THE UNIVERSITY OF CHICAGO

NONCOMPLIANCE IN RANDOMIZED EXPERIMENTS: A STOCHASTIC PERSPECTIVE

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

DEPARTMENT OF COMPARATIVE HUMAN DEVELOPMENT

BY

ARVIND VARADHARAJULU ILAMARAN

CHICAGO, ILLINOIS

DECEMBER 2023

Table of Contents

List of Figures

List of Tables

Acknowledgments

I dedicate this dissertation to my family whose unconditional love and support made this accomplishment possible. The values of my grandparents, the sacrifice of parents, and the emotional support of my sister have shaped my growth as an individual and as a scholar. My wife, Dr. Meril Antony, has been my bedrock through various challenges and milestones in the last decade. Her compassion and intelligence have made me a better scholar.

I would like to acknowledge the members of my dissertation committee for their utmost support throughout this dissertation work. My special gratitude to the dissertation committee chair Professor Guanglei Hong for her inspiration, mentorship, and unwavering support in pursuing a challenging dissertation topic. I will always be thankful to Professor Yanyan Sheng for her methodological guidance and ever accessible mentorship. Other members of my committee, Professors Stephen Raudenbush, Donald Hedeker and Fan Yang, have greatly impacted this dissertation with their insightful feedback.

I would also like to acknowledge the wonderful and collegial peers at the Department of Comparative Human Development, and the larger University of Chicago's peer community.

Abstract

The purpose of this dissertation was to estimate the average effect (ATE) of choosing a treatment in a randomized experiment with noncompliance. This required modeling noncompliance as a hybrid choice model or an integrated choice and latent variable model (ICLV). The identification of ATE required an econometric model of noncompliance choice under inherent uncertainty (ex-ante choice) as an ICLV model. The situated expectancy value theory (SEVT) provided a model for the cognitive process underlying individual noncompliance behavior. SEVT provided a plausible model of vocational education and training choice (VET choice) among at-risk youth. SEVT helped in identifying the pretreatment covariates – observed and unobserved – which constitute a sufficient information set to fully describe the noncompliance behavior. These are also a sufficient set of confounders which can be adjusted with to obtain unbiased ATE of a job-training program (Job Corps) participation on the risk of violent crime victimization among at-risk youth. I estimated a four percent reduction in the risk of violent crime victimization by participating in the Job Corps program.

Glossary

ATE - Average treatment effect of program participation on desired outcome(s)

JC - Job Corps, the largest federal residential career training program for vulnerable youth.

$NJCS$ - National Job Corps Study

$SETV$ - Situated expectancy value theory

VAS - Vocational anticipatory socialization

STV - Subjective task value

ES - Expectancy of success

SV - Situational value

AV - Attainment value

$ACAD$ - Expected improvement in academic skills

$PERS$ - Expected improvement in personality skills

Z - random variable denoting binary random assignment in NJCS

D - random variable denoting binary voluntary enrollment status in NJCS

Y - outcome of interest in NJCS

S - state of the world

H - information set

H_e - information set of the analyst or economist

H_a - private information set of compliance decision-making agent

H_{ea} - full information set of the agent

X - covariate vector of observed (by analyst) attributes in baseline survey of NJCS

U - covariate vector of unobserved or latent (by analyst) attributes in baseline survey of NJCS

X^* - random vector denoting SETV latent constructs

C - random variable denoting the SETV latent construct, VAS

X_1^* - random variable denoting the SETV construct, STV

X_2^* - random variable denoting the SETV construct, ES

I - measurement indicators

L - size of the measurement indicator set

$\tilde{X}$ - random vector denoting H_{ea}

θ - vector of parameters describing a probability distribution

α - factor loadings in latent variable models

β, λ - regression coefficients

ϵ, ν, ω - additive random disturbances

1. Introduction

1.1 Motivation

The motivation behind this dissertation is to provide an unbiased statistical summary of social program effectiveness. Policymakers often design and implement policy interventions to promote positive youth development for vulnerable youth. Such youths are **at-risk** of not achieving a healthy transition to adulthood. Vocational education and training (or job training) programs (VET programs) are often used as a bridge to healthy adulthood for at-risk youth. For such youth reduced exposure to violence is considered important for successful transition to adulthood. Such a program's effectiveness is then measured by estimating the average impact of participation on the outcome of interest over the target population. For the purpose of this study, I analyze the Job Corps programs randomized evaluation called the National Job Corps Study (NJCS), which is the largest federal residential program on violent crime victimization for the population of at-risk youth. The purpose of this dissertation is to identify and estimate this Average Treatment Effect (ATE) in an evaluation of the Job Corps program.

1.2 Average treatment effect (ATE)

The ATE is a summary measure of the causal impact of the program measured as the average gains from program participation among the target population. The identification assumptions required to identify ATE when participation is endogenous due to compliance (latent ignorability) is weaker than those required to identify ATE when endogeneity in participation is due to selection bias (strong ignorability). This summary measure is of use to policymakers when the policy is intended to be implemented across the target population (Greifer and Stuart, 2021). An example would be making VET curriculum compulsory for at-risk youth. It is also important when causal mechanisms mediating the effect of intervention on outcome is of interest (Hafeman and VanderWeele, 2011; Kisbu-Sakarya et. al., 2020). For example, when Exposure to Violence (ETV) mediates the impact of job training on long term wages for at-risk youth.

1.3 ATE under noncompliance

To identify the average treatment effect or ATE in the Job Corps study without bias, it is required that everyone ends up participating according to their random assignment. So, everyone assigned to treatment participates in the program and vice-versa. Under this condition of perfect or full compliance behavior, ATE can be identified as the difference in average outcomes for those in the treatment and control groups. But what is actually observed in the study, is that nearly 23 percent of those assigned to the treatment group did not comply and chose not to participate. Under such noncompliance which is one-sided in the Job Corps study, due to control group embargo, ATE cannot be identified without further assumptions over the observed and unobserved data.

1.4 Compliance as choice in NJCS

Among those assigned to the treatment group, since program participation is a voluntary choice made by individuals looking to maximize their perceived or subjective gains, the compliance choice is a utility-maximizing choice in which an individual chooses to participate only if their net subjective gains from participation is greater than non-participation. But before making the choice or ex-ante choice situation, the individuals do not know with certainty whether they will achieve the desired outcome. Ex-ante choices are made by individuals, based on expected outcomes rather than outcomes known with certainty. They naturally represent compliance choice in Job Corps study. Because the encouragement design of the study requires voluntary participation choice - after receiving assignment. This choice is based on uncertain future outcomes.

Therefore, compliance choice is made based on expected net gains between participation and non-participation, given the information the individuals possess at the time of decision-making. This is called the agent information set. Vocational choices are often made in pursuit of long-term career identity development. Therefore, individual motivation for such choices is influenced by factors across an at-risk youth's ecosystem and life experiences. Therefore, a conceptual model of program participation in Job Corps can be developed based on theories of motivation from vocational choice research among youth.

1.5 Causal mechanism of noncompliance

Job Corps study is an encouragement design RCT in which assignment to participate acts as an encouragement to actually participate. It is important to identify the common causes (confounders) of choice and outcome since they create a backdoor path that induces an association between choice and outcome different from the true effect of interest, the ATE. While the decision-making individual would know all such common causes the analyst might observe typically the baseline covariates in a RCT which may or may not contain all the common causes. The psychological and other latent constructs are usually unobserved by the analyst. Sometimes they can be estimated with appropriate models. In this dissertation, I estimated such latent variable models to be incorporated directly or indirectly into models of compliance choice.

1.6 Identification of ATE

Compliance choice probabilities obtained from discrete choice models of compliance are used in the identification of ATE. If the compliance choice is formulated as ex-ante or stochastic, it would violate the Stable Unit Treatment Value Assumption (SUTVA) in the counterfactual framework (Rubin, 1978). Under stochastic model, both sub-assumptions of SUTVA are violated - the treatment variation irrelevance assumption or policy invariance and the consistency of deterministic counterfactuals assumption (Cole and Frangakis, 2009; VanderWeele, 2009). Since the random assignment is being used as instrument variable, the deterministic IV assumptions are generalized here to the stochastic setting. The IV assumptions are discussed in chapter two in the same order as in the original Angrist, Imbens and Rubin paper on IV under deterministic counterfactuals (Angrist, Imbens and Rubin, 1996). Under these assumptions, a weighted two stage least squares estimator (W-2SLS; Aronow and Carnegie, 2013; Small and Tan, 2017) consistently recovers ATE. It identifies ATE by using compliance scores as a balancing score. The intuition is that compliance scores represent the influence of encouragement on participation. The strength of this influence is measured as the relative likelihood of participation experienced under alternate encouragement levels from a randomly assigned instrument variable. To incorporate uncertainty, the compliance scores - conditioned on the agent information set.

1.7 Organization of the Dissertation

In chapter two, I have described the problem posed for my dissertation work. The conceptual model based on Situational Expectancy Value Theory (SETV) provides a representation of how observable attributes and unobservable psychological constructs can predict the choice to participate in Job Corps. This chapter proposes an econometric causal framework for the binary compliance choice of participation vs. non-participation in the Job Corps program when the outcomes are uncertain. In chapters three and four, I systematically analyzed the secondary survey data from the National Job Corps Study (NJCS) to estimate the three important latent constructs that influence compliance choice according to SEVT. In chapter five, I show how choice probabilities can be obtained from sequential estimation by including the estimated latent class membership and factor scores from chapters three and four with logistic regression and conditional logit models (McFadden and Train, 2009). Then I show how the integrated choice and latent variable model (ICLV) can be modeled as a structural equation model (SEM) for obtaining choice probabilities. These choice probabilities consistently estimate the compliance scores for one-sided noncompliance. In the end, I show how the Average Treatment Effect (ATE) can be obtained even under noncompliance by using the estimated compliance scores as inverse weights in conventional IV estimators. The concluding chapter of this dissertation briefly summarizes the main findings, robustness of the underlying assumptions and future research agenda with implications for policy decision-makers and researchers.

1.8 Contributions of the dissertation

This dissertation work contributes to the scholarship in applied causal inference by integrating stochastic counterfactual framework from statistics with ex-ante stochastic choice framework from econometrics. The econometric framework requires various assumptions and restrictions to identity the ATE and thus has not been widely adopted in the non-econometric program evaluation scholarship. I have showed that a well-defined conceptual model of choice explains the cognitive choice mechanism behind motivated choice. Such a theory helps in the identification of the agent's information set used in the decision making. Having theoretical guidance on a sufficient set of confounders can help in the validation or violation of various assumptions made in both econometric and statistical causal inference methods.

The resulting workflow offers a strong methodological tool for studying adolescent decision-making in various contexts of interest for policymakers. Moreover, this work accentuates the need for experiment designers to conduct discrete choice preference surveys. Such surveys can help us understand how various attributes of choice alternatives increase or decrease the likelihood of choosing different alternatives. Finally, I have shown that the importance of success expectations in influencing choice is significant even after controlling for all observable attributes of the individual. This is of importance to policymakers and program designers on what the youth need from vocational programs for their long term success. I have also clarified that this workflow opens up exciting areas of research for methodology, especially in integrating latent variable models in traditional causal inference research.

2. Overview

2.1 Problem statement

This dissertation aims to identify and estimate the average treatment effect (ATE) of participating in the Job Corps program for the target population. Job Corps is a federal education and training program that provides residential facilities. Its target population consists of youth aged 16-24 who are from deprived families and communities, are disconnected from school and work, and have applied to Job Corps and been deemed eligible for the program. The study uses data from the National Job Corps Study (NJCS) – a multisite randomized experiment conducted nationally by Mathematic Policy Research. Yet only about 70% of the individuals who were assigned to the program group eventually enrolled in Job Corps. This is one-sided noncompliance since those in the control group could not exhibit noncompliance by joining the program elsewhere.

I have adopted the stochastic potential outcomes framework (VanderWeele, 2009) as a generalization of the potential outcomes framework of Neyman and Rubin for the causal analysis, when the deterministic counterfactuals are not well-defined (Small and Tan, 2017). The primary motivation for this dissertation is to challenge the deterministic classification of noncompliance behavior observed in randomized experiments. In the process, we develop a methodological workflow to identify, and estimate ATE when psychometric data on sample members are available and can serve as proxies for unobserved confounding.

The ATE can be identified with Aronow and Carnegie's (2013) inverse compliance score weighted estimator (ICSW) or the weighted least squares estimator (W-2SLS) suggested by the same authors. The ICSW estimator was computationally intensive since it required bootstrapping the multiple complex structural equation models (SEMs). The primary challenge, however, is to estimate the compliance scores after incorporating structural uncertainties in the choice environment as described below. I propose to use the Integrated Choice and Latent Variable model (ICLV), or Hybrid Choice Model (HCM) (Ben-Akiva and Walker, 2002). The ICLV framework was developed to incorporate latent variable models (leveraging psychometric data on sample members' attitudes and perceptions) with traditional discrete choice modeling.

In the Neyman-Rubin framework, potential outcomes are usually assumed to be the result of a deterministic process and thus satisfying the Stable Unit Treatment Value Assumption (SUTVA). This results in well-defined counterfactuals. But there are many situations in which such determinacy may not be valid (VanderWeele, 2009; Small et. al., 2017; Sobel, 2006). For such situations, papers by VanderWeele and Robins (2009, 2012) propose a stochastic potential outcomes framework. A closely related paradigm is the ex-ante choice modeling of Heckman. There is a conceptual relationship between the ex-ante approach and stochastic potential outcomes approach. The ex-ante approach requires probabilistic modeling of choice under subjective expectations of the decision-maker. The choice modeling is probabilistic or stochastic since at the time of decision-making, the agent cannot know what outcomes they will achieve under alternate choices. So as a rational agent they form subjective expectations of the benefits and costs before choosing an alternative. The ex-ante choice model therefore requires the analyst to model the process by which an agent arrives at such subjective expectations and determine the probability of choosing different alternatives given their information set (agent information set) at the time of decision-making.

Existing work on stochastic potential outcomes is extremely sparse. The current dissertation aims to fill this gap by adapting this framework to the empirical context of NJCS. An important theoretical question is about sources of stochasticity in the NJCS context. I posit that it arises largely from the uncertainty in information (about the Job Corps program) that sample members in NJCS had to acquire from multiple information sources – parents, friends, relatives etc. Most of them spoke to more than one source. This is in alignment with what we know about social influences on adolescent decision-making. To reduce uncertainty when making choices with long term rewards, adolescents are known to seek information from as many sources as possible with negligible information acquisition cost. In our case, such easily available sources are the close relationships for adolescents – parents, friends, and relatives, in addition to Job Corps outreach offices.

Using indicators in the baseline data on how individuals acquired information, we model this uncertainty through estimating probability distribution of membership in latent classes. Each latent class displays a distinct set of information acquisition behaviors. The latent class model is then incorporated with the choice model. The individual choice probabilities (i.e., compliance scores) thus estimated would take into consideration the inherent information uncertainty (a fundamental motivation for Heckman's ex-ante approach). The inverse of the estimated choice probabilities is then used as weights with the weighted two-stage least squares estimator (W-2SLS) (Aronow and Carnegie, 2013).

2.1.1 Probabilistic noncompliance

The deterministic worldview is not supported in the ex-ante choice situations. Therefore, the well-defined joint distribution of potential outcomes may not always hold. Treating the counterfactual distribution as a predetermined attribute of individuals has been called ‘fatalistic’ because it negates by definition the possibility of stochastic influences on the individual’s participation decision (Dawid, 2021). Therefore, if we have reasons to believe that compliance behavior is not deterministic but stochastic and happens under Roy-type selection. A different approach is required for identifying ATE under such circumstances. I have considered the example of a job training program evaluation to elaborate this point. In the National Job Corps Study - a nationally representative multisite randomized trial to evaluate the Job Corps (JC) program. If the noncompliance decision (choice) made by those assigned to the program group (Schochet et al., 2008) is probabilistic in nature. Such stochasticity is not fundamentally allowed in the deterministic potential outcomes framework and this shortcoming has been identified in both the econometric literature as well in epidemiology (Cunha et al., 2007; VanderWeele and Robins, 2012). While stochasticity in outcome is permitted in the Heckman setup of latent index threshold models as ‘essential heterogeneity’, stochasticity in participation (or compliance decision) decision was ruled out. It was also clarified that if stochasticity is allowed in the participation choice, then instrument variable methods may not be suitable for causal inference of mean treatment effects (Heckman and Pinto, 2022).

2.1.2 Job Corps program and evaluation

Job Corps plays a central role in federal efforts to provide employment assistance to disadvantaged youths ages 16 to 24. The program’s goal is to help disadvantaged youths become “more responsible, employable, and productive citizens" by providing comprehensive services, including basic education, vocational skills training, counseling, and residential support. It serves more than 60,000 new enrollees each year at an annual cost of more than $1 billion (GAO, 2009).

The National Job Corps Study, funded by the U.S. Department of Labor (DOL), was designed to provide information about the effectiveness of Job Corps in obtaining its goal. The cornerstone of the study is the random assignment of all youth found eligible for Job Corps to either a program group or a control group. Program group members were permitted to enroll in Job Corps, and control group members were not (although they could enroll in other training or education programs). The research sample for the study consists of approximately 9,400 program group members and 6,000 control group members randomly selected from among nearly 81,000 eligible applicants nationwide. Sample intake occurred between November 1994 and February 1996. This study exhibited one-sided noncompliance by which nearly 30 percent of those assigned to the treatment did not end up receiving it (not participating in the program). By design control group members could not access the treatment (except for a trivially few).

The decision to not comply among those assigned to the treatment was stochastic or probabilistic due to the following reasons. In the National Job Corps Study, eligible participants reached out to mentors and peers for advice after receiving their JC eligibility confirmation. This was possible due to a delay of one year between participants receiving confirmation about their eligibility to enroll in JC and their random assignment to one of the experimental groups. According to the supplemental survey data collected in the study, participants reached out to peers and mentors for advice post-eligibility confirmation and before randomization. Participants could have also learned about threats to personal safety, food and other resource quality at the JC centers from alumni or outreach and admissions staff at JC centers. Therefore, each individual has a likelihood of participation, under each assignment condition given these other factors. This probability does not have to be zero or 1 and is subjected to influence by both information observed by the analyst X and latent information U. The other source of stochasticity lies in the psychological processes that underly the ex-ante decision process (Aakvik et. al., 2005). Since there is within person variation in psychological attributes under various environmental influences, modeling the ex-ante choice process requires measurement models for U and its structural relationship with the information observed by the analyst X.

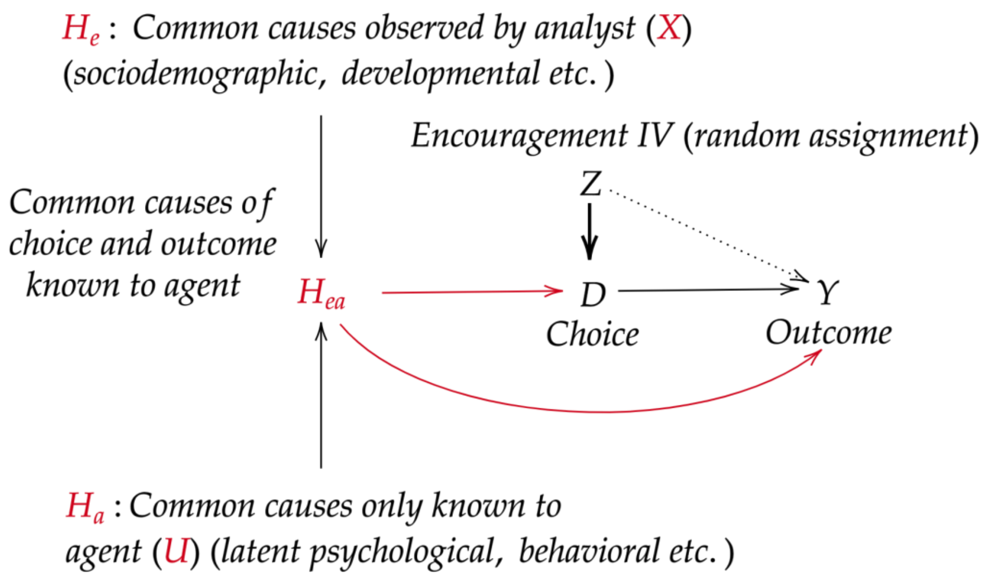

Figure 1 Directed acyclic graph of noncompliance causal mechanism

2.1.3 Notation

There are totally N individuals in the study sample which is a randomly chosen sample from the target population. Individuals in this sample are indexed by the letter i. Study sample of size N be indexed by individual i: $i \in \{1, \ldots N\}$.

Z is the random variable denoting two possible random assignment groups. Z=1 denotes being randomly assigned to participate in the program, while Z=0 denotes those assigned to a control condition which embargoed access to Job Corps program. Random assignment of individual i, $Z_i = z: z \in \{0,1\}$

- $Z_i = 1$ denotes assignment to the treatment or program group
- $Z_i = 0$ denote assignment to the control group. The control group were embargoed from joining (for 36 months from randomization). Therefore, $D_i = 0, \forall i: Z_i = 0$

Similarly, D is the random variable denoting actual participation choice made by each individual. D=1 denotes that the individual chose to participate in the program while D=0 denotes non-participation as a choice. Due to the control group embargo, only those in the assigned treatment group had to decide between participation vs. non-participation. Participation choice of individual i, $D_i = d: d \in \{0,1\}$

- $D_i = 1$ denotes enrollment or participation in the program
- $D_i = 0$ denotes non-participation in the program.

Finally, the exposure to violence is denoted as *a violent crime victimization event* that happened between participation decision and endline survey. Y=1 denotes that the individual was a victim of violent crime and Y=0 denotes non-victimization. Individual i experienced an event-based outcome, $Y_i = y: y \in \{0,1\}$

- $Y_i = 1$ denotes that the event of interest happened

- $Y_i = 0$ denotes that the event of interest did not happen

2.2 Compliance as choice in NJCS

Job Corps study is an encouragement design RCT in which assignment to participate acts as an encouragement to actually participate. It is important to identify the common causes (confounders) of choice and outcome since they create a backdoor path - highlighted in red - that induces an association between choice and outcome different from the true effect of interest, the ATE.

