357.914	2420.752

Note: AIC: Akaike's information criterion, BIC: Bayesian information criterion, BIC uses N = number of observations.

Table C.3: College Information Criterion

Model	N	$ll(\text{null})$	$ll(\text{model})$	df	AIC	BIC
1 st step	3,959	.	- 48673.14	56	97458.28	97810.17

Model	N	$ll(\text{null})$	$ll(\text{model})$	df	AIC	BIC
2 nd step	3,959	- 2483.372	- 1949.814	10	3919.627	3982.465

Note: AIC: Akaike's information criterion, BIC: Bayesian information criterion, BIC uses N = number of observations.

Figure C. Receiver Operating Characteristic (ROC)

Figure C.1.a: ROC - High School (1-Step)

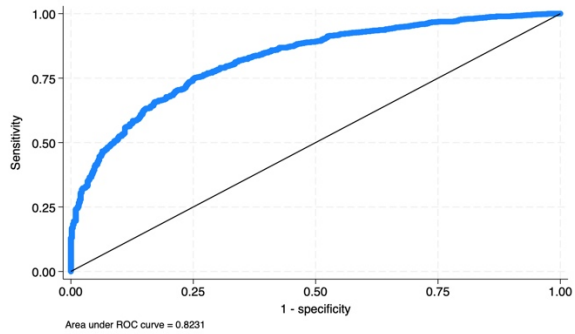


Figure C.1.b: ROC - High School (2-Step)

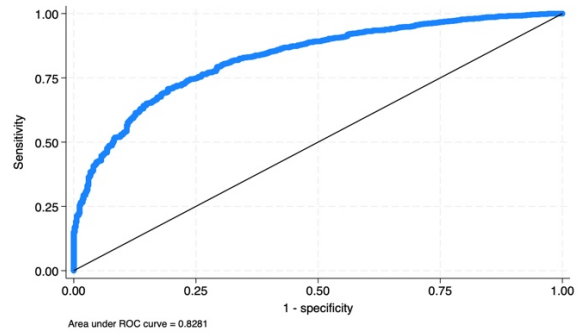


Figure C.2.a: ROC - College (1-Step)

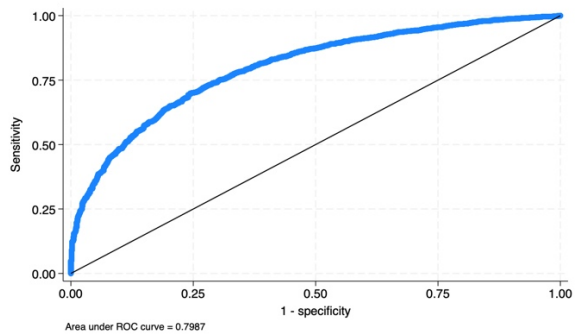


Figure C.2.b: ROC - College (2-Step)