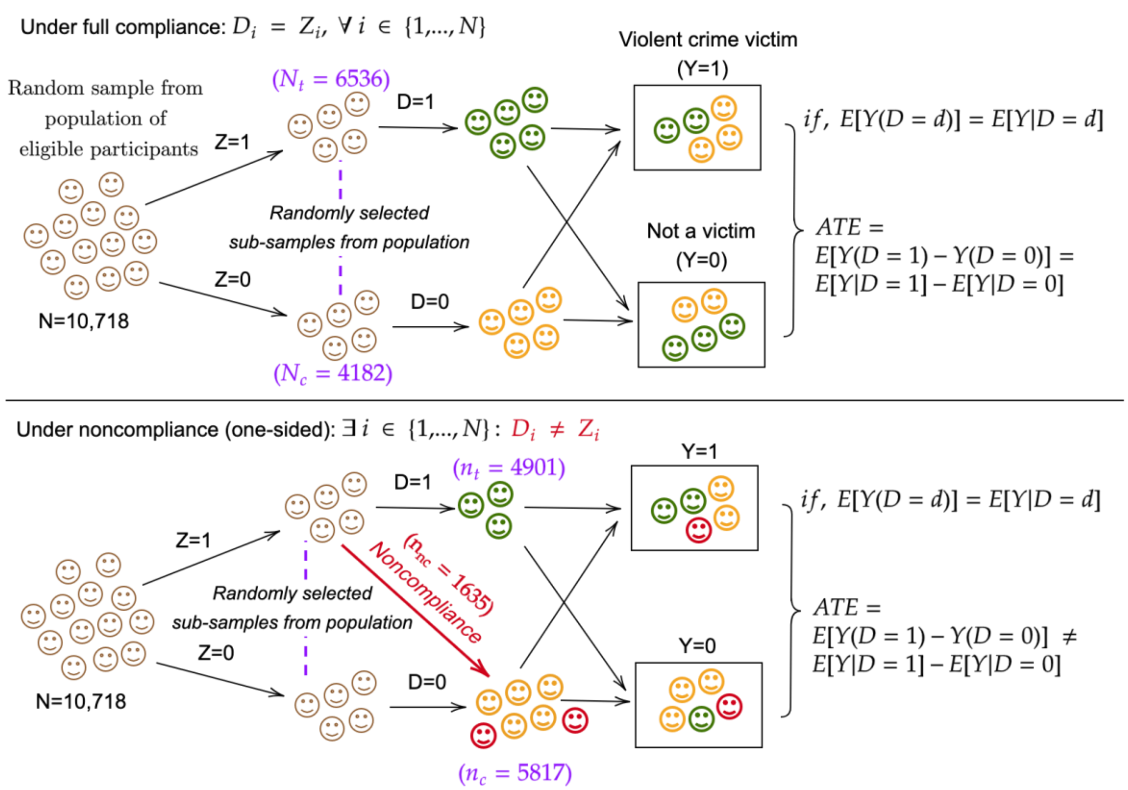

Figure 2 Graphical representation of the National Job Corps Study with noncompliance

While the decision-making individual would know all such common causes, the analyst might observe only a covariate vector X, typically the baseline covariates in a RCT. The psychological and other latent constructs U are usually unobserved by the analyst. Sometimes they can be estimated with appropriate models. In this study, among those assigned to program $\forall i: (Z_i = 1)$, approximately 77 percent chose to participate in the program $(D = 1)$ while 23 percent did not choose to participate $(D = 0)$. This compliance choice has the following features.

2.2.1 Compliance is a utility-maximizing choice

It is made by individuals based on comparison of unobserved (by analyst) subjective gains from different choices. Among those assigned to the treatment group, since program participation is a voluntary choice made by individuals looking to maximize their perceived or subjective gains, the compliance choice is a utility-maximizing choice in which an individual chooses to participate only if their net subjective gains from participation is greater than non-participation.

2.2.2 Compliance is chosen under uncertainty

Before making the choice or ex-ante choice situation, the individuals do not know with certainty whether they will achieve the desired outcome. Therefore, compliance choice is made based on expected net gains between participation and non-participation, given the information the individuals possess at the time of decision-making. So, compliance choice is an ex-ante stochastic choice (Heckman, 2007; Heckman and Vytacil, 2007a).

2.2.3 Compliance is an achievement-motivated vocational choice

It is influenced by individual characteristics, life experiences, perceptions, and attitudes about the program etc. (Eccles and Wigfield, 2020). Vocational choices are often made in pursuit of long-term career identity development. Therefore, individual motivation for such choices are influenced by factors across an at-risk youth's ecosystem and life experiences. Therefore, a conceptual model of program participation in Job Corps can be developed based on theories of motivation from vocational choice research among youth.

2.3 Ex-ante model of compliance choice

This figure represents the compliance choice as an ex-ante choice. Ex-ante choices are made by individuals, based on expected outcomes rather than outcomes known with certainty. They naturally represent compliance choice in Job Corps study. Because, the encouragement design of the study requires voluntary participation choice - after receiving assignment. This choice is based on uncertain future outcomes.

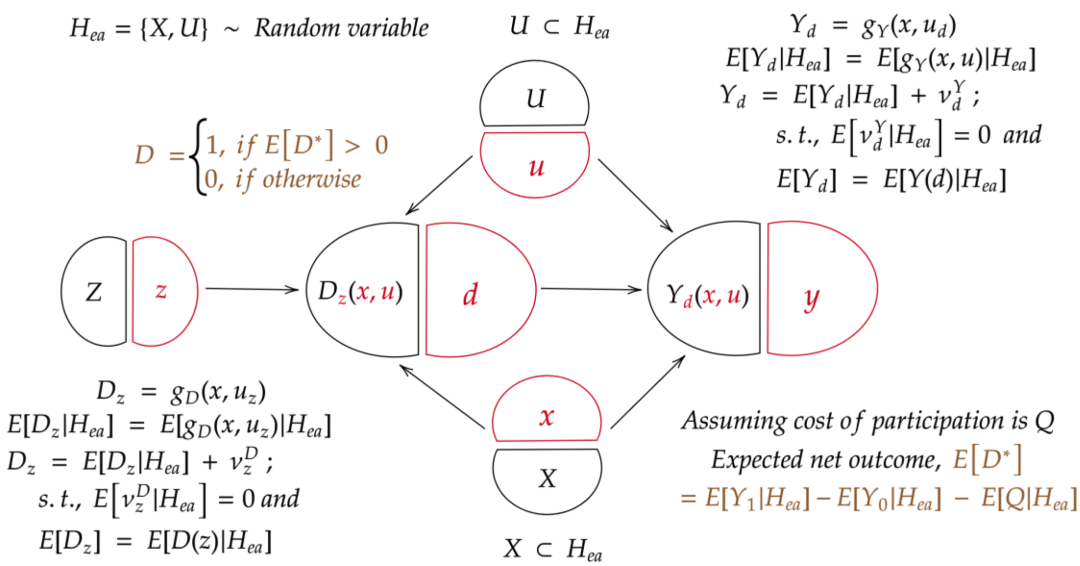

Figure 3 Single World Intervention Graph (SWIG) of noncompliance in randomized experiment

The graph itself is a Single World Intervention Graph - SWIG for short - of noncompliance behavior in Job Corps study. The black nodes denote random variables while red nodes denote a realization of the corresponding random variable.

The random variables for participation choice D and outcome Y are here mentioned in a functional form. This is to represent them as counterfactual generators given the input arguments. These input arguments are information from the agent information set H_{ea}. There is inherent uncertainty in this information set due to sources of randomness across the process of decision-making.

Due to this information set uncertainty, the counterfactuals generated with this information are also inherently random. Therefore, both $D(x,u)$ and $Y(x,u)$ are random variables with small d and small y as the realized values.

An additively separable model decomposes these realized counterfactual values into two parts. The first part is the expected value of the counterfactual conditioning on agent information set in a hypothetical assignment condition for D and participation condition for Y. This implies that while individual counterfactual realizations might not be well-defined, their expectations over the information set can be. The second part of the separable model is an additive error component which averages to zero once information uncertainty is known.

With this formulation, the expected net gains- denoted by D^* - can be defined as difference in expected gains under counterfactual participation choices. A cost component Q can also be included in the decision-process. An example is cost of childcare arrangements to facilitate participation in Job Corps. The utility maximizing individual decision maker then decides to participate if the expected net gains is positive while not participate, if otherwise. This formulation characterizes decision-making under uncertainty in Job Corps study. In econometric causality framework, this model represents a generalized Roy model in an ex-ante choice framework.

2.4 SUTVA violation

If the compliance choice is formulated as stochastic, it would violate the Stable Unit Treatment Value Assumption (SUTVA). To setup the discussion and later analysis, assume that the information unobserved by the analyst U is known to the agent as X^*. Further assume that this latent X^* is composed of two latent factors X_1^* and X_2^*. Let $\tilde{X}$ denote the entire agent information set H_{ea} as a random variable. Then X^* has a distribution both within and between persons based on uncertainty in agent information set.

Let, $U = \{X_1^*, X_2^*\} = \{X^*\}, s.t. H_{ea} = H_e \cup H_a = \{X, U\} = \{\tilde{X}\} = \{X, X_1^*, X_2^*\}$

Stochastic model violates SUTVA

Violation of *treatment variation irrelevance*: $Y(d, \tilde{x}) \neq Y(d, \tilde{x}') : \forall \tilde{x}, \tilde{x}' \in \tilde{X}, s.t. : \tilde{x} \neq \tilde{x}'$

Similarly, for choice counterfactuals: $D(z, \tilde{x}) \neq D(z, \tilde{x}') : \forall \tilde{x}, \tilde{x}' \in \tilde{X}, s.t. : \tilde{x} \neq \tilde{x}'$

Violation of *consistency* between observed and counterfactual data: $Y_i^{obs} \neq Y_i(d, \tilde{x}), \forall \tilde{x} \in \tilde{X}: D_i = d$ and $D_i^{obs} \neq D_i(z, \tilde{x}), \forall \tilde{x} \in \tilde{X}: Z_i = z$

Under stochastic model, both sub-assumptions of SUTVA are violated - the treatment variation irrelevance assumption or policy invariance and the consistency of deterministic counterfactuals assumption.

2.5 Stochastic counterfactuals

The Expected version of SUTVA outlined below establishes the invariance and consistency assumptions for stochastic counterfactuals.

Expected Stable Unit Treatment Value Assumption (ESUTVA)

(Assumption 1a): Expected treatment variation irrelevance

$$E[Y_d] = E[Y(d)|H_{ea}]$$

$$E[D_z] = E[D(z)|H_{ea}]$$

(Assumption 1b): Consistency in stochastic counterfactuals

$$Y_i^{obs} = Y_i\big(D_i = d, \tilde{X}_i = \tilde{x}|H_{ea}\big)$$

$$D_i^{obs} = D_i\big(Z_i = z, \tilde{X}_i = \tilde{x}|H_{ea}\big)$$

An individual's observed outcome is the potential outcome realized from a distribution of potential outcomes when the unobserved (by analyst) covariates X^* take a particular value x^*

The expected treatment variation irrelevance assumption implies that the expected value of a counterfactual is obtained by averaging over uncertainty in agent information set. The consistency in stochastic counterfactuals assumption implies that the observed value of Y or D is nothing but a realization from the distribution of their counterfactuals when the information set takes a fixed value $\tilde{x}$.

2.6 Compliance score or Strength-of-IV

To identify ATE under noncompliance I used the compliance score approach previously used in epidemiology. It is also called principal scores in the principal stratification literature. The intuition is that compliance scores represent the influence of encouragement on participation. The strength of this influence is measured as the relative likelihood of participation experienced under alternate encouragement levels from a randomly assigned instrument variable. To incorporate uncertainty, the compliance scores - conditioned on the agent information set- are estimated as the expected difference in probability of participation under alternate encouragement levels of IV (Z).

Based on the definitions above, the compliance score:

$$\pi(\tilde{x}) = \{E[D = 1|Z = 1, H_{ea}] - E[D = 1|Z = 0, H_{ea}]\}$$
$$= \int E[D = 1|Z = 1, X = x, X^* = x^*]f(X^*)d(X^*)$$

Here $f(X^*)$ denotes the population distribution of X^* as determined randomly by the agents when they are in the process of making the compliance choice. The expected probability of participation under control group assignment in the Job Corps study is zero due to the control group embargo from Job Corps enrollment.

2.7 Identification assumptions

Since the random assignment is being used as instrument variable, the deterministic IV assumptions are generalized here to the stochastic setting. The IV assumptions are discussed in the same order as in the original Angrist, Imbens and Rubin paper on IV under deterministic counterfactuals (Angrist, Imbens and Rubin, 1996).

The first assumption is SUTVA which was generalized to expected version of SUTVA earlier. Angrist, Imbens and Rubin (1996) IV assumptions for stochastic noncompliance (ex-ante version):

IV-1: Consistency of stochastic counterfactuals.

The second assumption of randomized encouragement IV (Z) is satisfied as in the deterministic compliance.

IV-2: Random assignment:

- IV 2(a): If H_{ea} was obtained before random assignment: $\{Y_1, Y_0, D_1, D_0\} \perp Z$

The third assumption is exclusion restriction requiring no direct impact of instrument on the outcome. This assumption has been relaxed in a bayesian deterministic compliance framework while estimating a compliance score for each individual (Esterling et. al., 2011). Since the same is achieved under stochastic compliance model, the exclusion restriction is relaxed.

IV-3': Exclusion restriction: Required to identify causal effects of unobserved compliance behavior. Not required in stochastic compliance since every individual's degree of ex-ante compliance is estimated (Esterling et. al., 2011).

The fourth assumption is that encouragement is a relevant IV with non-trivial impact on participation. This is assumed to be true since offer to enroll in JC is a strong encouragement to participate.

IV-4: Relevance of instrument for participation (non-trivial encouragement): $E[D_i(z = 1) - D_i(z = 0)] \neq 0$.

The fifth assumption is that of stochastic monotonicity originally discussed by Small and Tan (2017) and generalized here to stochastic behavior.

IV -5: Stochastic monotonicity: $E[D_{1i}|H_i] - E[D_{0i}|H_i] \geq 0$

- IV-5(a) Small and Tan (2017) describe the same effectively as: $P\left(D = 1|Z = 1, \tilde{X} = \tilde{x}\right) \geq P\left(D = 1|Z = 0, \tilde{X} = \tilde{x}\right)$

Difference between the two versions is that the Small and Tan version **fixes** the value of the unobserved X^* while the latter **conditions** on the agent information set with intrinsic uncertainty (Heckman, 2007).

Empirical support for these assumptions is in the baseline survey. Nearly 99 percent of those who were asked about their plans to participate in JC, said they wanted to participate.

The final assumption required to identify ATE in this approach is a stochastic version of latent or principal ignorability assumption used in principal stratification. The principal stratification approach considers deterministic compliance behavior as latent classes - compliers and noncompliers.

ICSW - 1: Stochastic latent ignorability: $E[Y_1 - Y_0|H_{ea}] = E[Y_1 - Y_0|E[D_1] > 0, H_{ea}]$.

- This implies that the ATE for the population is same as that for those who are expected to comply with the random assignment: $P(E[D_{1i}|H_{ea}] > E[D_{0i}|H_{ea}]) = 1$

The stochastic latent ignorability implies that the average treatment effect (ATE) of the target population is the same as those who are likely to comply with the random assignment. In the case of one-sided noncompliance, it implies that there is a non-zero probability of participation or compliance when assigned to treatment. Since nearly all eligible participants expected to participate, under the ex-ante model, the ATE identified with compliance score approach in the Job Corps study, applies to the entire population of eligible participants.

2.8 Situated Expectancy Value Theory (SEVT)

2.8.1 Profile of an eligible participant in Job Corps

An average at-risk youth in the National Job Corps Study (NJCS) is a youth in the age group of 16-24 years exposed to factors that disrupt age-appropriate identity development processes (risk factors). The Job Corps program staff decide an applicant to be eligible (at-risk) to apply for the program if they satisfy eleven criteria. In other words, an applicant is eligible because they are deemed to be at-risk due to eleven factors that are detrimental to healthy identity development. But practically any individual satisfying the age requirement and belonging to low-income groups can enroll in Job Corps (Schochet and Burghardt, 2007). While job training programs are known crime reduction strategies, it is not entirely clear what the mediating mechanisms are. At-risk youth's exposure to adverse life experiences or criminal involvement is known to affect vocational identity development (Bartlett and Domene, 2014). The risk factors affecting identity development also impact vocational identity development. Vocational identity is a critical component of an individual's integrated sense of self (core identity). Therefore, vulnerable youth might seek job training programs as a corrective action to pursue normal vocational identity development. We find evidence for such motivations and expectations in the baseline NJCS data.

2.8.2 Vocational identity development

Vocational identity is a core component of overall identity development in adolescence. It can be defined as how an individual sees themselves as a worker in a profession. There are three main components of vocational identity – self-image, future image and self-efficacy. Self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments (Bandura, 1977, 1986, 1997). Job training programs help in the exploration and commitment of vocational identities. This is because job training increases the career adaptability of at-risk youth. Career adaptability is known to be correlated with multiple life-course labor market outcomes. Recent work finds a strong role for career adaptability in vocational identity development (Kirchknopf, 2020). Savickas conceptualizes career adaptability as 'an individual's psychosocial resources (expected benefits) for coping with current and anticipated vocational development tasks, occupational transitions, and work traumas that alter their social integration' (Savickas 2013, p. 157). Consequently, career adaptability is an important construct regarding adolescent career development as well as vocational development in adults and has thus to be considered highly relevant for vocational education and training (VET).

2.8.3 A proposed model of vocational choice for at-risk youth

In this study, I proposed an integrated model of vocational education and training (VET) choice based on the Situational Expectancy Value Theory (SEVT; Eccles and Wigfield, 2020). The expectancy value theory (EVT) provides a socio-cognitive framework to study the causal mechanisms that determine 'motivated achievement-related choices and outcomes.

Vocational education and training (VET) choice refers to an individual's decision to enroll in a VET program. Assuming that access to the program is available, we do not discuss the processes by which access was gained. VET choice is a motivated achievement-related choice. A critical component of VET is to facilitate the development of a healthy vocational identity (Klotz et. al., 2014). A free career choice and the provision of maximal functional integration into operating processes at the workplace are key factors underlying identity formation (ibid.). These two factors underly vocational identity formation because they facilitate vocational identity exploration, commitment, and reconsideration. Therefore, the motivation behind choosing VET is to foster a healthy vocational identity. In NJCS, at-risk youth might choose to enroll in Job Corps (VET program) to foster skills relevant for a healthy vocational identity.

2.8.3.1 Subjective task value or Motivations to participate in Job Corps

In the SEVT framework, VET choice is motivated by the subjective value of participating in Job Corps. For a typical Job Corps applicant, I hypothesize that this motivation derives from the subjective value of Job Corps in aiding vocational identity development processes. Higgins (2007) provides five sources of such motivation, where the last two sources are more relevant for adolescents. Despite the categorical distinction, these causes seem to interact depending upon the domain of application. For example, in the case of VET choice I explain these overlaps using NJCS. These five sources justify the choice of various items in NJCS data to represent the subjective value (motivation) of Job Corps to at-risk youth. What would at-risk youth subjectively value about participating in Job Corps?

2.8.3.2 Sources of subjective task value (motivation)

2.8.3.2.1 Need satisfaction

The *first source* is 'need satisfaction', referring to biological needs satisfied by the VET choice. At-risk youth on average are exposed multiple adverse life events. Exposure to such events increases the allostatic load or toxic stress levels in the body of the individual. This load manifests as both internalizing and externalizing mental health symptoms (Romeo, 2013; McEwen and

McEwen, 2017). VET would be a desired choice if it helps in alleviating such toxic stress exposure. Since most incidence of violent crimes involving youth (perpetration and victimization) happen around home and community, moving away from home and community from toxic stress levels can be a strong motivation.

2.8.3.2.2 Shared beliefs

The *second source* of motivation is shared beliefs on what is desirable. For youth, a desirable transition to adulthood involves appropriate occupational choice to ensure job and life satisfaction. For at-risk youth job training programs offer a healthy pathway for this transition. Therefore, lack of necessary resources in the extant developmental ecosystem for vocational development can act as strong motivation for choosing VET.

2.8.3.2.3 Relation to future self

The *third source* of value is derived from the relation of ones' current actual self to either desired or undesired end states. Discrepancies between where one is and where one thinks one should be (the ideal or ought self) are also crucial; when actual and ought selves are closer to congruence, then the individual is better off psychologically. Thus, activities that help promote congruence between the actual and ideal self should have more value to the individual. In NJCS, youth who value self-esteem and self-control may have an "ideal self" with respect to those qualities. Activities that help them attain aspects of this ideal self will be perceived as valuable to these individuals. VET helps in this process because there is a causal impact of competency on self-efficacy. As the training increases, one's skill level in a job trade and one's core self-evaluation improves resulting in greater self-esteem. Due to allostatic load from chronic stress exposure, at-risk youth have heightened emotional sensitivity which often is disadvantageous in professional settings since lack of self-regulation at work results interpersonal conflicts. This results in negative peer relationships at work which in turn is a barrier to vocational identity development. Therefore, an ideal self in a vocational sense would have greater self-control. Therefore, self-control and self-esteem are a component of the subjective value of Job Corps participation due to their impact on vocational identity development towards a subjective perception of the ideal self.

2.8.3.2.4 Intrinsic value

The fourth source of value arises when an individual pursues an activity out of their own volition or voluntary participation. This might be true since at-risk youth enrolled in Job Corps often because of the need to get away from negative life circumstances in their ecosystem. Some examples are, domestic violence, peer violence, violent crime threat, drug related problems, lack of opportunities etc. Such reasons motivated individuals to join the program. It is difficult for analysts to have information on this source of value unless explicit preference surveys or discrete choice experiments were conducted prior to the baseline or during the baseline survey (Humburg and van der Velden, 2015).

2.8.3.2.5 Experiential value

The fifth source is the value from one's experiences. How might the life experiences of an at-risk youth motivate them to join Job Corps? As explained earlier, at-risk youth are exposed to multiple risk factors. Such complex risk exposure is correlated with incidence of multiple adverse childhood experiences (Metzler et. al., 2017). Exposure to such experiences is also known to be detrimental for college success (Hinojosa et. al., 2018). Low high school academic engagement is also prevalent among adolescents exposed to adverse childhood experiences. Low academic engagement in high school results in lower academic performance and therefore lower college aspirations.

Adverse experiences in the childhood can impact multiple developmental domains including how youth evaluate themselves (core self-evaluation). Therefore, it is desirable for an at-risk youth to improve their core self-evaluation through VET. This is conceptualized in an EVT construct called future orientation. It has been defined as “a self-produced personality organization achieved by integrating the self in time and social settings” (4). The power of future orientation to influence adolescent behavior is based on expectancy-value theory, which posits that individuals modify current behavior based on their judgment of future outcomes (7) and specifically: (1) how much one values an outcome and (2) the likelihood of the outcome occurring. Literature shows that vocational choices are often determined by factors related to opportunity, environment, and personality. When these risk factors are detrimental to vocational identity development, they motivate an individual’s vocational choices. Given the life experiences and attitudes (low core self-evaluation and college aspirations) of at-risk youth, Job Corps is a vocational choice that increases the opportunities available for identity exploration, its residential component provides a safer environment for identity development, and personality (read as core self-evaluation or perceived self-efficacy) improvement is possible due to increased competency from VET.

2.8.3.2.6 Measures of motivation in NJCS

The measures of subjective task value or motivation of Job Corps participation in NJCS are binary indicators of whether a factor strongly motivated an at-risk youth to participate in Job Corps. These factors are – wanting to leave home, wanting to leave community due to violence, personal reasons, wanting job training, wanting to achieve career goals, and wanting to get GED. All these indicators are related to one or more of the sources of subjective value we discussed earlier (Higgins, 2007). Therefore, they have conceptual construct validity as a measure of the subjective task value of participation in Job Corps.

Table 1 Measurement indicators from NJCS data for Subjective Task Value (STV) in the SETV model

Notation	Indicator	Treatment group (Z=1; n=6536) (Mean, SD)	Control group (Z=0; n=4182) (Mean, SD)
I_1^{f1}	Motivated to leave home (RHOME)	0.57 (0.50)	0.59 (0.49)
I_2^{f1}	Motivated to leave community (RCOMM)	0.62 (0.49)	0.60 (0.49)
I_3^{f1}	Motivated by other personal reasons (ROTHER)	0.73 (0.44)	0.73 (0.45)
I_4^{f1}	Motivated by training aspiration (RTRAIN)	0.98 (0.12)	0.98 (0.14)
I_5^{f1}	Motivated by achieving career goals (RCRGOAL)	0.95 (0.23)	0.95 (0.25)
I_6^{f1}	Motivated by unemployment (RNOWORK)	0.91 (0.29)	0.91 (0.29)

2.8.3.3 Expectations of Success or Expected benefits from Job Corps participation

In the SEVT framework, VET choice is also influenced by expectations of success. Eccles and Wigfield (2020) defined expectancies for success (ESs) as individuals' beliefs about how well they will do on an upcoming task. In NJCS, eligible participants (at-risk youth) were asked to what extent they thought Job Corps will help them improve in math, reading, getting along with peers, making new friends, making new friends, self-control, and self-esteem. These items represent various overlapping constructs of self-efficacy depending upon which theory was used to conceptualize efficacy (for details: Eccles and Wigfield, 2020). Mathematics and reading are related to academic efficacy (Bong and Clark, 1999) in socio-cognitive theories of cognition, positive peer relationships are related to socialization efficacy in vocational achievements (Boat et. al., 2022) and self-esteem and self-control are included as measures of self-efficacy in multiple domains (Gecas, 1989).

Among the different domains of vocational identity, self-efficacy is positively correlated with multiple desired life course outcomes. Self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments (Bandura, 1977, 1986, 1997). Therefore, in the vocational identity domain, self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce occupational performance attainment. Self-control, self-esteem, and positive peer relationships are desirable behaviors necessary for job satisfaction across domains, and life satisfaction in general. Therefore, improvement in these behaviors could increase the likelihood of occupational success in the future. A more general notion of cognitive efficacy is composed of cognitive abilities and self-efficacy (Berry, 1989). It is described as increases in the rate, amount, or conceptual clarity of knowledge, versus costs, such as cognitive effort, needed to attain knowledge (Hoffman, 2012). Cognitive abilities such as mathematics and literacy are strongly correlated and are essential for occupational success (Newsome, 1978; Pierce, 2013). Therefore, individuals exploring their identity might want to improve these skills before committing to vocational choices.

2.8.3.3.1 Measures of expectations in NJCS

The measures of expectations of success or expected benefits of participating in Job Corps are binary indicators of how much improvement the at-risk expected in – mathematics, reading, getting along with peers, being able to make new friends, getting a specific job training, self-esteem and self-control. As a latent construct, these items measured in NJCS baseline survey correspond to expectations of success in the SEVT conceptual model and therefore, influence the VET choice (choice to participate in Job Corps or not). These success expectancies are part of the 5C model of positive youth development (PYD) (Lerner et. al., 2005; Catalano et. al., 2004; Dvorsky et. al., 2019).

Table 2 Measurement indicators from NJCS data for Expectancies of Success (ES) in the SETV model

Notation	Variable	Experimental treatment (Z=1; n=6536) (Mean, SD)	Experimental control (Z=0; n=4182) (Mean, SD)
I_1^{f2}	Expected benefit in math (EMATH)	0.70 (0.46)	0.68 (0.47)
I_2^{f2}	Expected benefit in reading (EREAD)	0.54 (0.50)	0.53 (0.50)
I_3^{f2}	Expected benefit in getting along (EALONG)	0.60 (0.49)	0.59 (0.49)
I_4^{f2}	Expected benefit in self-control (ECONTRL)	0.57 (0.49)	0.58 (0.49)
I_5^{f2}	Expected benefit in self-esteem (EESTEEM)	0.58 (0.49)	0.57 (0.50)

2.9 Integrated model of Job Corps participation choice

In Heckman and Smith (2003) the authors identified various determinants of participation in a vocational education and training (VET) program called JTPA. Since, JTPA is considered an alternative to Job Corps (LaLonde, 2003), the same factors could determine participation choice in Job Corps under NJCS. But the authors in aforementioned paper did not provide a behavioral model explaining why certain determinants were important for the participation choice. The conceptual model discussed above attempts to alleviate this gap by providing a behavioral (socio-cognitive) model of motivated vocational choice for youth, but especially for at-risk youth. This is because the life experiences of these youth require a clarification on how different expectations and motivations are developed in the context of choices pertaining to vocational education and training. Based on the discussion, I adopted the following behavioral model of participation choice in Job Corps among those randomly assigned to the treatment group. This model also provided the conceptual construct validity for the latent factors modeled in my analysis – expected benefits of Job Corps participation and motivations to participate in Job Corps. The empirical construct validity is analyzed through exploratory and confirmatory factor analysis. In order to make the choice on whether to participate or not in Job Corps - if an offer is made by the program staff - the individual has to collect information on what kind of experiences are realized by the individual when participating in the program. To obtain this information, youth seek the sources in their interpersonal relationships and external media.

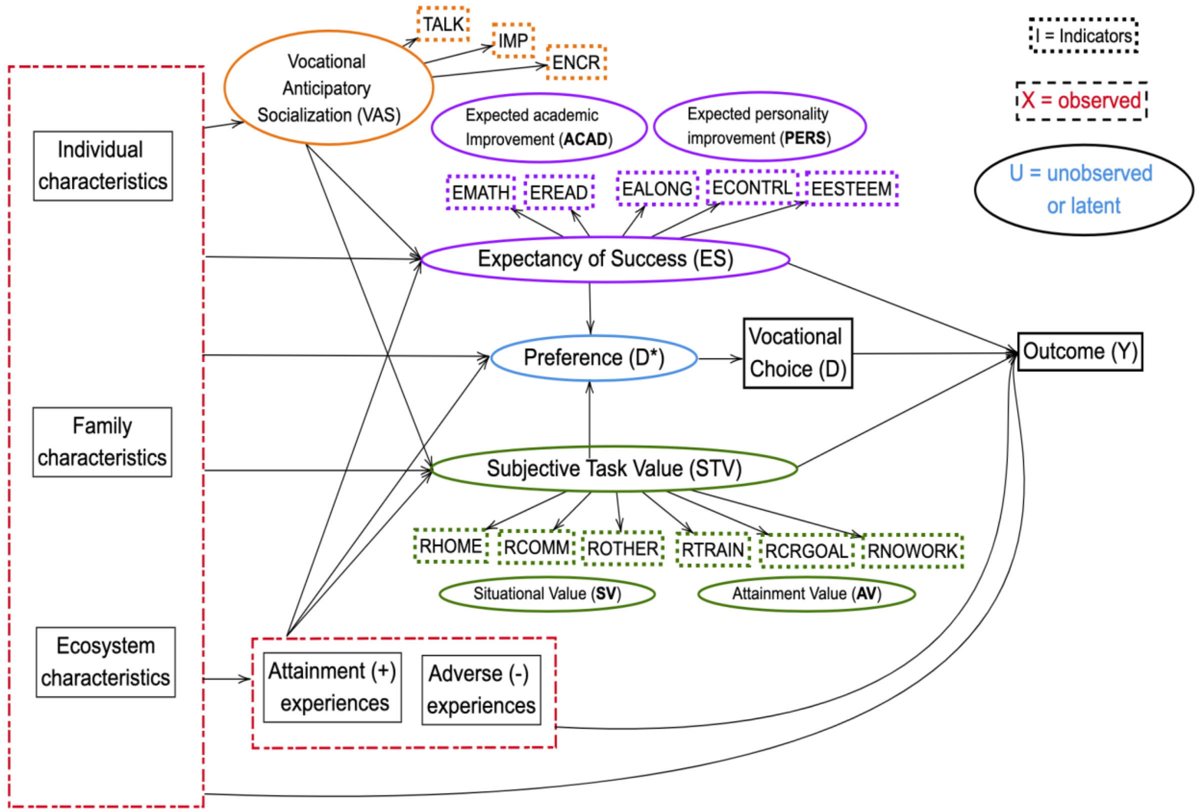

Figure 4 Graphical model of SETV-based compliance choice and outcome in NJCS

2.9.1 Vocational Anticipatory Socialization (VAS)

In NJCS, I define VAS interchangeably as the `**Information Acquisition Context (IAC)**`. The former construct is a well-established phenomenon of individuals seeking information from multiple sources regarding vocational choices (Powers and Myers, 2016). These sources are called sources of VAS in the vocational identity literature while they are referred to as socializers in the SEVT model shown earlier. The socializer's beliefs and perceptions about Job Corps is expressed to the guidance seeking youth during their interaction. This guidance on what life in Job Corps could be influences the formation of both expectations and motivations. In the latent class analysis, this effect is tested by testing for measurement invariance among latent groups of VAS or IAC while conducting factor analysis for expectations and motivations. Empirical analysis shows the presence of measurement invariance and therefore we cannot reject the null hypothesis that the same items are not measuring the same constructs for different latent classes of VAS. The classes of VAS/IAC describe different patterns of guidance seeking among parents, friends, and relatives. Research shows that the nature of information provided by these sources could qualitatively vary. Parental guidance is influenced by parental aspirations (Jahn and Myers, 2014) and tends to prioritize aspects of vocational choice relevant for youth's well-being. While parental messaging in VAS is usually positive, the evidence is mixed for other family members (relatives) and friends (Adkisson, 2013). Therefore, the pattern of who is providing the guidance, the importance given to it by the youth and encouragement from different sources can constitute distinct profiles of VAS captured in the latent class analysis.

2.9.2 Generalized stochastic random utility model (GSRUM)

2.9.2.1 Ex-ante choice process - a specific model

Let Y_1 be an indicator (in four years from randomization) of violent crime victimization if the individual attends the Job Corps and Y_0 if they do not. The decision to participate may be made on the expected probability of victimization under both choices: $E[Y_1|H], E[Y_0|H]$ and expected costs $E[Q|H]$. The expectations are those of the relevant decision maker or agent (at-risk youth eligible and with an offer to participate in Job Corps). These expectations are formed under the agent's information set $H \equiv H_{ea}^* = \{X, X^*\}$.

From an economist's point of view the data generation process or the counterfactual generation process for outcome $Y = y$ under participation $D = d$ and observed information $X = x$ and unobserved information $U = u$, $y_d = g_d(d, x, u)$, and the latent propensity to participate under encouragement level z , $d_z^* = g_z(z, x, u)$.

The economist's information set contains only the observable attributes of the individual, $H_e = \{X\}$. The agent's private information set H_a^* contains information known only to the agent and usually unmeasurable such as latent psychological perceptions and attitudes X^*. In this study the latent constructs of interest are situational task value (STV) of participating in Job Corps denoted by X_1^* and expectations of success by participating in Job Corps denoted by X_2^*. According to SEV theory (SEVT), the sufficient set of predictors of participation choice in JC or a relevant information set to predict choice is $\tilde{X} = \{X, X_1^*, X_2^*\}$ (Heckman, 2008). So the sufficient latent information set for predicting choice is $H_a^* = U = X^* = (X_1^*, X_2^*)$. Here U is the unobserved component of random utility not observed by the analyst. It is also the unobserved common causes of D and Y.

The full information available to the agent, $H \equiv H_{ea}^* = H_e \cup H_a^* = (X, X^*)$. For an analyst to use this full information set, they have to jointly model (joint estimation) both the participation choice and the latent constructs influencing the decision. In this study the joint estimation is achieved with structural equation models (SEM).

2.9.2.2 Random utility theory

Individuals derive utility such as achieving a desired outcome by choosing an alternative. In the case of social programs, individuals participate when they expect the program to provide them a net gain on a desired outcome (adjusting for cost of making the participation choice). The latent index of preference D^* is a manifestation of the underlying utilities. The utilities are functions of observed explanatory variables X about the individuals and choice alternatives, and other unobserved variables U. For all individuals $i \in \{1, \ldots N\}$,

Let,

$$Y = \beta X + U$$

$$Y_1 = \beta_1 X + U_1$$

$$Y_0 = \beta_0 X + U_0$$

Here Y is the indicator variable denoting whether an individual was a victim of violent crime in the time since they applied to Job Corps program. The information osbervable to the analyst is X and not observed by the analyst but known to the agent is U.

Let U contain information about the latent constructs suggested as choice determinants from the Situational Expectancy Value Theory (SETV). The Subjective Task Value of Job Corps participation (STV) is denoted by X_1^* and Expectations of Success (ES) denoted by X_2^*. Therefore, the SEVT determinants, $X^* = \{X_1^*, X_2^*\} \subset U$. According to SEVT the most proximal choice determinants of JC participation are $\{X, X^*\}$. Therefore, once this information is controlled for, the unexplained variation in participation is considered orthogonal to the covariate space spanned by this information set.

$$U = \lambda X^* + \epsilon;$$

$$Y = \beta X + \lambda X^* + \epsilon; \epsilon \sim distr(\theta_\epsilon)$$

$$X^* = \gamma X + \omega; \omega \sim distr(\theta_\omega)$$

But as defined earlier, X_1^* and X_2^* are latent constructs representing STV and ES respectively. The assumption here is that individuals indicate their underlying STV (X_1^*) through indicator variables or proxy measures $I^{X_1^*}$. Similarly, ES (X_2^*) through indicator variables or proxy measures $I^{X_2^*}$. The latent constructs X^* are perceptions and attitudes which are also informed by the information individuals acquire about JC experiences (VAS or IAC).

The latent classes of Vocational Anticipatory Socialization (Powers and Myers, 2016) denoted by C. In the context of NJCS, the VAS construct is interchangeably referred to as VAS or Information Acquisition Context (IAC).

Indicators $I = \{I^C, I^{X_1^*}, I^{X_2^*}\}$ corresponding to indicator sets for each of the three latent factors of VAS, STV and ES, respectively. The total number of indicators is denoted respectively by $L = \{L^C, L^{X_1^*}, L^{X_2^*}\}$. For example, indicator $I_l^C: l = 1, \ldots, L^C$ denotes the l^{th} indicator or item for latent class C and total number of indicators is L^C. Similarly, $I_l^{X_1^*}$ and $I_l^{X_2^*}$ are the l-th indicators for X_1^* and X_2^*. The latent variables can be decomposed into a factor structure that explains the common variance (f) and unique variance (Γ), such that:

$$X^* = F + \Gamma$$

Both ES and STV do not have a well-defined test to extract the underlying X^*. So, I used factor analysis to extract the common factor structure (F). The measurement equations for X^* can be written as:

2.9.2.3 Under joint estimation - Integrated choice and latent variable (ICLV) model

2.9.2.3.1 Measurement equations

For STV:

$$I_m^{X_1^*} = \alpha_{1m} X_1^* + \nu_m^{X_1^*} : m = \{1, \ldots, L^{X_1^*}\}$$

For ES:

$$I_m^{X_2^*} = \alpha_{2m} X_2^* + \nu_m^{X_2^*} : m = \{1, \ldots, L^{X_2^*}\}$$

In joint estimation with SEM, the structural equations are expressed as below:

2.9.2.3.2 Structural equations

$$X_1^* = \Sigma_{k=1}^{K} \eta_{1k} X_k + \kappa_1 C + \tau_1$$

$$X_2^* = \Sigma_{k=1}^{K} \eta_{2k} X_k + \kappa_2 C + \tau_2$$

Where K represents the total number of observed covariates included in the model and C represents the latent class of VAS (IAC) the individual has been assigned at the end of latent class analysis (Weller, 2020). The individual is usually assigned the latent class to which they have the maximal posterior probability of belonging.

From the point of view of the agent the expected utility or value of participation is $E[Y_1|H]$ and not participating is $E[Y_0|H]$. The expected net value is

$$E[Y_1|H] - E[Y_0|H]$$

Then for agents who choose to participate based on maximum gain, the decision to participate is taken as

$$D = \begin{cases} 1, & \text{if } E[Y_1|H] - E[Y_0|H] \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

This is the generalized Roy model (Cunha et. al., 2005; Heckman, 2007).

Let ψ denote an individual belonging to the target population of at-risk youth denoted by Ψ. Then H_ψ represents the information set of the agent ψ. The agent evaluates participation in JC over non-participation (non-JC) using information H_ψ. Then the proportion of people who prefer participating in JC over non-participation in JC (non-JC) are given as:

$$P(D = 1|H_\psi) = P(E[Y_1|H_\psi] - E[Y_0|H_\psi] \geq 0)$$

So, the unconditional probability of participation in JC for each individual is obtained by integrating over the uncertainty inherent in their information set H_ψ. The unconditional probability is the probability of choosing JC given the two alternatives of JC and non-JC. It is given as

$$P_i(JC|JC, non-JC) = \int \mathbb{1}(E[Y_1|H_\psi] \geq E[Y_0|H_\psi])d\mu(H_\psi)$$

here, $\mu(\psi)$ is the distribution of ψ in the population (at-risk youth) whose preferences over outcomes are being studied.

2.9.2.3.3 Estimating choice probabilities - joint estimation

Given the above formulation of joint estimation, the conditional probability of participation is

$$P(D = 1|X, X^*; \beta, \theta_\epsilon)$$

But to get the unconditional probability $P(D = 1|X; \Theta)$ we have to integrate over X^*. Using the structural equations for X^* given above, we can get the density $\mathbb{f}(X^*|X; \eta, \kappa, \theta_\tau)$, where $\tau \sim distr(\theta_\tau)$. But X^* cannot be measured except through the indicator set I. So given the measurement equations above for the relationship between I and X^*, we can obtain the density $\mathbb{f}(I|\alpha, \theta_\nu)$, where $\nu \sim distr(\theta_\nu)$.

Let $i = 1, \ldots, N$ denote the index for individuals in the research sample. Under joint estimation and using these densities we can estimate the unconditional probability of participation in JC can be estimated as

$$P(D_i, I_i|X_i; \beta, \eta, \kappa, \alpha, \theta_\epsilon, \theta_\tau, \theta_\nu) = \int P(D_i|X_i, X_i^*; \beta, \theta_\epsilon) * \mathbb{f}(I_i|X^*, \alpha, \theta_\nu) * \mathbb{f}(X^*|X_i; \eta, \kappa, \theta_\tau) dX^*$$

Given the structural model for X^* we can substitute it into the equation above and get the unconditional choice probability (compliance score) of participation in JC:

$$\pi(\tilde{x}) = P(D_i, I_i|X_i; \beta, \eta, \kappa, \alpha, \theta_\epsilon, \theta_\tau, \theta_\nu) = \int\int P(D_i|X_i, X_i^*; \beta, \theta_\epsilon) * \mathbb{f}(I_i|X^*, \alpha, \theta_\nu) * \mathbb{f}(\tau|\theta_\tau) d\tau$$

Here $\tilde{x} = \{x, x^*\}$ denoted for ease of representation in later analysis.

2.9.2.4 Sequential estimation

But under sequential estimation, the economist's augmented set, $H_{ea} = H_e \cup H_a = (X, F)$. But as discussed earlier $F \neq \Gamma$. Therefore, including the estimated factor scores as choice determinants is prone to bias. The literature suggests the use of plausible values rather than factor scores (Wu, 2005). Plausible values are multiple imputations of the unobservable latent variables X^* for each individual. But this is not a widely adopted practice yet and therefore, the same has not been used in this analysis. It nevertheless offers a possible extension for future work.

2.9.2.4.1 Measurement equations

For STV:

$$I_m^{f1} = \alpha_{1m} f_1 + \nu_m^{f1} : m = \{1, \ldots, L^{f1}\}$$

For ES:

$$I_m^{f2} = \alpha_{2m} f_2 + \nu_m^{f2} : m = \{1, \ldots, L^{f2}\}$$

2.9.2.4.2 Structural equations

For STV:

$$f_1 = \Sigma_{k=1}^{K} \eta_{1k} X_k + \kappa_1 C + \tau_1$$

For ES:

$$f_2 = \Sigma_{k=1}^{K} \eta_{2k} X_k + \kappa_2 C + \tau_2$$

2.9.3 Compliance scores

2.9.3.1 Joint estimation compliance scores - from ICLV

Under general compliance behavior, the compliance score can be defined as

$$\pi(x, x^*) = \pi(\tilde{x}) = E[D = 1 | Z = 1, X = x, X^* = x^*] - E[D = 1 | Z = 0, X = x, X^* = x^*]$$

Since those in the control group did not get access to Job Corps, $E[D = 1 | Z = 0, X = x, X^* = x^*] = 0$. So, in this case, the compliance score is the same as the propensity score (compliance score, henceforth). If the control group members could have also participated in JC then propensity and compliance scores would be different. For this reason, I will continue using the term compliance score $(\pi(\tilde{x}))$.

$$\hat{\pi}(\tilde{x}) = P(D = 1|Z = 1, X = x, X^* = x^*)$$

The estimated compliance score model is used to estimate compliance scores for the control group members as well so that, $\exists\hat{\pi}_i(\tilde{x})\forall i \in \{1, \dots, N\}: 0 < \hat{\pi}(\tilde{x}) < 1$. There is a non-negative compliance score for every individual in the sample.

2.9.3.2 Sequential estimation compliance scores - Logit and Conditional logit models

Under general compliance behavior, the compliance score can be defined as

$$\pi(\tilde{x}) = \pi(x, f) = E[D = 1|Z = 1, X = x, F = f] - E[D = 1|Z = 0, X = x, F = f]$$

Since those in the control group did not get access to Job Corps, $E[D = 1|Z = 0, X = x, F = f] = 0$. So, in this case, the compliance score is the same as the propensity score (compliance score, henceforth). If the control group members could have also participated in JC then propensity and compliance scores would be different. For this reason, I will continue using the term compliance score $\left(\pi(x')\right)$.

$$\hat{\pi}(\tilde{x}) = P(D = 1|Z = 1, X = x, F = f)$$

The estimated compliance score model is used to estimate compliance scores for the control group members as well so that, $\exists\hat{\pi}_i(\tilde{x})\forall i \in \{1, \dots, N\}: 0 < \hat{\pi}(\tilde{x}) < 1$. There is a non-negative compliance score for every individual in the sample.

2.10 Estimating ATE

The obtained compliance scores can be used with inverse compliance score weighted estimator (ICSW) or weighted two stages least squares estimator of ATE (W-2SLS) (Aronow and Carnegie, 2013; Small and Tan, 2017). It identifies ATE by using compliance scores (strength-of-IV) as inverse weights on the SIV-WATE (Strength-of-IV weighted ATE) estimand (2SLS under stochastic compliance) (Small and Tan, 2017) where U denotes the sufficient set of common causes of $D \rightarrow Y$.

2.10.1 Inverse compliance score weighting (ICSW)

$$\hat{\Delta}_{ICSW} = \frac{\frac{\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}Z_iY_i\right)}{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}Z_i\right)\right)} - \frac{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}(1-Z_i)Y_i\right)\right)}{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}(1-Z_i)\right)\right)}}{\frac{\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}Z_iD_i\right)}{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}Z_i\right)\right)} - \frac{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}(1-Z_i)D_i\right)\right)}{\left(\left(\Sigma_{i=1}^{n}\widehat{w}_{\pi_i}(1-Z_i)\right)\right)}} : \widehat{w}_{\pi_i} = \frac{1}{\widehat{\pi}_i}$$

2.10.2 Weighted Two-stage least squares (W-2SLS)

$$\Delta_{2SLS} = \int E[Y_1 - Y_0 | U = u] w(u) dF(u)$$

$$w(u) = E[D = 1 | Z = 1, U = u] - E[D = 1 | Z = 0, U = u]$$

If, $U: H_{ea} = \{X, X^*\} = \{\tilde{X}\}$. Then $w(\tilde{x}) = \pi^{-1}(\tilde{x})$, such that:

$$\Delta_{W-2SLS}^{ATE} = \int E[Y_1 - Y_0 | \tilde{X} = \tilde{x}] dF(\tilde{X})$$

2.11 Conclusion

This chapter described an overview of the problem posed in my dissertation work. The conceptual model based on Situational Expectancy Value Theory (SETV) provides a representation how observable attributes and unobservable psychological constructs can predict the choice to participate in Job Corps. This chapter also explained that an econometric causal framework clarifies the expected utility maximizing behavior of those facing the binary choice problem of participation vs. non-participation in the Job Corps program. The primary approach to identifying the average treatment effect (ATE) in this context relies on choice probabilities to be used as inverse weights in appropriate weighting estimators (Aronow and Carnegie, 2013; Small and Tan, 2017). The conventional approach to incorporating latent variables for choice estimation requires the estimation of factor scores and then include them as predictors in the choice model. In chapters three and four I analyze the three important latent constructs that influence choice - vocational anticipatory socialization (VAS-IAC), situational task value or motivations to participate in Job Corps (STV), and expectations of success or expected benefits from participating in Job Corps (ES).

3. Latent Class Analysis

3.1 Introduction

3.1.1 Purpose of the study

Vocational anticipatory socialization (VAS) is the communicative process by which individuals intentionally and unintentionally receive socializing occupational messages from their environment that affect their career expectations (Aley and Levine, 2020; Powers and Myers, 2016). In NJCS, eligible participants sought information and guidance on expected Job Corps experiences from two main sources – close relationships such as parents, friends and relatives, and non-close relationships such as teachers, guidance counselors, probation officers, church leaders, mail, JC outreach and admissions (OA) staff etc. Based on VAS messages, their own self-concept, and available alternatives, individuals make a series of choices that determine, or at least affect, the direction of their careers (Aley and Levine, 2020).

In NJCS, VAS can be characterized by three dimensions – relationship with the VAS source, perceived importance of their guidance (agent's perception of the value of information), and the explicit level of encouragement from each source. The inherent uncertainty in VAS arises because for each individual the set of sources approached, the perceived support and explicit encouragement are not deterministic given their observed attributes. Therefore, latent class analysis is used to model the probability with which each eligible participant belongs to different classes or patterns of VAS. Since all these patterns are measured by categorical data, latent class analysis is a plausible method to represent VAS as a categorical latent construct. Each latent category will correspond to a distinct combination of different attribute levels of the three VAS dimensions. The messaging could also vary based on sociodemographic factors like race, gender, and socioeconomic status (Metheny & McWhirter, 2013; Tate et al., 2015).

3.1.2 Latent class analysis

LCA has been used to study a variety of issues and vulnerable populations, such as mental health among Black youth (Rose et al., 2017), adolescent perceptions of in-school discrimination (Byrd & Carter-Andrews, 2016), and young Malawian adults with or at-risk for HIV (Weller & Small, 2015). As with all research, the choice of the population in LCA studies needs to be theoretically justified. In this study, the population represents at-risk youth in the age group of 16-24 years in the United States, who are eligible to participate in the Job Corps (JC) program. The LCA studies the unobserved heterogeneity in how members of this population acquire information and seek guidance on joining JC from parents, relatives, friends, and other non-close relationships in their ecosystem (school, welfare institution etc.) For example, LCA has been used to identify latent classes based on youth's experience with vicarious and anticipated strain (Weller et al., 2013). Four classes of strain were identified and then linked to appropriate interventions. LCA is useful here because it can help improve information dissemination or outreach interventions by identifying subgroups of individuals who could benefit from a common intervention based on their shared characteristics.

3.2 Data

3.2.1 NJCS sample

The data was obtained from the National Job Corps Study (NJCS) with N = 10970 individuals who completed the baseline and endline at 48 months, and not enrolled in Job Corps anymore. The dataset contains sampling weights to control for sample design, survey, baseline and endline response (Schochet et. al., 2008). The final estimates would be weighted accordingly. In this sample, I further removed 194 observations corresponding to individuals who were randomly assigned to the control group but participated in the Job Corps program (before the 3-year embargo). This is done to homogenize the choice set for all members of the control group so that none of them had a chance to participate in the Job Corps program.

3.2.2 NJCS indicators for Information Acquisition Context (IAC)

Once the sample was selected, indicator variables were selected and used to define the hypothesized unobserved classes. Although we can use LCA as an exploratory statistical approach, theory should guide the choice of indicator variables. Studies have suggested that items should be selected that as a set covers the full range of the construct theorized to drive classification among individual cases in a population (Lubke & Luningham, 2017). Additionally, if there are "good" items that separate classes well, then the analysis would not need as many items (Collins & Wugalter, 1992).

3.2.2.1 Choosing the indicators

Having a strong theoretical rationale for using specific indicator variables makes the process of identifying the classes easier, helps with interpreting the results, and results in class solutions that have clearer application to practice. However, the selection of items that can effectively identify the subgroups that are hypothesized to exist in the population are often difficult to anticipate in applied modeling scenarios. Currently, no consensus exists on the number of indicator variables to include in a model, but generally more indicator variables lead to better results (Wurpts & Geiser, 2014; Weller et al., 2020). Studies have used as few as four indicator variables (Travis & CombsOrme, 2007), whereas other studies have used more than 20 indicators (Rosato & Baer, 2012).

3.2.2.2 Indicators for Information Acquisition Context (IAC)

I hypothesized that the IAC can be modeled as a latent categorical construct. Here each category will represent a latent class to which each sample member can belong. There can be multiple classes or categories representing IAC with each class describing a certain pattern of guidance received from different sources. This pattern is defined by questions that also act as indicators for IAC as a construct. Broadly they ask whether the sample member spoke to a source? If yes, was that information important in making the decision to join JC? If yes, did the source also provide additional encouragement to join JC? Most sample members seek multiple sources. Nearly 79% of the sample spoke to parents, 72% to friends and 44% to relatives. Among those who speak to each source, nearly 60% of the sample received important guidance and encouragement to join JC while only 40% (approx.) got the same from friends and relatives.

Table 3 Observed indicators of Vocational Anticipatory Socialization (VAS) by eligible participants of Job Corps

Type	Indicators	Values
TALK	**Parent** or guardian talked with youth about going to Job Corps	0-No, 1- Yes
IMP	Parent or guardian's advice was important	9-Did not talk; 0-No; 1 -Yes
ENCR	Parent or guardian encouraged youth to go to Job Corps	9- Did not talk; 99-Did not find advice important; 0-No; 1-Yes
TALK	**Other relatives** talked with youth about going to Job Corps	0-No, 1- Yes
IMP	Other relative's advice was important	9-Did not talk; 0-No; 1 -Yes
ENCR	Other relatives encouraged youth to go to Job Corps	9- Did not talk; 99-Did not find advice important; 0-No; 1-Yes
TALK	**Friends** talked with youth about going to Job Corps	0-No, 1- Yes
IMP	Friends' advice was important	9-Did not talk; 0-No; 1 -Yes
ENCR	Friends encouraged youth to go to Job Corps	9- Did not talk; 99-Did not find advice important; 0-No; 1-Yes

In this study, I consider parents, relatives and friends as important individual sources, rest are commonly categorized as others – church leaders, teachers, probation officers, school guidance counselor etc. Due to sparsity, I categorized all non-close relationships into the 'others' category. Among those individuals for whom parents are the most informative source, nearly 58% are 16-17 years old, 29% are 18-19 years old and 13% are 20-24 years old. When relatives are the most informative source the proportion is 47%, 30% and 22% respectively. The same for friends as source is 40%, 32% and 28% respectively. I find that across the age groups, friends and non-close relationships have similar likelihood of being the most informative sources about JC for youth while parents and relatives while important in middle adolescence, lose significance towards later adolescence. The same patterns hold good when we observe the distribution of first sources of JC information. Therefore, peers and non-close relationships can act as channels through which information about vocation choices is shared across social networks of adolescents and youth (Goza and Ryabov, 2009)

Table 4 Descriptive statistics of indicators of Vocational Anticipatory Socialization (VAS)

Characteristic	Overall, N= 10,779	16-17 yrs., N = 4,438	18-19 yrs., N = 3,399	20-24 yrs., N = 2,942
Did not speak to parent	2224 (21%)	401(9%)	771(23%)	1052(36%)
Spoke to parent	8528(79%)	4033(91%)	2618(77%)	1877(64%)
Did not speak to friend	2988(28%)	1166(26%)	936(28%)	886(30%)
Spoke to friend	7778 (72%)	3266(74%)	2459(72%)	2053(70%)
Did not speak to relative	4758 (44%)	1766 (40%)	1551 (46%)	1441 (49%)
Spoke to relative	6001 (56%)	2665 (60%)	1840 (54%)	1496 (51%)
Parental advice important	6894 (64%)	3382 (77%)	2069 (61%)	1443 (49%)
Parental advice not important	3813 (36%)	1031 (23%)	1303 (39%)	1479 (51%)
Friends' advice important	4794 (45%)	1981 (45%)	1522 (45%)	1291 (44%)

Table 4, continued

Friends' advice not important	5922 (55%)	2432 (55%)	1858 (55%)	1632 (56%)
Relatives' advice important	4666 (43%)	2115 (48%)	1414 (42%)	1137 (39%
Relatives' advice not important	6064 (57%)	2304 (52%)	1969 (58%)	1791 (61%)
Encouraged by parents	6466 (62%)	3182 (74%)	1919 (58%)	1365 (47%)
Not encouraged by parents	3993 (38%)	1121 (26%)	1363 (42%)	1509 (53%)
Encouraged by friends	4218 (40%)	1684 (39%)	1359 (41%)	1175 (41%)
Not encouraged by friends	6329 (60%)	2667 (61%)	1969 (59%)	1703 (59%)
Encouraged by relatives	4386 (41%)	1980 (45%)	1338 (40%)	1068 (37%)
Not encouraged by relatives	6223 (59%)	2381 (55%)	2014 (60%	1828 (63%)

3.2.3 Demographic predictors

The sample represents at-risk youth in the age group of 16-24 years in the United States eligible to participate in the Job Corps program. In this analysis sample (N=10779) 61% were from the treatment group and 39% from the control. In the whole sample, nearly 46% enrolled in Job Corps by the 48 months endline. Nearly 70% of the sample are in the age group 16-19 (middle adolescence) and 30% are 20-24 years (late adolescence). It has approximately 58% men and 80% of them have held a part-time or full-time job longer than two weeks. Nearly 65% of them held a job in the last year. Nearly 49% of them are Black, 26% are White and 17% are Hispanic. With a 24% missingness, nearly 66% percent of the sample has at least one parent who completed high school.

Table 5 Demographic descriptive statistics by age-group

Characteristic	16-17 yrs., N = 4,438	18-19 yrs., N = 3399	20-24 yrs., N = 2,942
Random assignment			
Assigned to control group	1774 (40%)	1312 (39%)	1118 (38%)
Assigned to program group	2664 (60%)	2087 (61%)	1824 (62%)
Gender			
Female	1708 (38%)	1491 (44%)	1375 (47%)
Male	2730 (62%)	1908 (56%)	1567 (53%)
Race			
White	1193 (27%)	905 (27%)	758 (26%)
Black	2257 (51%)	1620 (48%)	1396 (47%)
Hispanic	742 (17%)	615 (18%)	525 (18%)
Other races	246 (5.5%)	259 (7.6%)	263 (8.9%)
Prior HS/GED credential	126 (2.8%)	937 (28%)	1481 (51%)
Missing	3	9	45

3.2.4 Missing data

To deal with missing data I used Full Information Maximum Likelihood (FIML) over multiple imputation. This is because both FIML and MI have similar results asymptotically when missingness is not severe. Probably the most pragmatic missing data estimation approach for structural equation modeling is full information maximum likelihood (FIML), which has been shown to produce unbiased parameter estimates and standard errors under MAR and MCAR (Enders & Bandalos, 2001). FIML, sometimes called "direct maximum likelihood," "raw maximum likelihood" or just "ML," is currently available in all major SEM packages. FIML requires that missing values to be at least MAR (i.e., either MAR or MCAR are ok). The process works by estimating a likelihood function for each individual based on the variables that are present so that all the available data are used.

3.3 Analytical procedure

3.3.1 Model

The three latent constructs of interest are:

- latent classes of Vocational Anticipatory Socialization (Powers and Myers, 2016) denoted by C. In the context of NJCS, the VAS construct is interchangeably referred to as VAS or Information Acquisition Context (IAC)

Indicator set for latent class is I^C. The total number of indicators is denoted respectively by L^C. For example, indicator $I_l^C : l = 1, \ldots, L^C$ denotes the l^{th} indicator or item for latent class C and total number of indicators is L^C.

Measurement equations:

$$I_m^C = \alpha_{0m} C + \epsilon_m^C : m = \{1, \ldots, L^C\}$$

Structural equation:

$$C = \Sigma_{k=1}^{K} \lambda_{0k} X_k + \omega_0$$

When the model above is estimated, *the most likely class variable* S is created using the latent class posterior distribution obtained during the LCA estimation, i.e., for each observation, S is set to be the class c for which $P(C = c|I^C)$ is the largest, where I^C represents the latent class indicators (Asparouhov and Muthen, 2013).

We then compute the classification uncertainty rate for S, as follows

$$p_{c_1,c_2} = P(C = c_2|S = c_1) = \frac{1}{N_{C_1}} \Sigma_{S_i=c_1} P(C_i = c_2|I^C)$$

where N_{c_1} is the number of observations classified in class c_1 by the most likely class variable S, S_i is the most likely class variable for the i^{th} observation, C_i is the true latent class variable for the i^{th} observation and I^C represents the class indicator variables for the i^{th} observation. The probability $P(C_i = c_2|I^C)$ is then computed from the estimated LCA model.

3.3.2 Model specification and fit indices, and diagnostic criterion

The standard procedure for conducting LCA is to conduct a sequence of models, starting with a one-class model and then specifying models with one additional class at a time. The models are compared based on statistical and substantive criteria. I ran models with one additional class at a time until the best model was identified. In this analysis, I estimated models with up to ten latent classes.

Concerning parameter restrictions, I started the analysis with the local independence model since this is the traditional basis of LCA, and potentially consider cross class equality constraints on the indicator variances. Any other restrictions were made on substantive grounds. Attention was also paid to the default restrictions implemented by specific software packages. For example, Mplus by default imposes local independence and homogeneity across classes.

3.3.2.1 Identifying a class model solution

Typically, model quality improves with additional classes until an optimal solution is found, and then model quality begins to deteriorate. Although comparing models based on criteria sounds uncomplicated, in practice the process of choosing the best model is often not straightforward. Moreover, it is important to include various combinations of indicator variables prior to finding a final class model.

3.3.2.2 Model fit indices

The most reported is the Bayesian Information Criterion (BIC; Killian et al., 2019). Some researchers consider it the most reliable indicator of model fit (Nylund et al., 2007; Vermunt, 2002). The BIC rewards parsimony in models and can be used to compare competing LCA solutions. Lower BICs indicate better fit. Other information criterion (IC) can also be examined, including the Akaike information criterion (AIC), sample-size adjusted Bayesian information criterion (SABIC), and consistent Akaike information criterion (CAIC). Lower ICs also indicate better fit. Nylund-Gibson and Choi (2007) also introduce the concept of using an elbow plot of fit statistics to examine model fit. With this approach, I also plot a fit statistic and identify where the fit visually changes. Other fit statistics can also be used to select a final class, such as likelihood tests (i.e., Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (Lo et al., 2001; Vuong, 1989) and the bootstrapped likelihood ratio test (McLachlan & Peel, 2000). These statistics provide a p value, which indicates if one model is statistically better than another (Nylund et al., 2007).

In addition to evaluating fit, classification diagnostics was also reviewed (Masyn, 2013). Although diagnostic statistics are not used to select the final class model, they are important for consideration. It should be noted that historically some of the diagnostics were used to select a final model; however, suggestions on their use have recently changed (Nylund-Gibson & Choi, 2018).

3.3.2.3 When model indices do not have a global minimum

In practice, it is not uncommon that the BIC continues to decrease for each additional class added (e.g., there is not a global minimum) and in these instances these plots can be particularly useful to inspect for an "elbow" of point of "diminishing returns" in model fit (e.g., small decreases in the IC for each additional latent class), akin to how one interprets a scree plot in exploratory factor analysis. Additionally, when the available ICs, like the BIC, fail to reach a minimum, some have suggested that this may be an indication that the particular mixture model may not be correctly specified and that other models may be more appropriate (Liu et. al., 2023). This may be another type of mixture model (e.g., factor mixture model), one with correlated disturbances (Asparouhov & Muthén, 2015), or perhaps not a mixture model at all, although more research is needed in this area. Taking together these considerations, as well as results of auxiliary variable analysis, a final model was selected.

3.3.3 Estimation

I used Maximum Likelihood estimation with robust standard errors (MLR in Mplus specification). For mixture models, there is a known sensitivity of the likelihood function to converge on a local, instead of a global solution (McLachlan & Peel, 2000). To circumvent this problem, the suggestion is to use a set of random start values, estimate the model many times, and see if across the set of random start values, there is convergence on a similar solution (Berlin, Williams, & Parra, 2014; Masyn, 2013). This process is automated in some software packages. In Mplus, for example, researchers can specify how many random starts to consider. Bayesian estimation methods can be useful when modeling assumption are not met (e.g., conditional independence). For example, by using noninformative priors, researchers can specify small within-class item correlations that better approximate the within-class dependency without significantly reshaping the emergent classes (Asparouhov & Muthén, 2011). In other mixture modeling contexts, simulation studies have shown that if accurate and informative priors are available, including them in the model estimation process can reduce parameter bias and enhance mixture class recovery (Depaoli, 2013).

3.3.3.1 One-step vs. three-step approaches

An evolving topic in the LCA literature is including covariates in models. It is often of substantive interest to identify and examine the antecedents and consequences of latent class membership. Covariates and distal outcomes, often called auxiliary variables, provide a context for understanding more about the emergent latent classes and the people who comprise them. Covariates can be used to explore whether class prevalence is equivalent across levels of a predictor of class membership (e.g., treatment vs. no treatment). Distal outcomes can be used to examine whether the latent classes display statistically significant mean-level differences in the selected distal outcome variables (e.g., mental health). Including covariates in LCA allows researchers to answer questions such as “Does the composition of the classes differ by socio-demographic characteristics?”

3.3.3.1.1 One-step approach or joint estimation

Ideally, the joint estimation of the latent class measurement model and the association among the latent class variable and auxiliary variables would be conducted in a 1-step method as commonly done in a general SEM context. Previously, researchers would include covariates in the same model as the model used to identify the class solution (Vermunt, 2010). This one-step approach, however, can result in flawed, miss-specified models (Nylund-Gibson & Masyn, 2016) because including an auxiliary variable can and may unintentionally influence the formation of the latent class variable, both in relative class size and type (Asparouhov & Muthén, 2014; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014; Vermunt, 2010). Specifically, the joint estimation of the measurement model and auxiliary relations can lead to vastly different latent class solutions, which has led to the recent research activity around three-step methods which circumvent these issues. Recent simulation studies have recommended that we enumerate classes prior to estimating auxiliary variable relations (Nylund-Gibson & Masyn, 2016).

3.3.3.1.2 Improvements over one-step approach

The one-step approach has been replaced with a number of newer approaches. Currently, studies have shown to employ either a new three-step approach (Asparouhov & Muthén, 2014; B. O. Muthén & Muthén, 2000; Vermunt, 2002) or the Bolck et al.'s (2004) approach. The three-step approach requires identification of class size (class enumeration), assigning a latent class to each individual in the sample. The third step is to regress the assigned latent class membership on covariates with correction. The correction is to adjust for the uncertainty of latent class membership by treating the posterior cross-classification probability as measurement errors

(Vermunt, 2010). The nuances of including covariates in LCA models vary by statistical software (e.g., Asparouhov & Muthén 2014; Nylund-Gibson & Choi, 2018; Nylund-Gibson & Masyn, 2016; Vermunt & Magidson, 2016).

I used Mplus software for estimation. This is because it automates the three step process by internally fixing the measurement parameters in the model with covariates with those obtained in the model without covariates. I followed the Vermunt (2010) bias-adjusted approach and implemented the analysis in the MPlus software using their inbuilt R3STEP routine for 3LCA. Full Information Maximum Likelihood estimation approach was adopted to deal with missing data issue. If we wanted to instead implement multiple imputations, we will have to implement the 3-step method manually as demonstrated by Asparuhov (2014).

3.3.4 Latent class enumeration

The current recommendation is to separate the class enumeration step from any subsequent structural analyses, wherein classes are enumerated solely with the chosen latent class indicators measuring the substantive domain of interest (Nylund-Gibson & Masyn, 2016). Once a final class solution is determined, the 3-step or the BCH method can be used to estimate covariate and/or distal outcome relations. In these approaches the measurement parameters of the latent classes are held fixed while accounting for classification error, and then auxiliary variables are subsequently included and their relation to the latent class variable is estimated. Nylund-Gibson, Grimm, Quirk, and Furlong (2014) present a detailed discussion about using the three-step method. For more guidance on the BCH method as implemented in Mplus, see Asparouhov and Muthén (2014). Both articles include Mplus syntax for using these methods with LCA and advanced mixture models.

The goal is to yield a solution that balances model parsimony and fit, and that delivers substantively interpretable classes. For this purpose, one estimates a series of models from 1 to K latent classes and compares them on indices of relative model fit and classification diagnostics. The final model was selected based on (a) multiple fit statistics should be used (or at least reported); (b) the Bayesian information criterion (BIC) may be the most reliable fit statistic and should routinely be reported (Nylund et al., 2007; Vermunt, 2002); and (c) theoretical interpretability should be considered in choosing a solution (B. O. Muthén & Muthén, 2000; Nylund et al., 2007; Shanahan et al., 2013; Stringaris et al., 2013).

I began the modeling process by estimating a 1-class LCA model, which is a model that is simply estimating the observed indicator endorsement probability for the item set (the observed item proportions in the sample statistics). This 1-class model serves as a comparative baseline for models with more than one class. Then, I increased the number (k) of classes by one, examining whether the addition of each class results in conceptually and statistically superior solutions. Studies suggest stopping estimating additional classes when empirical under-identification (e.g., overparameterization) or convergence issues are encountered (which is generally indicated by error messages from the software being used) (Weller, 2020). Once all the LCA models are fitted, I had collected fit information from each one and summarized them in a single table for ease of evaluation.

Table 6 Enumeration of latent classes with approximate proportion of sample in each class

Class	**Count**	**Proportion**
1	1216.1807	0.11286
2	581.7162	0.05398
3	2841.2247	0.26366
4	1415.8410	0.13139
5	4721.0375	0.43811

Results from the latent class analysis (LCA) suggested classes of information acquisition context (IAC). These classes are characterized by the information sources and the nature of the interactions. Table 1 presents LCA results for different class models. As discussed earlier that the best model fit for a class solution usually corresponds with the lowest or the highest values of a model fit indices. For example, we know that as model fit increases, BIC value decreases. So, we choose the class solution whose BIC is the lowest.

Table 7 Model performance criteria for latent class models with class sizes 1 - 10

Title	LL	AICC	aBIC	CAIC	VLMR _2LL	AWE	BF
Class 1	-61997.7	124013.5	124050.4	124088		124092.5	
Class 2	-50113.1	100264.2	100342.1	100421.5	23769.4	100431	1183.8
Class 3	-44559.8	89177.7	89296.7	89417.8	11106.5	89432.3	550.7
Class 4	-41313.4	82705.1	82865	83027.9	6492.8	83047.4	320
Class 5	**-38856.7**	**77811.8**	**78012.6**	**78217.3**	**4913.5**	**78241.8**	**241**
Class 6	-36399.3	72917.2	73158.9	73405.3	4910.7	73434.8	241.1
Class 7	-34606.2	69351.3	69633.8	69922.1	3586.1	69956.6	174.7
Class 8	-33782.3	67723.9	68047.1	68377.2	1647.7	68416.7	77.7
Class 9	-33647.5	67474.4	67838.5	68210.3	269.7	68254.8	8.8
Class 10	-33589.9	67379.7	67784.5	68198.1	115.1	68247.6	1.1

Sometimes, as class size increases, the BIC keeps decreasing without ever increasing again. In such cases, it is not obvious what is the lowest BIC class solution. For such scenarios, it has been suggested to choose the class solution at which the model index value acts as an inflection point – a point roughly at which the change in model index value is marginal with each unit increase in class size. As shown in the table, I find class size 5 to be such an inflection point in the LCA.

3.3.5 Evaluating class differentiation - diagnostic criteria

After a solution is selected and interpreted, there are several guidelines for evaluating how well the classes are differentiated (Masyn, 2013).

3.3.5.1 Entropy

Entropy is another diagnostic statistic (Wang et al., 2017). It indicates how accurately the model defines classes. In general, an entropy value close to 1 is ideal (Celeux & Soromenho, 1996) and above .8 is acceptable. There is no agreed upon cutoff criterion for entropy (B. O. Muthén, 2008);

It is important to note that reporting entropy might not be enough as it may not be prudent to rely on the value to determine the final class solution.

3.3.5.2 Item probability plot

In choosing class solutions in LCA it is also recommended to check the substantive interpretability of the classes. The high entropy also indicates good class separation so that each class can plausibly correspond to a distinct of profile of information acquisition. Although LCA is an exploratory technique, substantive theory and model utility (including the parsimony principle) should contextualize the interpretation of fit indices and the selection of the final model (Masyn, 2013), as with all latent variable models. Indeed, Morgan (2015) advises that model selection will be facilitated to the extent that researchers can anticipate the prevalence of theoretically expected classes and their degree of differentiation. As incongruent information among fit indices is common, it is crucial to gauge the conceptual meaningfulness and plausibility of each class solution when interpreting and labeling the classes (B. O. Muthén, 2003). One approach for doing so is to visually inspect the item probability plot and to examine the qualitative differences among the classes.

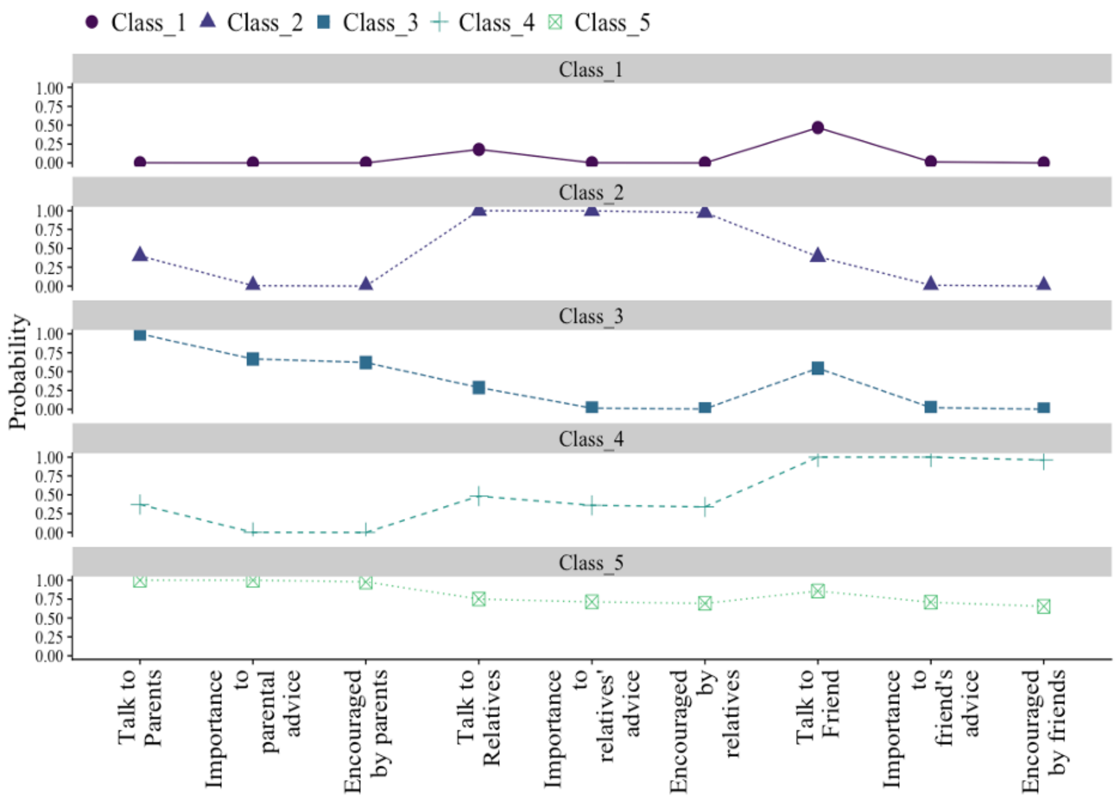

Figure 5 Item probability plot of estimated probability of responding 'yes'

Figure 5 above shows a graphical representation of the five-class model. The x-axis lists the indicators of information acquisition context. The y-axis provides the average probability of class membership for each of the indicators; as the number approaches 1, the probability of class membership is higher. All indicator variables were coded with higher scores for positive aspect of the interaction; therefore, probabilities closer to 1 indicates a richer information acquisition process.

3.3.5.3 Average posterior probability

Average posterior probabilities (AvePP) provide information about how well a given model classifies individuals into their most likely class. It is the average probability of the class model accurately predicting class membership for individuals (B. O. Muthén & Muthén, 2000). The average latent posterior probabilities are presented in a matrix with diagonals representing the average probability of a person being assigned to a class given his or her scores on the indicator variables used to create the classes. Higher diagonal values (i.e., closer to 1.0) are desirable. Off-diagonal elements in the posterior probability matrix contain probabilities of cases that belong in one class being assigned to another class in the current solution. Lower values off the diagonal (i.e., closer to 0) are desirable.

Table 8 Posterior probabilities of class classifications

Class	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Class 1	**0.995**	0.003	0.000	0.003	0.000
Class 2	0.001	**0.991**	0.004	0.003	0.000
Class 3	0.001	0.001	**0.990**	0.000	0.007
Class 4	0.003	0.001	0.007	**0.989**	0.000
Class 5	0.000	0.000	0.014	0.001	**0.985**

Individuals' AvePP values are reported for their most likely class assigned, where values > .70 indicate well-separated classes (Nagin, 2005). Some researchers using LCA use a .80 cutoff for acceptable diagonal probabilities (Weden & Zabin, 2005). Others suggest a cutoff value of greater than .90 (B. O. Muthén & Muthén, 2000). But if other criteria are met and the model is theoretically supported, probabilities between .80 and .90 are acceptable. Although meeting the .90 criterion for all average latent class posterior probabilities is not required when other criteria are met, values less than .80 should be considered unacceptable.

3.3.6 Interpretation of classes

3.3.6.1 Class size

There are no existing guidelines on determining class size (Muthén, personal communication, May 4, 2011). Previously, LCA scholars have contended that researchers should not have class sizes with fewer than 50 cases (B. O. Muthén & Muthén, 2000) and classes should not contain less than 5% of the sample (Shanahan et al., 2013). However, these suggestions have been relaxed and a number of publications have included class sizes smaller than 5% or 50 cases (e.g., O'Donnell et al., 2017). Finally, solutions with several small classes (say ≤ 5%) may be indicative that too many classes have been extracted (Nylund et al., 2007). Though such small classes can be of substantive interest, it should be checked critically whether they have a distinct and interpretable profile.

Based on the analysis, the largest class (44%) is class 5 representing those who access all close relationships as potential information sources for JC. The smallest class (5%) is class 2 representing those who access friends (high probability) and parents (moderate probability) for information. Classes 1 and 4 representing those who access no close relationship and those who access only relatives, respectively each comprise of 11% and 13% respectively. Nearly a quarter (26%) belong to class representing those for whom parents are most likely to be accessed as a source of information for JC. The important issues to consider when deciding if a class size is too small is whether the model fit statistics support the selected model, and whether the small class makes conceptual sense.

3.3.6.2 Class interpretation

In general, no solution should be retained that is not well interpretable, regardless of model fit. The interpretation process in LPA/LCA is like traditional cluster analysis or exploratory factor analysis. For this purpose, one inspects the class-specific mean/probability profiles across the indicators and differences in these profiles across classes. These latent classes characterize how different sub-populations might be using unique ways to acquire information about Job Corps.

Table 9 Factor loading of indicator items on corresponding latent classes

Indicators	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Talk to parents	0.482	**0.754**	**1.000**	0.357	**1.000**
Importance to parental advice	0.008	**0.619**	**1.000**	0.000	**1.000**
Encouraged by parents	0.000	**0.596**	**0.972**	0.000	**0.979**
Talk to relatives	0.295	0.165	**0.567**	**1.000**	**1.000**
Importance to relatives' advice	0.012	0.007	0.451	**1.000**	**1.000**
Encouraged by relatives	0.001	0.000	0.425	**0.988**	**0.971**
Talk to friend	**0.531**	**1.000**	0.489	**0.691**	**1.000**
Importance to friend's advice	0.000	**1.000**	0.000	0.470	**1.000**
Encouraged by friends	0.000	**0.920**	0.000	0.431	**0.900**

Class homogeneity reflects how similar people are to each other with respect to their item responses in each class, where conditional item probabilities > .70 and < .30 indicate high homogeneity. In this regard, I find that our identified classes are plausibly homogenous with respect to the sub-population it represents.

3.3.7 Characteristics of IAC that differentiate the latent classes

Based on the tabulated results from above, I make the following interpretations for the profiles of IAC:

1. Class 1 – No close relationships: This group seems most vulnerable to lack of information because the only source sought with moderate probability seems to be friends and even their advice is not deemed important.
2. Class 2 - Friends: This latent group has individuals who are most likely to talk to parents and friends but more importance to friends; find their advice important and receive encouragement to participate in Job Corps.
3. Class 3 - Parents: This group seeks guidance only from parents and values their advice as important in addition to receiving encouragement from them to join the Job Corps program.
4. Class 4 - Relatives: This latent group has individuals who are most likely to talk to relatives; find their advice important and receive encouragement to participate in Job Corps.
5. Class 5 - All sources: This latent group has individuals who are most likely to talk to all close relations; find their advice important and receive encouragement to participate in Job Corps.

As you can see, class 3 represents those who talk to parents mainly to obtain information about JC. Since it approximates or represents the ideal at-risk youth seeking information from their closest relationship with least information acquisition cost (rational thinking under complete information). So, I use class 3 as the reference class in the discussion. More insights can be obtained by studying the predictors of class membership. I also tested whether sociodemographic characteristics and contextual factors such as first source of information about JC and the source that provided the most information, predict class memberships.

3.3.8 Descriptive differences between latent classes of VAS in Job Corps

I used the 3-step approach (3LCA) to model and estimate the latent class analysis with covariates. I follow the Vermunt (2010) bias-adjusted approach and implement the analysis in the MPlus software using their inbuilt R3STEP routine for 3LCA. Full Information Maximum Likelihood estimation approach was adopted to deal with missing data issue. If we wanted to instead implement, multiple imputation we will have to implement the 3-step method manually as demonstrated by Asparuhov and Muthen (2014). The table below provides the estimated coefficients (in logit and probability scale) for all the covariates included in the model as predictors of latent classes. For example, let us look at how covariates predict the membership in each class relative to our reference group – class 3 – that represents seeking information about JC from parents in comparison to other close and non-close relationships.

Table 10 Impact of characteristics of information acquisition on latent class membership

Variable	Class 1	Class 2	Class 4	Class 5
Knew JC alumni	.0079*(0.152) (OR: 1.082)	.287*(.205) (OR: 1.332)	.423(.154) (OR: 1.527)	.575(.107) (OR:1.778)
First source- Par vs. Oth	-1.360(.306) (OR: 0.257)	-1.269(.504) (OR: 0.281)	-0.869(.317) (OR: .419)	0.011*(.163) (OR: 1.011)
First source- Rel vs. Oth	-.094*(0.214) (OR: 0.910)	0.756(0.260) (OR: 2.130)	-0.039*(.223) (OR: .962)	.321(.150) (OR: 1.378)
First source- Friend vs. Oth	-.194*(.173) (OR:.824)	-.270*(.250) (OR: .764)	.566(.163) (OR: 1.761)	.203*(.126) (OR: 1.224)
Most info- Par vs Oth	-.726(.364) (OR: .484)	-.980*(.648) (OR: .375)	-1.196(.476) (OR: .302)	-.083* (.189) (OR:.920)
Most info- Rel vs Oth	-.390*(.244) (OR: .677)	.418*(.260) (OR:1.519)	.103*(.234) (OR: 1.109)	.253*(.157) (OR: 1.288)
Most info- Friends vs Oth	.053*(.173) (OR: 1.054)	.082*(.234) (OR: 1.086)	.549(.153) (OR: 1.731)	.255(.122) (OR: 1.290)
Male	-.240*(.133) (OR: .787)	-.404(.172) (OR: .668)	-.425(.128) (OR: .654)	-.165*(.093) (OR: .848)
Black	.551 (.277) (OR: 1.735)	.226*(.339) (OR: 1.254)	.009*(.243) (OR: 1.010)	.157*(.175) (OR: 1.170)
White	.333*(.29) (OR: 1.395)	.319*(.364) (OR: 1.376)	.417*(.251) (OR: 1.517)	.017*(.187) (OR: 1.017)
Hispanic	-.151*(.308) (OR: .859)	-.019*(.373) (OR: .981)	-.471*(.278) (OR: .625)	.012*(.191) (OR: 1.012)
Prior HS/GED	-.150*(.145) (OR: .861)	-.698(.213) (OR: .498)	-.194*(.139) (OR: .824)	-.286(.101) (OR: .751)
Age group 16-17 vs 20-24	-.016*(.015) (OR: .984)	-.007*(.017) (OR: .993)	-.015*(.012) (OR: .985)	-.008*(.009) (OR: .992)
Age group 18-19 vs 20-24	.000*(.000) (OR: 1.000)	.000*(.000) (OR: 1.000)	.000*(.000) (OR: 1.000)	.000*(.000) (OR: 1.000)
Worked previous year	-.042*(.144) (OR: .958)	-.096*(.187) (OR: .908)	.095*(.139) (OR: 1.099)	-.04*(.102) (OR: .960)

Class 3 (only parents; reference group): In class 3 the members seek information about JC from only parents among the close relationships. They also find information from each close relationship to be important and receive encouragement from each source to join JC.

Class 1 (no close relationships): Compared to those who only approach parents for guidance on JC (class 3), members of class 1 are more likely to be black whose first source of JC and most informative source of JC are more likely to be non-close relationships than parents. There is no difference between class 3 and class 1 by age, gender or prior work experience.

Class 2 (Friends and parents): Compared to class 3, members of this class are more likely to hear about JC from relatives for the first time even though they seem more likely to take guidance from friends and parents, in the decreasing order of importance. They are also more likely to be females without a prior secondary school degree (HS or GED). There is no difference between class 3 and class 2 by age or gender.

Class 4 (Relatives mostly): Compared to class 3, members of this class are most likely to consider relatives as their first and most important source of JC. They are likely to know a JC alumna. They are also less likely to have parents as the first or most informative source in comparison to non-close relationships. They are also more likely to be black than other races in reference to class 3.

Class 5 (all close relationships): Compared to class 3, members of this class are more likely to consider relatives as their first source of JC information even though they take guidance from all the close relationships. Members of class 5 are also more likely to know a JC alumna and less likely to have a secondary school degree. There is no difference between class 3 and class 5 by gender, age, or prior work experience.

3.4 Conclusion

3.4.1 Major findings

3.4.1.1 Variation among latent classes of IAC?

The latent classes differ primarily based on the sources an individual speaks with. Class 1 comprises of individuals who are more likely to approach non-close relationships for VAS than close relationships. Two classes comprised of individuals with two important sources. Friends and parents were prominent sources for Class 2 while all close relationships were important VAS sources for Class 5. Two classes comprised of individuals with only one prominent VAS source. Parents only for Class 3 and relatives only for Class 4.

3.4.1.2 Demographic composition of latent classes

In comparison to a reference group – class 3 - significant predictors of latent class membership for other classes included: knowing a JC alumna, first source of JC information, most informative source of JC information, race, age and previous year working experience.

Compared to reference class 3, all the remaining class members are likely to be older and less likely to have worked in the last year, except class 4. Class 4 comprises of individuals for whom relatives are the primary VAS source. This is plausible compared to class 3, those in class 4 are more likely to consider relatives as both the first source of information about JC, and also the most informative source. Class 4 is more likely to be white than any other race. Those who speak to all close relationships (Class 5) and those who do not speak to any close relationship (class 1), are both less likely to be male than the reference group. In addition, class 1 members are also less likely to have a prior high school credential than class 3.

3.4.1.3 Variation among latent classes in Job Corps enrollement

The latent class composition between those who enrolled in JC and did not enroll in JC, varies from 9 percent to 32 percent. Within each latent class, proportion of unenrolled ranged from 52 percent to 59 percent while the enrolled ranged from 40 percent to 48 percent.

3.4.2 Discussion

3.4.2.1 Support for original hypothesis

Earlier I hypothesized the VAS to be a latent categorical construct where each category represents a unique pattern of information acquisition about JC. Using latent class analysis, five such latent classes of IAC in NJCS context were identified. It was also hypothesized that observed individual attributes could predict latent class memberships. Results analyzed earlier show multiple individual attributes as significant predictors of latent class membership. I also found that the latent class compositions change when include and not include predictors. Literature suggests that in such cases there could be direct effect of attributes on the measurement indicators. Therefore, the class composition with inclusion of covariates (3-step approach) is considered for all secondary analysis.

3.4.2.2 Implications for understanding youth behavior

This study shows that with the availability of appropriate data we can model the intrinsic uncertainty in vocational information acquisition. Understanding the structural heterogeneity in information acquisition among individuals can help in including such factors in the information set of an analyst. Modeling of VAS was also required for subsequent latent variable modeling since messaging can influence the formation of expectations and motivations. Collecting data to fully characterize VAS in future experiments can help us to systematically study the role of a youth's information ecosystem on relevant choices in the lifetime of an intervention. It can also help us understand how the content of the messages can influence the formation of various non-cognitive factors that mediate the impact of the intervention on the outcomes of interest.

3.4.3 Methodological considerations

In the study of adolescent decision-making often psychological and behavioral constructs of interest are multidimensional. For example, both depression and anxiety are now considered to be multidimensional. Victimization experiences are also considered to be multidimensional. Latent constructs of importance in theories of motivation such as self-efficacy are also multidimensional. Very often available proxy measures for such constructs might not identify the exact dimensional structure of the underlying latent constructs. In such cases, patterns of responses on the proxy measures can be used to define categories or classes of the underlying construct. Latent class analysis is a powerful tool to incorporate such behavioral constructs in any secondary quantitative analysis. In this study, I used LCA to characterize patterns of socialization to acquire vocational information on Job Corps experiences. Since individuals inherently need not adhere to one particular pattern, the class memberships are probabilistic. Therefore, LCA provides a natural framework to model stochastic latent behaviors that can be meaningfully categorized.

4. Latent variable analysis

4.1 Introduction

4.1.1 Purpose of the study

In the SEVT framework, VET choice is motivated by the subjective value of participating in Job Corps. For a typical Job Corps applicant, I hypothesized that this motivation derives from the subjective value of Job Corps in aiding vocational identity development processes. Higgins (2007) provides five sources of such motivation discussed below. Despite the categorical distinction, these causes seem to interact depending upon the domain of application. For example, in the case of VET choice I explain these overlaps using NJCS. These five sources justify the choice of various items in NJCS data to represent the subjective value (motivation) of Job Corps to at-risk youth. What would at-risk youth subjectively value about participating in Job Corps?

4.1.2 Literature review

4.1.2.1 Subjective task value (STV)

VET choice is motivated by the subjective value of participating in Job Corps. For a typical Job Corps applicant, I hypothesize that this motivation derives from the subjective value of Job Corps in aiding vocational identity development processes. Higgins (2007) provides five sources of such motivation, where the last two sources are more relevant for adolescents. Despite the categorical distinction, these causes seem to interact depending upon the domain of application. For example, in the case of VET choice I explain these overlaps using NJCS. These five sources justify the choice of various items in NJCS data to represent the subjective value (motivation) of Job Corps to at-risk youth. What would at-risk youth subjectively value about participating in Job Corps?

The *first source* is 'need satisfaction', referring to biological needs satisfied by the VET choice. At-risk youth on average are exposed to multiple adverse life events. Exposure to such events increases the allostatic load or toxic stress levels in the body of the individual. This load manifests as both internalizing and externalizing mental health symptoms (Romeo, 2013; McEwen and McEwen, 2017). VET would be a desired choice if it helps in alleviating such toxic stress exposure. Since most incidence of violent crimes involving youth (perpetration and victimization) happen around home and community, moving away from home and community from toxic stress levels can be a strong motivation (Sabri et. al., 2013).

The *second source* of motivation is shared beliefs on what is desirable. For youth, a desirable transition to adulthood involves developing necessary vocational skills for long term job and life satisfaction (Hirschi, 2009). For at-risk youth job training programs offer a healthy pathway for this transition by helping them improve their vocational skills (DeLuca et. al., 2014; Choi et. al., 2019). Therefore, lack of necessary resources in the youth's current home and community environments for vocational development can act as strong motivation for choosing VET (Pratt and Turonovic, 2015).

The *third source* of value is derived from the relation of ones' current actual self to either desired or undesired end states. Discrepancies between where one is and where one thinks one should be (the ideal or ought self) are also crucial; when actual and ought selves are closer to congruence, then the individual is better off psychologically. Thus, activities that help promote congruence between the actual and ideal self should have more value to the individual (Husman and Lens, 2010; Jiang, 2015). In NJCS, youth who value self-esteem and self-control may have an "ideal self" with respect to those qualities. Activities that help them attain aspects of this ideal self will be perceived as valuable to these individuals. VET helps in this process because there is a causal impact of competency on self-efficacy. As the training increases one's skill level in a job trade, one's core self-evaluation improves resulting in greater self-esteem. Due to allostatic load from chronic stress exposure, at-risk you have heightened emotional sensitivity which often is disadvantageous in professional settings since lack of self-regulation at work results interpersonal conflicts. This results in negative peer relationships at work which in turn is a barrier to vocational identity development by reducing social supports (Hlado et. al., 2019). Therefore, an ideal self in a vocational sense would have greater self-control. Therefore, self-control and self-esteem are a component of the subjective value of Job Corps participation due to their impact on vocational identity development towards a subjective perception of the ideal self.

The fourth source of value arises when an individual pursues an activity out of their own volition. In the case of at-risk youth, this seems to be unlikely in NJCS. While this might be true technically, in the case of at-risk youth, enrollment in Job Corps often resulted because of the need to get away from negative life circumstances in their ecosystem and develop self-efficacy skills to deal with adversities (McDonal et. al., 2011; Egondi et. al., 2013; Wood-Jaeger et. al., 2020). For Some examples are, domestic violence, peer violence, violent crime threat, drug related problems, lack of opportunities etc. Such reasons motivated individuals to join the program and therefore, the fourth source of value from Higgins (2007) does not seem plausible in the case of NJCS.

The fifth source is the value from one's experiences. How might the life experiences of an at-risk youth motivate them to join Job Corps? As explained earlier, at-risk youth are exposed to multiple risk factors. Such complex risk exposure is correlated with incidence of multiple adverse childhood experiences (Metzler et. al., 2017). Exposure to such experiences is also known to be detrimental for college success (Hinojosa et. al., 2018). Low high school academic engagement is also prevalent among adolescents exposed to adverse childhood experiences. Low academic engagement in high school results in lower academic performance and therefore lower college aspirations.

Adverse experiences in the childhood can impact multiple developmental domains including how youth evaluate themselves (core self-evaluation). Therefore, it is desirable for an at-risk youth to improve their core self-evaluation through VET. This is conceptualized in an EVT construct called future orientation. It has been defined as "a self-produced personality organization achieved by integrating the self in time and social settings (Seginer, 2009)." The power of future orientation to influence adolescent behavior is based on expectancy-value theory, which posits that individuals modify current behavior based on their judgment of future outcomes (Wigfield & Eccles, 2000) and specifically: how much one values an outcome (DiClemente et al., 2009), and the likelihood of the outcome occurring (Fischhoff, 2008). Literature shows that vocational choices are often determined by factors related to opportunity, environment, and personality (Borchert, 2002). When these risk factors are detrimental to vocational identity development, they motivate an individual's vocational choices. Given the life experiences and attitudes (low core self-evaluation and college aspirations) of at-risk youth, Job Corps is a vocational choice that increases the opportunities available for identity exploration, its residential component provides a safer environment for identity development, and personality (read as core self-evaluation or perceived self-efficacy) improvement is possible due to increased competency from VET.

4.1.2.2 Expectancy of Success (ES)

In this study the underlying construct of interest is the expectations of success (ES) participating in Job Corps. This is because all the indicator variables were survey questions on how much the participants thought the Job Corps program would benefit them by improving their skills in - math, reading, getting along well with peers and staff at Job Corps, self-esteem, self-control, getting trained in a specific job and being able to make new friends. So the ES represents the expected benefits of participating in Job Corps. To be more specific, these are the benefits which will facilitate the individual's vocational identity development. For a rational decision maker keeping everything else constant, increase in expected benefits should increase the likelihood of participation in JC (Eccles and Wigfield, 2020).

Social cognitive career theory (Lent 2005) acknowledges and hypothesizes that career interests, choice, and personal goals form a complex human agency process that includes performance, self-efficacy, and outcome expectations. For example, self-efficacy is positively related to student academic performance and science self-efficacy has been shown to impact student selection of science-related activities, which impacts their ultimate success and helps maintain interests (Britner and Pajares 2006; Parker et al. 2014; Richardson et al. 2012). Students with greater interest in technical and scientific skills were also more likely to consider a STEM career than those who preferred career activities that involved practical, productive, and concrete activities (Blotnicky et. al., 2018).

From the NJCS data I wanted to model the latent construct of expected benefits from participation in Job Corps. Henceforth, I will refer to this latent construct as expectations. Beginning in middle adolescence, an individual begins to make choices by objectively comparing the benefits and costs of alternative choices. If we define utility of a choice as the net benefit (expected benefits – expected cost) an individual can realize by making the choice, then individuals try to maximize their utility by choosing the choice with maximum expected benefit and least expected cost. This is the expected utility maximization theory in economic decision making (Train, 2009). Therefore, the expected benefit of a choice is an important piece of information when a decision-maker is choosing between multiple choices. In this study I use factor analytic methods to estimate the expected benefits of participating in the Job Corps program. Since vocational choices are economic choices, the expected benefits of participating in Job Corps is a critical determinant of the participation choice (Banerjee & Newman, 1993; Heckman & Smith, 2003).

In the SEVT framework, VET choice is also influenced by expectations of success. Eccles and Wigfield (2020) defined expectancies for success (ESs) as individuals' beliefs about how well they will do on an upcoming task. In NJCS, eligible participants (at-risk youth) were asked to what extent they thought Job Corps will help them improve in math, reading, getting along with peers, making new friends, self-control, and self-esteem. These items represent various overlapping constructs of self-efficacy depending upon which theory was used to conceptualize efficacy (for details: Eccles and Wigfield, 2020). Mathematics and reading are related to academic efficacy (Bong and Clark, 1999) in socio-cognitive theories of cognition; positive peer relationships are related to socialization efficacy in vocational achievements (Boat et. al., 2022); and self-esteem and self-control are included as measures of self-efficacy in multiple domains (Gecas, 1989).

Among the different domains of vocational identity, self-efficacy is positively correlated with multiple desired life course outcomes. Self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments (Bandura, 1977, 1986, 1997). Therefore, in the vocational identity domain, self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce occupational performance attainment. Self-control, self-esteem, and positive peer relationships are desirable behaviors necessary for job satisfaction across domains, and life satisfaction in general. Therefore, improvement in these behaviors could increase the likelihood of occupational success in the future. A more general notion of cognitive efficacy is composed of cognitive abilities and self-efficacy (Berry, 1989). It is described as increases in the rate, amount, or conceptual clarity of knowledge, versus costs, such as cognitive effort, needed to attain knowledge (Hoffman, 2012). Cognitive abilities such as mathematics and literacy are strongly correlated and are essential for occupational success (Newsome, 1978; Pierce, 2013). Therefore, individuals exploring their identity might want to improve these skills before committing to vocational choices.

To clarify the nature of these expectations, I return to theories on vocational identity development (Klotz et. al., 2014). Adolescents develop their vocational identity as they explore themselves and the working world and get ready to make commitments to both (e.g., crystallizing work choices, personal values, and interests; Skorikov & Vondracek, 1998). As explained in the 'motivation' section, individuals are motivated to join Job Corps since it facilitates vocational identity exploration in breadth and depth.

Following exploration in depth, an individual will have to commit to a career choice (Porfeli et al., 2011). Therefore, the expected benefits as expressed by NJCS sample members is hypothesized to represent the expected benefits that would result in vocational commitment. This is also referred to as establishing 'achieved vocational identity' status – establish the status that one has achieved a career identity (ibid.) The vocational identity literature indicates that establishing an achieved identity status is associated with enhanced self-esteem, adjustment, life satisfaction, competence, academic adjustment, and performance (Meeus et al., 1999, Skorikov and Vondracek, 2007b, Vondracek, 1994). The indicators collected in the baseline survey to capture the expected benefits of Job Corps relate to academic adjustment (improvement in math and reading) & competence (getting specific job training). These expectations are directly related to positive youth development (PYD) through Lerner's 5C model of PYD (Lerner et. al., 2005). The 5Cs of positive youth development are - Competence (ability to do something successfully in academic, work, and social settings); Confidence (overall positive self-esteem and self-efficacy); Connection (positive and strong relationships with peers, family, school, and community); Character (respect for social and cultural norms, acquisition of appropriate role models, sense of right and wrong, and integrity); and Caring (feelings of sympathy and empathy and identification with others). Improvements in these domains (skills) can enhance the resilience and well-being of at-risk youth in the long term (Sander et. al., 2015). The other expected benefits of JC relate to getting along well with peers (Rageliene, 2016); being able to make new friends; Szczesniak et. al., 2022); and self-esteem and self-control (King, 2004; Welsh and Schmitt-Wilson, 2013; Shalala et. al., 2020; Quilez-Robres, 2021).

In this analysis, I would like to model these expectations as a continuous latent construct (Gupta et. al., 2014) and the seven variables from survey on 'expected benefits of enrolling in Job Corps' will be used as measurement indicators for this underlying latent variable. Similar to vocational identity, the correlated domain of self-efficacy is also socio-cognitive (Bandura, 1977). The expectations from Job Corps could be hypothesized as expected improvement in integrated efficacy comprising of academic efficacy (improvements in math and reading), personality efficacy (getting specific job training, getting along with peers and being able to make new friends (Lent and Hackett, 1987), and self-efficacy (self-esteem and self-control). These personality efficacy skills are essential for a youth's ability to plan for their career and execute the necessary tasks. Broadly this is called career-self management (King, 2004; Lent et. al., 2013; Wilhelm and Hirschi, 2019).

Vocational identity develops through the interplay between process and content dimensions (Lee et al., 2020). The content domain refers to intrinsic and extrinsic career goals. Intrinsic work values mainly concern immaterial values satisfied by work itself, such as achievement or autonomy, whereas extrinsic work values refer to the monetary rewards or conditions of work (George & Jones, 1997). When looking at vocational development as a socio-cognitive process, the construct of career self-efficacy is correlated significantly to self-esteem, vocational identity, peer support, vocational outcome expectation, and career indecision variables (Lent & Hackett, 1987; Choi et al., 2011). Therefore, I hypothesize that the seven items broadly represent different forms of efficacy pertaining to an integrated identity of self and vocation. Self-esteem and self-control are correlated with self-efficacy while academic efficacy is measured by math and reading. I hypothesized personality efficacy to be measured by competency (getting specific job training) and socialization (getting along with others and being able to make new friends). Competency is a well-known constituent of vocational efficacy. Socialization is important for vocational identity development since positive peer relationships are known to positively impact commitment to a career (Ashforth et. al., 2014; Hafferty, 2016). Peers are also important in co-structuring vocational identities and therefore, being able to make new friends in the identity exploration stage is an expected benefit of a job training program.

4.1.3 Latent variable analysis

Both STV and ES are multidimensional constructs, and the dimensions can overlap conceptually. The baseline data is not suitable to characterize this multidimensionality. Since the dimensions are not conceptually well-separated, each indicator can be a partial measure of multiple dimensions. I primarily assume both STV and ES to be univariate latent variables – each latent variable has only one underlying factor of which the available indicators are proxy measures. Therefore, the study identified the set of indicators and the latent construct they represent with the highest plausible validity and reliability. Exploratory factor analysis (EFA) was used to identify the number of factors underlying each latent variable and the how the observed indicators are correlated with these factors. At the end of EFA, we have a hypothesized factor structure for each latent variable. In confirmatory factor analysis (CFA), the proposed factor structure is confirmed by restricting the underlying factors to be orthogonal and allowing each indicator to represent only one of the factors.

4.2 Data

4.2.1 The NJCS sample

From the NJCS data I wanted to model the latent construct of motivation to participate (enrollment) in Job Corps. In order to clarify what this motivation means; I refer to theories of vocational identity development. Identity development is a key human developmental goal for adolescents (14-17 years) and emerging adults(18-24 years). Together, these age groups are subjectively referred to as 'youth', hereafter. Based on Marcia's model of identity development, identity exploration and commitment are important stages in the developmental process (Marcia, 1966). The career or vocational choices made in this age contribute significantly to the overall integrated identity (Porfeli et al., 2011). Extended models such as the dual-cycle model of identity formation expand the exploration stage in two parts – exploration in breadth and exploration in depth (Luyckx, Goossens, & Soenens., 2006; Luyckx, Goossens, Soenens, & Beyers, 2006). According to the literature on determinants of career or vocational choices, such factors can be broadly categorized as – environment, opportunity, and personality. Some of these factors could act as motivation towards vocational choices.

Table 11 Means of covariates and indicators of latent constructs across experimental groups

Variable	Experimental treatment (Z=1; n=6536) (mean, SD)	Experimental control (Z=0; n=4182) (mean, SD)
Motivated to leave home	0.57 (0.50)	0.59 (0.49)
Motivated to leave community	0.62 (0.49)	0.60 (0.49)
Motivated by other personal reasons	0.73 (0.44)	0.73 (0.45)
Motivated by training aspiration	0.98 (0.12)	0.98 (0.14)
Motivated by unemployment	0.91 (0.29)	0.91 (0.29)
Expected benefit in math	0.70 (0.46)	0.68 (0.47)
Expected benefit in reading	0.54 (0.50)	0.53 (0.50)
Expected benefit in getting along	0.60 (0.49)	0.59 (0.49)
Expected benefit in self-control	0.57 (0.49)	0.58 (0.49)
Expected benefit in self-esteem	0.58 (0.49)	0.57 (0.50)
Job Corps participation (choice)	0.75 (0.43)	0.00 (0.00)
Latent class of JC-VAS	2.91 (1.36)	2.90 (1.34)
Male (gender)	0.55 (0.50)	0.62 (0.49)
Prior HS credential	0.24 (0.43)	0.24 (0.42)
Arrested - year before	0.24 (0.43)	0.26 (0.44)
Worked - year before	0.65 (0.48)	0.64 (0.48)
Grew up mostly on welfare	0.20 (0.40)	0.19 (0.40)
Black	0.49 (0.50)	0.49 (0.50)

Table 11, continued

White	0.26 (0.44)	0.27 (0.44)
Hispanic	0.17 (0.38)	0.18 (0.38)
Other races	0.07 (0.26)	0.07 (0.25)
Age (in years)	18.89 (2.23)	18.78 (2.17)
Age2 (18-19 vs. 16-17 yrs.)	0.32 (0.47)	0.31 (0.46)
Age3 (>= 20 vs. 16-17 yrs.)	0.27 (0.45)	0.26 (0.44)
Sampling Weights	11.71 (2.58)	17.86 (4.48)
Age (centered)	0.04 (2.23)	-0.07 (2.17)
Treatment (randomized)	0.99 (0.08)	0.99 (0.07)
Assigned to residential	0.80 (0.40)	0.84 (0.37)
Worry about Job Corps	0.37 (0.60)	0.33 (0.59)
Had father	0.62 (0.49)	0.61 (0.49)
Father had HS credential	0.43 (0.49)	0.42 (0.49)
Household income 2	0.21 (0.40)	0.20 (0.40)
Household income 3	0.12 (0.32)	0.11 (0.32)
Household income 4	0.24 (0.43)	0.24 (0.43)
Household income 5	0.18 (0.38)	0.18 (0.39)
Availed welfare prev. yr.	0.59 (0.49)	0.59 (0.49)
Lived in public housing	0.21 (0.41)	0.19 (0.39)
Married	0.02 (0.15)	0.02 (0.15)
Living with spouse	0.07 (0.25)	0.06 (0.24)
Separated/widowed/divorced	0.07 (0.25)	0.06 (0.24)

Table 11, continued

Had a child at baseline	0.21 (0.41)	0.18 (0.39)
MSA category	2.11 (0.72)	2.10 (0.73)
PMSA	0.32 (0.47)	0.32 (0.47)
MSA	0.46 (0.50)	0.46 (0.50)
Full/part-time work - ever before	0.80 (0.40)	0.79 (0.41)
Arrested - ever before	0.24 (0.43)	0.26 (0.44)
Bad health during baseline	0.13 (0.33)	0.14 (0.34)
Taken drug treatment - ever before	0.05 (0.21)	0.05 (0.23)
Marijuana usage - year before	0.24 (0.43)	0.25 (0.43)
Hard drugs usage - year before	0.06 (0.24)	0.06 (0.24)

Table 12 Coverage of data among the baseline covariates and latent construct indicators

Variable	**% data observed**	**Missing obs.**	**% missing obs**	**abbr**
Motivated to leave home	95.1	521	4.9	rhome
Motivated to leave community	95.8	445	4.2	rcomm
Motivated by other personal reasons	95.8	445	4.2	rother
Motivated by training aspiration	99.8	20	0.2	rtrain
Motivated by unemployment	98.4	174	1.6	rnowork
Expected benefit in math	98.8	133	1.2	emath
Expected benefit in reading	99.3	71	0.7	eread
Expected benefit in getting along	99.3	73	0.7	ealong
Expected benefit in self-control	99.3	71	0.7	econtrl
Expected benefit in self-esteem	99.3	74	0.7	eesteem
Job Corps participation (choice)	100.0	0	0.0	choice

Table 12, continued

Latent class of JC-VAS	100.0	0	0.0	lclass
Male (gender)	100.0	0	0.0	male
Prior HS credential	100.0	0	0.0	bhsged
Arrested - year before	100.0	0	0.0	barrest
Worked - year before	100.0	0	0.0	byrwrk
Grew up mostly on welfare	100.0	0	0.0	welfkid
Black	100.0	0	0.0	black
White	100.0	0	0.0	white
Hispanic	100.0	0	0.0	hisp
Other races	100.0	0	0.0	otherrac
Age (in years)	100.0	0	0.0	age
Age2 (18-19 vs. 16-17 yrs.)	100.0	0	0.0	age2
Age3 (>= 20 vs. 16-17 yrs.)	100.0	0	0.0	age3
Age (centered)	100.0	0	0.0	agecent
Motivated by career goals	99.7	31	0.3	rcrgoal
Treatment (randomized)	100.0	0	0.0	treatment
Assigned to residential	100.0	0	0.0	resid
Worry about Job Corps	100.0	0	0.0	jcworry
Had father	100.0	0	0.0	hadfath
Father had HS credential	100.0	0	0.0	fathhs
Household income 2	100.0	2	0.0	hhinc2
Household income 3	100.0	2	0.0	hhinc3

Table 12, continued

Household income 4	100.0	2	0.0	hhinc4
Household income 5	100.0	2	0.0	hhinc5
Availed welfare prev. yr.	100.0	0	0.0	byrwelf
Lived in public housing	100.0	0	0.0	publich
Married	99.9	6	0.1	married
Living with spouse	100.0	0	0.0	livspous
Separated/widowed/divorced	99.9	6	0.1	sepwidiv
Had a child at baseline	100.0	0	0.0	bchild
MSA category	100.0	0	0.0	jcmsa
PMSA	100.0	0	0.0	pmsa
MSA	100.0	0	0.0	msa
Full/part-time work - ever before	100.0	0	0.0	evrwrk
Arresred - ever before	100.0	0	0.0	evarrst
Bad health during baseline	100.0	0	0.0	badhlth
Taken drug treatment - ever before	100.0	0	0.0	drugtrt
Marijuana usage - year before	100.0	0	0.0	potuse
Hard drugs usage - year before	100.0	0	0.0	harduse

The Job Corps program serves the at-risk youth population in the United States. For at-risk students, the need for a safe environment for vocational identity exploration is an important factor in vocational choice process. The Job Corps program offers accommodation (residential campus) for enrollees and therefore a safe environment in which alternative trades can be explored in breadth and a specific trade can be explored in depth for certification). Therefore, the extent to which an individual is motivated to enroll in Job Corps could be correlated to their desire for a safe environment. This is one of the latent constructs of interest in this study. I assume that this underlying construct is continuous and denote it by the label 'motivation'.

4.2.2 NJCS indicators for STV

In this study, I use categorical indicator variables (I) as proxies measuring the underlying continuous latent construct of *motivation* (I^M). There are seven different indicators corresponding to seven different motivating reasons for wanting to enroll in Job Corps. These seven reasons are: (1) wanting to leave home (2) wanting to leave community due to violent crimes (3) getting job training (4) achieving a career goal (5) Getting GED (6) Being unable to find work (7) Other personal reasons. The other personal reasons have actual verbal responses in the raw data but not included in the analysis. Visual inspection of this publicly available data suggests that personal reasons vary from family instability and criminal participation to raising a family, and career progress. But they broadly refer to reasons that motivate the need for an environment in which a new vocational identity can be explored and established.

The indicators are in three ordered categories for increasing levels of motivation from any given motivating reason – not important, somewhat important, and very important. These categories were dichotomized as – important (very important or somewhat important) vs. not important (not important).

4.2.3 NJCS indicators for ES

The measures of expectations of success or expected benefits of participating in Job Corps are binary indicators of how much improvement the at-risk expected in – mathematics, reading, getting along with peers, being able to make new friends, getting a specific job training, self-esteem and self-control. As a latent construct, these items measured in NJCS baseline survey correspond to expectations of success in the SEVT conceptual model and therefore, influence the VET choice (choice to participate in Job Corps or not).

In this study, I use categorical indicator variables as proxies measuring the underlying continuous latent construct of *expectation* (I^E). There are seven different indicators corresponding to seven different topics in which sample members expect to benefit by enrolling in Job Corps. These seven areas are – (1) mathematics (2) reading (3) getting along well with others (4) self-control (5) self-esteem (6) getting a specific job training, and (7) being able to make new friends. Competency in math and reading increases vocational opportunities, leading to more exploration and commitment to a high value trade requiring mathematical literacy.

The respondents were asked how much they thought Job Corps could help them improve in the seven domains. The response indicators are in three ordered categories for increasing levels of expectation from any given domain – a lot (expect to benefit a lot), a little, and not at all. These categories were dichotomized as – a lot (expect to improve a lot) vs. not a lot (expect to improve a little or not at all). I follow the same workflow as done with *motivation* and therefore begin with an exploratory factor analysis (EFA) of these seven indicators.

4.2.4 Demographic predictors

The demographic predictors considered in this analysis are the set of variables used as determinants of participation in Job Corps and JTPA (Job Training Partnership Act, 1982) vocational education and training (VET) programs.

In the context of the SEVT theory they are classified into three groups based on their relevance to the bio-ecological model of child development (Bronfenbrenner, 2001) and also provides an intuition about the underlying causal mechanisms. The first group of variables are individual characteristics, the second set of variables are household characteristics as well as that of the ecosystem of habitation such as public housing or private housing, urbanicity of the residential administrative unit etc.

4.2.5 Missing data

I used full information maximum likelihood methods (FIML) using Mplus (Version 8.2.) software to account for missing data in the models (Muthén & Muthén, 1998–2010). The advantage of FIML is that it “makes use of all available data, even those from partially missing cases and will provide valid point estimates and confidence intervals for population parameters” (Davey & Savla, 2010, p. 54). Thus, I was able to use data from the entire sample to evaluate the models.

4.3 Analytical procedure

4.3.1 Setup

Let $i = 1, \dots, N$ denote the index for individuals in the research sample.

Economist information set $H_e = X$.

Agent private information set $H_a^* = U = X^* = (X_1^*, X_2^*)$

Agent's full information set, $H_{ea}^* = H_e \cup H_a^* = (X, X^*)$.

The common factor structure F of X^* that can be extracted as factor scores (Wall and Li, 2003; DiStefano et. al., 2009). Let the information available to the analyst about the agent's private information be denoted $H_a = \{F\}$ form the economist or analyst's augmented set (under sequential estimation), $H_{ea} = H_e \cup H_a = (X, F)$.

4.3.2 Latent variable analysis

Let the common latent factor for Subjective Task Value (STV) denoted by f_1 and Expectancy of Success (ES) denoted by f_2.

Indicators $I = \{I^C, I^{f1}, I^{f2}\}$ corresponding to indicator sets for each of the three latent factors of VAS, STV and ES, respectively. The total number of indicators is denoted respectively by $L = \{L^C, L^{f1}, L^{f2}\}$.

For example, indicator $I_l^C : l = 1, \dots, L^C$ denotes the l^{th} indicator or item for latent class C and total number of indicators is L^C. Similarly, I_l^{f1} and I_l^{f2} are the l-th indicators for f_1 and f_2.

4.3.3 Factor analysis

4.3.3.1 Measurement equations

Situational Task Value (STV)

$$I^{f1}m = \alpha_{1m} f_1 + \epsilon_m^{f1} : m = \{1, \dots, L^{f1}\}$$

Expectations of Success (ES):

$$I_m^{f2} = \alpha_{2m} f_2 + \epsilon_m^{f2} : m = \{1, \ldots, L^{f2}\}$$

4.3.3.2 Structural equations:

Situational Task Value (STV)

$$f_1 = \Sigma_{k=1}^{K} \lambda_{1k} X_k + \beta_1 C + \omega_1$$

Expectations of Success (ES):

$$f_2 = \Sigma_{k=1}^{K} \lambda_{2k} X_k + \beta_2 C + \omega_2$$

4.4 Model specification, fit indices and diagnostic criteria

4.4.1 Exploratory Factor Analysis (EFA)

Exploratory factor analysis or EFA (henceforth) is a method primarily used to study the factor structure of the indicators representing an underlying latent construct. EFA typically requires decisions about three key issues, factor extraction strategy, factor retention criteria, and factor rotation (Patil et. al., 2008). I wanted to study the underlying factor structure of the seven indicators. In EFA, I explored various factor structures by choosing different number of factors to hypothetically represent the underlying latent construct. In choosing the final factor structure, I looked at the eigenvalues of the factors, factor loadings, construct validity based on theory and uniqueness of the individual items. It is also suggested that a factor be composed of at least three items for identifiability in confirmatory factor analysis (CFA)[1]. I also use the CFI and Tucker Lewis Index (TLI) as metrics of how well an estimated factor structure fits the data. The values of

[1] CFA does not allow cross-loading of factors.

both indices range from 0 to 1 (lowest model fit to best model fit). Therefore, higher the indices values, better the model fit.

The eigenvalue represents the amount of variance contained by a factor. The suggested guideline is to extract the factors that have eigen value greater than 1. But recent criticisms have suggested extracting factors with eigenvalues slightly less than 1 or significantly higher than 1 (Patil et. al., 2008). Factor loadings are estimates of the correlation between an item and a factor. The suggested guideline is to consider an item to have loaded on a factor only if the loading is greater than 0.5 in standardized value of the magnitude. But recent literature has suggested that in many applied settings one could consider factor loading of 0.3 and above as an indication of moderate correlation between an item and the factor(s) representing the latent construct. Because the results of an EFA, in large part, depend on the choices a researcher makes, the technique has the potential to produce nonsense factors (Ehrenberg, 1968) and even mislead theory development efforts (Armstrong, 1967). Therefore, a strong theoretical framework underlying the proposed latent construct can help in more informed model comparison. As explained earlier, I analyze the factor structures based on vocational identity development theories (Tavakol and Wetzel, 2020).

4.4.2 Confirmatory Factor Analysis (CFA)

In confirmatory factor analysis, we assume that each item loads onto only one factor at a time and that factors can be correlated. This is different than EFA in which we assume the factors to be orthogonal and allow cross loading of the same item on multiple factors. I test multiple models for motivation in CFA as following.

4.4.2.1 Identification issues in CFA

At least three indicators are required to identity a single factor model. For such a case, each indicator loads on only one factor and the measurement error terms are not correlated with one another. In a multifactor model (two or more factors), two indicators per factor are enough to identify a model if each indicator loads onto only one factor and the measurement error terms are not correlated, but the factors themselves can be correlated. In empirical settings, usually it is best to identity two or three indicators that best measure the underlying latent construct. In terms of the number of indicators required to identity the CFA model, we adopt the thumb rule that in single factor models we need at least three indicators while in two factor models that are strongly correlated (two sub-domains of a potential second order factor or latent construct), two indicators are sufficient for model identification.

4.4.3 Estimation

Maximum likelihood estimator was used in Mplus 8.2. to estimate the exploratory factor models. Sampling weights from the survey were included in the analysis. Multiple random starts were conducted to ensure that the results did not converge in a local minimum. Missing data was handled with the full information maximum likelihood method. Standard errors were obtained via bootstrap procedures.

4.5 Subjective Task Value (STV)

4.5.1 Exploratory Factor Analysis (EFA)

This section discusses the results for exploratory factor analysis of the Subjective Task Value (STV) construct in NJCS study. STV refers to the perceived value of participating in JC given the life experiences of the agent. This perceived value acts as a motivation to participate. In the NJCS study there were six indicators of such motivation – wanting to be away from home (RHOME), wanting to be away from community due to violence exposure (RCOMM), other personal reasons (ROTHER), wanting to get vocational training (RTRAIN), aspiring for career goals (RCRGOAL) and lack of current employment opportunities (RNOWORK). The first three indicators – RHOME, RCOMM, and ROTHER – refer to adverse conditions that the agent wants to get away from while the other three – RTRAIN, RCRGOAL and RNOWORK – are related how much JC would facilitate vocational identity development. In this regard we can expect a two-factor model with RHOME, RCOMM, and ROTHER representing situational value (SV) of participating in JC. The second factor of aspirational value (AV) being represented by RTRAIN, RCRGOAL and RNOWORK. There is an additional indicator RGETGED representing wanting to get a GED through JC. This is also a part of attainment value but due to its relevance for only those without a high school credential (HS or GED), its relevance to the overall construct has to be analyzed.

4.5.1.1 Estimation

The EFA was conducted in Mplus with a sample size of N=10776. The primary estimator was MLR since it can handle non-normal data with missingness. Full information maximum likelihood (FIML) helps to deal with missing data. Even though WLSMV is recommended for categorical data (Brown, 2015; Proitsi et. al., 2011), it handless missingness through complete case analysis which can lead to biased results. Robust Maximum Likelihood (MLR) estimator was also used to get model performance indices such as AIC and sample-adjusted BIC (aBIC). I used the Geomin (oblique) rotation algorithm. This rotational algorithm is recommended when the hypothetical factors have strong theoretical overlap. Since the SV and UV represent the intrinsic and attainment value of STV construct (Eccles and Wigfield, 2020), they are expected to have a strong overlap. Another way to test this overlap is to explore the factor structure with orthogonal rotation. If most of the indicators load onto both the orthogonal factors it is indicative of the strong underlying overlap of these factors within the STV construct. Multiple random starts were used in all the estimation routines to avoid convergence problems (Asparouhov and Muthen, 2019). Even though convergence issues were not expected in the EFA I used 30 random starts. Sampling weights were included in the analysis[2].

4.5.1.2 Results

The eigenvalue correlation matrix showed seven eigenvalues with the first three being greater than one (2.564, 1.347, and 1.00). Based on this, I analyzed the results for one, two and three factor models.

[2] The R package 'lavaan' has EFA routine that does not allow sampling weights.

Table 13 EFA for Situational Task Value: Model performance for different factor structures

Model/Performance index	**AIC (MLR)**	**aBIC (MLR)**	**CFI (WLSMV)**	**TLI (WLSMV)**	**RMSEA (prob RMSEA <= 0.05)**	**SRMR (WLSMV)**	**Chisq (LR)**	**Df**	**p-value**
Single factor (1F)	59996	60053	0.872	0.808	0.046*	0.146	330.71	14	0.00
Two factors (2F)	59755	59837	0.972	0.926	0.029*	0.06	78.110	8	0.00
Three factors (3F)			0.999	0.995	0.007	0.014	4.72	3	0.19

Table 14 EFA for Situational Task Value: Factor loadings for different factor structures

Measurement Indicator	**Factor loadings**					
	Single factor model (1F)	*Two factors model (2F)*		*Three factors model (3F) (WLSMV)*		
Construct/factor interpretation	*Subjective Task Value (STV)*	*Situational Value (SV)*	*Aspirational Value (AV)*	*SV*	*AV (vocational)*	*AV (educational)*
RHOME	0.60 (0.63)	0.49 (0.68)		0.66 (0.56)		
RCOMM	0.63 (0.60)	0.78 (0.39)		0.62 (0.54)		
ROTHER	0.512 (0.73)	0.40 (0.73)		0.49 (0.70)		
RTRAIN	0.670 (0.74)		0.75 (0.34)		0.80 (0.74)	
RCRGOAL	0.707 (0.50)		0.95 (0.11)		1.00 (0.15)	
RNOWORK	0.314 (0.90)		0.46 (0.77)		0.50 (0.74)	
RGETGED	0.172 (0.97)	0.28 (0.89)				0.87 (0.24)

4.5.1.2.1 Single factor model (1F)

In the single factor model the underlying construct is hypothesized to represent the subjective task value (STV) of participating in Job Corps. As STV for a choice alternative increase, individuals are more likely to choose that alternative (Eccles and Wiglfield, 2020).

In this model, indicators with statistically significant factor loadings with values greater than or equal to 0.4 were RHOME (0.6), RCOMM (0.63), ROTHER (0.512), RTRAIN (0.67), and RCRGOAL (0.70). Two indicators did not load significantly (loading < 0.4) - RNOWORK (0.3) and RGETGED (0.17). The single factor loads indicators related to both situational value (SV) and aspirational value (AV). In the literature review, both RNOWORK and RGETGED were hypothesized as indicators of aspirational value. But they failed to load onto a common single latent construct.

It is plausible that RGETGED does not load onto the common factor because it is more of an academic attainment aspiration than vocational attainment aspiration as indicated by RTRAIN and RCRGOAL. It was hypothesized that RNOWORK should be a part of vocational attainment aspiration. But this not being the case brings forth the distinction that RTRAIN and RCRGOAL are more future oriented vocational attainment indicators (Spurk, 2021). But RNOWORK is more indicative of lack of current vocational opportunities. Unemployment is known to be a risk factor for healthy transition to adulthood among at-risk youth (Rahmani and Groot, 2023; Damaske et. al., 2023; Ivzori et. al., 2020). But it might not be loading along with RHOME, RCOMM and ROTHER because the variation in RNOWORK is already captured in ROTHER. In the raw data, the respondents were asked to specify the exact reason if they answered that they want to participate in JC due to other personal reasons (ROTHER). An analysis of the text response shows that for many individuals lacking employment opportunities was a personal reason to want to participate in JC.

4.5.1.2.2 Two factor model (2F)

The two-factor structure represents the correlated SV and AV factors of the STV construct. The two-factor model (2F) showed statistically significant (at 5 percent significance) standardized loadings for all indicators. As expected, RGETGED (loading 0.3 approx.) did not load strongly (loading > = 0.4) on any factor. But surprisingly it loaded positively and significantly on SV than on AV. But wanting educational attainment could still influence participation in JC for those without high school credentials and therefore, it was included as a predictor in the final choice model.

The first factor representing SV loaded RHOME (0.5), RCOMM (0.8), and ROTHER (0.4). The second factor representing AV loaded RTRAIN (0.75), RCRGOAL (0.95) and RNOWORK (0.45). This factor structure is supported by SEVT as discussed in the literature review. Even though SV and AV are strongly correlated in theory the results show a moderate level of correlation - correlation coefficient of 0.5. The NJCS data might not reflect the true relationship between the factors if the measurement indicators are not good proxies for the underlying factors.

Despite the strong support for the 2F structure in theory, the extent to which the observed measures represent the underlying latent construct could be uncertain. I checked whether the extracted factors explain sufficient variation in the observed measures (communalities or common variance). Therefore, communality values for each measure or indicator being close to one suggests that extracted factors explain more of the variance of the individual measure. But in this analysis the observed communalities (rounded off) were RHOME (0.3), RCOMM (0.26), ROTHER (0.17), RTRAIN (0.32) and RCRGOAL (0.23). Osborne et. al. (2008) suggests that in such cases either the individual item is not related to other items, or an additional factor has to be explored. The latter option was already tried and resulted in lack of model convergence.

4.5.1.2.3 Three factor model (3F)

A three-factor structure (3F) was explored to accommodate the possibility that wanting to get a GED might not correlate well with AV. This is possible because while AV represents vocational attainment value, RGETGED is more relevant for academic attainment. So, RGETGED might load onto the second factor in a 2F model along with RTRAIN, RCRGOAL, and RNOWORK, but become an independent factor in a 3F model. The three-factor model (3F) showed the best model fit with the third factor exclusively loaded by RGETGED (0.87). This shows that wanting to get a GED represents a distinct latent dimension not necessarily captured by STV under the SEVT mode.

Wanting to get a GED through JC seems to load neither on situational value or vocational aspirational value. Before investigating possible reasons, it should be noted that except RGETGED the proportion of missingness ranges from 0.2 percent to 4.8 percent. But RGETGED has nearly 25 percent missingness mostly because most of those with missing data are students in the age group of 16-17 years. For them getting a GED is requirement for any kind of vocational exploration and not necessarily a future orientation thinking implied in RTRAIN and RCRGOAL. Therefore, it is plausible that RGETGED does not orient with vocational aspirations (future orientation).

Similarly, individuals want to leave home and community due to higher risk of exposure to violent crimes and incidents. Not having a GED might not have a marginal risk exposure to violence after controlling for demographic, household and community risk factors.

4.5.2 Confirmatory Factor Analysis (CFA)

In confirmatory factor analyses (CFA) I tested the factor structures explored in the exploratory factor analysis (EFA) with the restriction that the measurement indicators can only load on a single factor. In other words, CFA does not allow for measurement indicators to load across factors. In the previous section, EFA helped to compare the factor structure modeled from observed response pattern (responses to indicator variables) with the underlying conceptual theory (SEVT). In CFA, the observed factor structures are confirmed, and the internal reliability of the factor models can be analyzed. Cronbach alpha is the measure of internal reliability used in this study. The estimated Cronbach alpha may not satisfy the conventional thresholds of being greater than 0.7 – 0.8 due to the fact that typical factor analysis assumes the underlying latent construct to be a reflective measure than a formative measure – an assumption that might be violated in the context of this study. Nevertheless, recent guidelines on factor analysis suggest the reporting of Cronbach alpha at least as a measure of relative model performance. Therefore, this analysis analyzes variations of a single factor model and concluding with the analysis of the two-factor model. Given the results of EFA, it is expected that the CFA results would also favor the two-factor model. The three-factor model is not analyzed in CFA because to do so would require at least 3 indicator variables for each factor if the factors are not correlated. If they are correlated, then some of the factors could potentially have two indicators and one indicator only when the correlation is very high.

4.5.2.1 Results

Table 15 CFA for Situational Task Value: Model performance for different factor structures

Model	**Indicators (R*)**	**AIC**	**aBIC**	**Loglikelihood**	**CFI**	**RMSEA**	**SRMR**
Model 1 (1F) – SV and AV	HOME, COMM, OTHER, TRAIN, CRGOAL, NOWORK	7014	7088	-3489	0.67	0.098	0.055
Model 2 (1F) – SV and AV	HOME, COMM, OTHER, TRAIN, CRGOAL	3213	3293	-1600	0.68	0.122	0.059
Model 3 (1F)	HOME, COMM, OTHER	39,994	40,031	-19988	0.972	1.00	0.000
Model 4 (2F)	SV – HOME, COMM, OTHER. AV – TRAIN, CRGOAL, NOWORK	6154	6232	-3058	0.974	0.03	0.01
Model 5 (2F)	SV – HOME, COMM, OTHER. AV – TRAIN, CRGOAL	2444	2509	-1206	0.99	0.98	0.004

Table 16 CFA for Situational Task Value: Factor loadings for different factor structures

Indicator/Model	Model 1	Model 2	Model 3	Model 4 (SV)	Model 4 (AV)	Model 5 (SV)	Model 5 (AV)
RHOME (α_{11})	1.00 (0.00) *	1.00 (0.00) *	1.00 (0.00) *	1.00 (0.00) *		1.00 (0.00) *	
RCOMM (α_{12})	0.94 (0.04) *	0.93 (0.05) *	0.94 (0.06) *	0.93 (0.05) *		0.93 (0.05) *	
ROTHER (α_{13})	0.74 (0.04) *	0.70 (0.04) *	0.68 (0.04) *	0.69 (0.04) *		0.68 (0.04) *	
RTRAIN (α_{14})	0.11 (0.02) *	0.09 (0.01) *			1.00 (0.00) *		1.00 (0.00) *
RCRGOAL (α_{15})	0.05 (0.01) *	0.04 (0.00) *			0.44 (0.07) *		0.5 (0.06) *
RNOWORK (α_{16})	0.21 (0.03) *				0.80 (0.16) *		
Correlation (SV, AV)					0.78 (0.15) *		
Cronbach Alpha (internal reliability)	0.43	0.43	0.48	0.48	0.24	0.48	0.40

4.5.2.1.1 Single factor model (1F)

In the exploratory factor analysis (EFA) I showed that in a single factor model all the indicators except RNOWORK and RGETGED loaded significantly to the underlying latent construct (STV). But in the two-factor model, RNOWORK loaded with the vocational attainment value (AV) construct. Therefore, in the CFA I investigate both single and two factor models. The purpose is to identify the factor structure that has balanced performance on both model fit and internal reliability measured as Cronbach's Alpha. In the single factor models I investigated various subsets of RHOME, RCOMM, ROTHER, RTRAIN, RCRGOAL and RNOWORK. Hence forth I shall refer to these set of indicator variables as 'motivation indicators' with RHOME, RCOMM and

ROTHER are ‘situational value (SV) indicators’, and RTRAIN, RCRGOAL and RTRAIN are ‘attainment value (AV) indicators.’

In the first single factor model (Model 1), all the motivation indicators were included for analysis. The loading on RHOME was fixed to 1 for model identification. Since RCOMM and ROTHER are strongly correlated to RHOME and RHOME has a loading fixed at 1, RCOMM and ROTHER also have high factor loadings of 0.94 and 0.74 respectively. The AV indicators load poorly with the highest loading value of 0.21 for RNOWORK. Which could imply that there is some situational value of unemployment but not strong enough to load on SV with the other SV indicators. The second single factor model (Model 2) re-estimated the model but without RNOWORK. There was no change in factor structure or internal reliability. But the internal reliability increased for a single factor model with only SV indicators (model 3).

4.5.2.1.2 Two factor model (2F)

In the two-factor model (2F) the first factor (SV) has three indicators that have loadings greater than or equal to 0.4 (RHOME, RCOMM and ROTHER). The same for the second factor (AV) are RTRAIN, RCRGOAL and RNOWORK. There are three indicators for each factor and therefore the model would be identified. In the 3F model, the third factor representing academic AV has only RGETGED loading but albeit very strongly (loading = 0.87). Therefore, for the 3F model to be identified, it has to be strongly correlated to one of the other two factors or have moderate correlations with both. The EFA results for the 3F model shows that the third factor has a correlation coefficient of 0.085 with the first factor and 0.06 with the second factor. So, this model will not be identified in CFA and therefore, is not analyzed.

The first factor representing SV loaded RHOME (0.5), RCOMM (0.8), and ROTHER (0.4). The second factor representing AV loaded RTRAIN (0.75), RCRGOAL (0.95) and RNOWORK (0.45). This factor structure is supported by SEVT as discussed in the literature review. Even though SV and AV are strongly correlated in theory the results show a moderate level of correlation - correlation coefficient of 0.5. The NJCS data might not reflect the true relationship between the factors if the measurement indicators are not good proxies for the underlying factors. The three-factor model (3F) showed the best model fit with the third factor exclusively loaded by RGETGED (0.87). This shows that wanting to get a GED represents a distinct latent dimension not necessarily captured by STV under the SEVT mode.

Finn and Wang (2014) suggest two further possibilities. Firstly, the direction of causality might be actually from indicators to the latent construct (formative measure: latent variable is formed by the indicator variables) rather than what is conventionally assumed in factor analysis – causal direction is from latent construct to the indicator variables (reflective measurement). They caution that using factor analysis on an endogenous construct (STV) – assuming the underlying latent construct to be a reflective measure – might underestimate the structural parameters (factor loadings and variances) and therefore make us delete valid indicators and undermining the construct validity. For this reason, I include the RNOWORK indicator in all subsequent analysis despite lack of significant factor loading. The low communality of the indicators could also be due to the same reason. Secondly, they suggest a violation of the assumption in classical test theory that there is only one legitimate source of variance (the individual in this study). They suggest that systematic variation can also arise from various environmental factors of the survey respondents. In the context of NJCS, the emphasis on 'situational value' implies the interaction of the individual with the environment (Bronfenbrenner, 2001). But in the context of including latent constructs in choice modeling, it is common practice to treat formative measurement as reflective measurements since the former lacks sufficient methodological support (Rose et. al., 2023). Integrating formative measurement in both latent and choice modeling is an exciting open area for future research. Therefore, for the purposes of this study I adopt the 2F model of STV for all subsequent analyses.

4.5.3 CFA with predictors - Multiple causes multiple indicator (MIMC) model

The purpose of this section is to investigate predictors of Situational Task Value (STV). Since STV is composed of SV (situational value) and AV (aspirational value), latent regressions are estimated on both the latent factors with all the choice determinants as independent variables. In accordance with the CFA analysis, SV and AV are allowed to be correlated. SV is measured by RHOME, RCOMM and ROTHER, while AV is measured by RTRAIN and RCRGOAL. This model has the best model fit and highest internal reliability (Cronbach Alpha was 0.48 for SV and 0.40 for AV).

CFA with covariates (MIMIC) includes models where the relationship between factors and a set of covariates are studied to understand measurement invariance and population heterogeneity. These models can include direct effects, that is, the regression of a factor indicator on a covariate in order to study measurement non-invariance. Structural equation modeling (SEM) includes models in which regressions among the continuous latent variables are estimated (Bollen, 1989; Browne & Arminger, 1995; Joreskog & Sorbom, 1979). In all of these models, the latent variables are continuous. Observed dependent variable variables can be continuous, censored, binary, ordered categorical (ordinal), unordered categorical (nominal), counts, or combinations of these variable types.

Since MIMIC is also a measurement invariance testing procedure, I also checked for measurement invariance in SV and AV to ensure that the regression coefficients of choice determinants on latent variables are unbiased (Guenele and Brown, 2014). Since most of the choice determinants in this study are categorical, I was able to use multi-category CFA (mgCFA) methods. I followed the procedure suggested in the literature (Putnick and Bornstein, 2016) to test for measurement invariance. Unless all three kinds of invariance are satisfied (configural, metric and scalar), we cannot rely on unbiasedness of regression coefficients and standard errors in the latent regression part of MIMIC models (Cieciuch et. al., 2019). I found complete measurement invariance (configural, metric and scalar) in the final MIMIC model being estimated in this study. Therefore, the regression coefficients in the regression results can be interpreted as unbiased differences in the means of the latent variables across different levels of the choice determinants.

4.5.3.1 Factor structure

The factor structure estimated jointly with the latent regression does not change the factor structure of model 5 in CFA. The correlation between the two latent variables is 0.16 after including the latent regressions in the MIMC model. Since the factor structure has not changed after inclusion of covariates, we can rule of direct effects of the choice determinants on measurement indicators.

4.5.3.2 Situational Value (SV)

The results suggest that situational value (SV) as the outcome is determined by a combination of individual, household and environmental characteristics. The coefficients reported below are after standardization based on the variance of the latent variable alone. In addition to the reported impact of observable attributes on SV, there was a statistically significant positive impact of attainment value (AV) on SV.

Table 17 Estimated coefficients from regressing Situational Value (SV) and Attainment Value (AV) on covariates

Predictor	**Situational Value (SV) (Coeff. $\widehat{\lambda_1}$)**	**Situational Value (SV) (z-statistic)**	**Attainment Value (AV) (Coeff. $\widehat{\lambda_1}$)**	**Attainment Value (AV) (z-statistic)**
Male	**0.012**	2.100	**-0.007**	-2.422
Black	**0.114**	13.679	0.002	0.684
Hispanic	**0.064**	7.509	**0.008**	2.227
Age (18-19 vs. 16-17 yrs.)	0.005	0.605	**0.009**	2.144
Grew up on welfare as kid	**0.019**	2.727	**0.008**	2.639
Living in (PMSA)	**0.026**	3.439	0.001	0.122
Lived in public housing	**0.034**	4.751	-0.001	-0.151
Prior high school credential	**-0.048**	-6.372	-0.002	-0.551
Prior child	-0.017	-2.124	**0.007**	2.654
Arrested before	**0.042**	6.654	0.006	1.811
Attended drug treatment	**0.030**	2.329	0.004	0.589
Marijuana use	**0.028**	4.246	-0.004	-1.046
Hard drugs use	**0.042**	3.283	-0.004	-0.581

4.5.3.2.1 Individual characteristics

Among the individual characteristics gender and race were associated with SV. Men are more likely to report higher values of SV. In comparison to white or other races, black and Hispanics report higher levels of SV. But being black has nearly double the impact on reported SV than being Hispanic.

4.5.3.2.2 Household characteristics

Among the household characteristics, growing up in primary metropolitan statistical areas (PMSA) had a statistically significant positive effect on SV. The US census documents define PMSA as - "A PMSA consists of a large urbanized county or a cluster of counties (cities and towns in New England) that demonstrate strong internal economic and social links in addition to close ties with the central core of the larger area".

4.5.3.2.3 Life experiences

Among the life experiences that significantly influence SV, the following adverse life experiences increased the reported levels of SV. Firstly, those who grew up on welfare benefits as a child reported higher levels of SV. Additionally, availing welfare benefits in the year before NJCS randomization also had a positive effect on SV after accounting for growing up on welfare as a child. Secondly, all adverse experiences related to substance abuse had a statistically significant effect of increasing the SV of Job Corps. Individuals who reported having gone through drug treatment ever in life reported higher levels of SV. Similarly, those who used either marijuana or hard drugs, both reported higher levels of SV than those who did not use those drugs in the year before NJCS randomization. The individuals who had a arrest history reported a similar magnitude and direction of impact on SV, as those who used hard drugs in the past year. Thirdly, those who grew up in public housing reported higher levels of SV while those who had a child at the time of randomization reported lower levels of SV.

4.5.3.3 Attainment Value (AV)

The attainment value (AV) of participating in Job Corps was influenced by much lesser factors than situational value (SV) discussed above. Among individual characteristics, men reported lower levels of AV while those in the age group of 18-19 years reported higher levels of AV than those who are 16-17 years old. None of the household characteristics had a statistically significant impact on the attainment value of participating in Job Corps. There was also no impact of prior educational or work experiences on AV. Among the adverse experiences, those who grew up on welfare benefits as a child and had a child at the time of NJCS randomization reported statistically significant positive impact on AV.

4.6 Expectancy of Success (ES)

4.6.1 Exploratory factor analysis (EFA)

4.6.1.1 Results

The results of EFA with indicators of ES are presented below. The eigenvalue correlation matrix showed seven eigenvalues with the first three being greater than one (2.564, 1.347, and 1.00). Based on this, I analyzed the results for one, two and three factor models.

Table 18 EFA for Expectancy of Success (ES): Model performance for different factor structures

Model/Performance index	AIC (MLR)	aBIC (MLR)	CFI (WLSMV)	TLI (WLSMV)	RMSEA	SRMR (WLSMV)	Chisq (LR)	Df	p-value
Single factor (1F)	79054	79137	0.965	0.947	0.062	0.070	589	14	0.00
Two factors (2F)	79054	79137	0.992	0.978	0.040	0.047	145	8	0.00
Three factors (3F)	78958	79060	0.999	0.994	0.020	0.016	16	3	0.00

Table 19 EFA for Expectancy of Success (ES): Factor loadings for different factor structures

Measurement Indicator	**Factor loadings (Proportion of residual variance)**					
	Single factor model (1F)	*Two factors model (2F)*		*Three factors model (3F) (WLSMV)*		
Construct/factor interpretation	*Expectancy of Success (ES)*	*Academic ES (ACAD)*	*Personality ES (PERS)*	*ACAD*	*PERS*	*Supported Future Orientation (SFO)*
EMATH	0.56 (0.70)	0.75 (0.44)		0.47 (0.63)		
EREAD	0.63 (0.60)	0.58 (0.47)		0.92 (0.16)		
EALONG	0.75 (0.44)		0.76 (0.42)		0.67 (0.44)	
ECONTRL	0.82 (0.33)		0.92 (0.23)		0.99 (0.15)	
EESTEEM	0.78 (0.39)		0.66 (0.40)		0.54 (0.41)	
ESPCJOB	0.43 (0.811)					0.60 (0.67)
EFRIEND	0.50 (0.75)					0.67 (0.55)

4.6.1.1.1 Single factor model (1F)

In the single factor model, all the indicators of ES were included. Since they are all hypothesized to represent different overlapping theoretical dimensions of the overall ES construct, the factor loading is expected to be high across the indicators. To review, EMATH and EREAD are hypothesized to be related to academic efficacy (ACAD). EALONG, ECONTRL and EESTEEM are hypothesized to represent Job Corps' ability to provide a socially supportive environment for improving personality related self-efficacy domains (Gecas, 1989; Bandura, 1997; Schunk and Zimmerman, 1996). Prior research shows that adolescents with greater self-esteem report greater self-control, and an individual's level of self-esteem is strongly influenced by the level of social support (Hu et. al., 2023).

All the indicators had factor loadings greater than or equal to 0.5. The indicators related to expected improvement in personality (PERS) had the highest loadings - EALONG (0.75), ECONTRL (0.82), and EESTEEM (0.78). The indicators related to academic efficacy (ACAD) had factor loadings - EMATH (0.56) and EREAD (0.63). The indicators related to future orientation (FO) had loadings - ESPCJOB (0.43) and EFRIEND (0.50). All the measurement indicators load onto a common factor strongly. The common latent construct of expectancy of success (ES) seems to represent well the underlying correlated latent factors such as academic efficacy (ACAD), self-efficacy (PERS), and future orientation (FO).

In the literature, academic efficacy, self-efficacy and future orientation are conceptually overlapping and yet distinct constructs. Youth with higher levels of academic efficacy have reported higher levels of self-efficacy. At the same time self-control is important for goal-directed behavior. Goal-directed behavior is positively correlated with academic outcomes in adolescence. An individual's perceived self-efficacy increases as their academic achievements increase. As youth transition to adulthood, formation of their vocational identity becomes an integral component of their overall identity development. Future orientation is positively correlated with various aspects of vocational identity development.

4.6.1.1.2 Two factor model (2F)

The two-factor model is hypothesized to represent academic efficacy and efficacy. Together they represent self-efficacy. But ESPCJOB and EFRIEND are more oriented conceptually with future orientation (FO). Therefore, in the two-factor model the indicators of FO may not load strongly on either factor.

In the two-factor model, the first factor conceptually representing academic efficacy (ACAD), is loaded strongly by EMATH (0.75) and EREAD (0.58). For EMATH loading has increased from single factor model (0.56) to the two-factor model (0.75) but decreased for EREAD, 0.63 in single factor model to 0.53 in the two-factor model. The second factor representing personality efficacy (PERS) is loaded strongly by EALONG (0.76), ECONTRL (0.92), and EESTEEM (0.66). The loading for EALONG decreased from 0.82 in the single factor model to 0.76 in the two-factor model. At the same time that of ECONTRL and EESTEEM have increased from 0.78 to 0.92 and 0.43 to 0.66. The future orientation (FO) indicators - ESPCJOB and EFRIEND - did not load onto either academic or personality efficacy.

The two factors represent academic and personality efficacy. Future orientation related indicators did not load strongly on either factor. For the first factor, expected improvement in math skills load more strongly than reading skills on the overall academic efficacy factor. For the second factor, improving self-control and self-esteem load more strongly on personality efficacy, than wanting to get along better with peers.

Literacy is an important element of vocational training (Mellard et. al., 2013). Improvement in math skills have been shown to improve emotional well-being by improving the adolescent's global concept of self, related to self-efficacy (Torppa et. al., 2023). Both math and reading have also been shown to be important in the education of at-risk youth (Slavin and Madden, 1989). Programs like GEAR UP (Gaining Early Awareness and Readiness for Undergraduate Programs) focused on both math and reading skills to increase the college preparedness for at-risk youth (Cabrera et. al., 2009). Therefore, expected success in math and reading skills represent expected success in general academic efficacy.

For the first factor (ACAD), factor loading of expected improvement in reading skills decreased from the single factor to two factor model. Is it because for at-risk youth, improvement in math skills is a greater expectation from vocational education programs than reading skills? In the baseline survey most of the respondents said they knew what kind of job training they wanted. Many of them expressed interest in STEM related training. The greater interest in STEM related training could be another reason for associating math skills more with vocational academic efficacy in this NJCS sample than reading skills (Blotnicky et. al., 2018).

In personality efficacy, self-control and self-esteem load more strongly on the latent factor than wanting to get along with peers. But in the single factor model it was the vice-versa. One potential explanation is that the second factor represents career self-management as a latent construct than a general personality trait. Desire for improved self-control has suggested as a possible determinant of career self-management (King, 2004). Since self-esteem strongly predicts self-control, the second factor broadly represents the youth's expected improvement in general career self-management through the vocational training program, Job Corps. Wanting to get along well with others might simply be a pre-requisite so that there is a supportive environment to learn career self-management skills. Due to this supportive nature, the indicator EALONG plausibly loads less on the second factor in the two-factor model, than in the generalized single factor model representing overall expectancy of success.

4.6.1.1.3 Three factor model (3F)

The three-factor model was explored to check whether academic efficacy, personality efficacy and future orientation are identified distinctly. The first factor represented academic efficacy with indicators and their corresponding factor loadings as - EMATH (0.47) and EREAD (0.92). The loading for EMATH has decreased compared to the two-factor model and that of EREAD has significantly improved from the two factor model. The second factor represented personality efficacy with indicators and their corresponding factor loadings as - EALONG (0.67), ECONTRL (0.99) and EESTEEM (0.54).

The three factors represent expected improvement in academic skills, career self-management skills and future oriented behavior through participation in JC. Together they form the overall concept of expected success (ES) in the Job Corps program. But we can look at the item correlation coefficients to see if there is sufficient overlap among the items of all three factors for a three-factor model. The table below shows that the indicators of future orientation - ESPCJOB and EFRIEND - have correlation coefficient of less than 0.3 with indicators of both academic efficacy (ACAD) and personality efficacy (PERS).

Table 20 Correlation matrix of indicators of Expectancy of Success (ES)

Indicators	EMATH	EREAD	ESPCJOB	EFRIEND	EALONG
EMATH					
EREAD	0.53				
ESPCJOB	0.28	0.20			
EFRIEND	0.29	0.30	0.39		
EALONG	0.34	0.43	0.31	0.36	
ECONTRL	0.37	0.44	0.33	0.37	0.68
EESTEEM	0.40	0.49	0.29	0.42	0.56

While the three-factor model shows the best fit for the observed indicators of ES, the indicators of the third factor (FO) are not strongly correlated with those of the first two factors - ACAD and PERS. Therefore, for purposes of subsequent analysis, I retain the two-factor model (model 4).

4.6.2 Confirmatory Factor Analysis (CFA)

4.6.2.1 Results

The results of confirmatory factor analysis of the latent construct - expectations of success (ES) or expected benefits of participation in JC - are presented below.

Table 21 CFA for Expectancy of Success (ES): Model performance for different factor structures

Model	Indicators (E*)	AIC	aBIC	Loglikelihood	CFI	RMSEA	SRMR
Model 1 (1F) – ES	MATH, READ, ALONG, CONTRL, ESTEEM	66215	66277	-33092	0.93	0.10	0.04
Model 2 (1F) – ES	MATH, ALONG, CONTRL, ESTEEM	52708	52758	-26342	0.99	0.06	0.01
Model 3 (1F) - ES	MATH, READ, CONTRL, ESTEEM	54318	54367	-27147	0.93	0.13	0.04
Model 4 (2F) – ACAD and PERS	ACAD – MATH, READ. PERS – ALONG, CONTRL, ESTEEM	65767	65833	-32867	0.99	0.05	0.02

Table 22 CFA for Expectancy of Success (ES): Factor loadings for different factor structures

Indicator/Model	Model 1	Model 2	Model 3	Model 4 (ACAD)	Model 4 (PERS)
EMATH (α_{21})	0.39 (0.01) *	0.34 (0.01) *	0.43 (0.01) *	0.51 (0.01) *	
EREAD (α_{22})	0.48 (0.01) *		0.51 (0.01) *	0.66 (0.01) *	
EALONG (α_{23})	0.62 (0.009) *	0.63 (0.01) *			0.63 (0.009) *
ECONTRL (α_{24})	0.70 (0.009) *	0.74 (0.009) *	0.63 (0.01) *		0.72 (0.009) *
EESTEEM (α_{25})	0.65 (0.009) *	0.63 (0.01) *	0.68 (0.01) *		0.64 (0.009) *
Correlation (ACAD, PERS)				0.521 (0.020) *	
Cronbach Alpha (internal reliability)	0.70	0.63	0.64	0.50	0.70

4.6.2.1.1 Single factor model (1F)

In the single factor model, all the ES indicators excluding those related to the latent construct of future orientation - ESPCJOB and EFRIEND. All the indicators had a factor loading of 0.4 and above, the minimum loading threshold used in this study. The indicators of personality efficacy (PERS) loaded more strongly - EALONG (0.62), ECONTRL (0.70) and EESTEEM (0.65). The internal reliability of this model was 0.7.

The general latent construct in this model seems more oriented with personality efficacy than academic efficacy. There is no difference between the EFA single factor model estimates and the CFA single factor model estimates. The single factor model as expected showed empirical support for a general ES latent construct with academic efficacy and personality efficacy being the underlying latent factors.

4.6.2.1.2 Two factor model (2F)

In the two-factor model, the first factor represents academic efficacy (ACAD) and the second factor represents personality efficacy (PERS). Results of the two-factor model show EMATH and EREAD loading onto the first factor with loading values of 0.51 and 0.66. This is an increase from the single factor model loading values - EMATH (0.39) and EREAD (0.48). In EFA the loadings for EMATH and EREAD in the first factor was 0.75 and 0.58. The internal reliability of the first factor was 0.5, lower than the reliability of the single factor model discussed above. But the internal reliability of the second factor representing personality efficacy stayed the same at 0.7. The indicators of PERS had strong factor loadings - EALONG (0.63), ECONTRL (0.72), EESTEEM

(0.64). The two factors are also strongly correlated with a correlation coefficient of 0.7 approximately.

The two-factor model confirms what was originally hypothesized. That the expectancy of success is a multidimensional construct (Eccles and Wigfield, 2021) composed of closely overlapping dimensions. Expected success in improving academic and career-self management skills (personality efficacy) are strong motivations to participate in JC. Academic efficacy or greater belief in one's academic skills are known to increase self-esteem. As discussed earlier, greater self-esteem is correlated with greater self-control and leads to better career self-management (Lent et. al., 2016).

The factor loadings of academic efficacy indicators - EMATH and EREAD - increased in the two-factor model because the first factor represented academic efficacy whose basic skills are numeracy and literacy. But the lower factor loadings in CFA than EFA for the same indicators is likely due to the fact that items are not allowed to cross-load across factors in CFA while it is allowed in EFA. In the two factor model we see that the general ES construct has strong factor loadings - indicators of PERS - and weak factor loadings - indicators of ACAD. Finding a combination of weak and strong factor loadings in the same general latent construct is common in empirical applications (Ximenez, 2009). In such cases, weak factor loadings are recovered well when the sample size is large and underlying factors are correlated. Ximenez (2009) also suggests the use of weighted least squares estimator (ULS) than maximum likelihood (robust version is MLR). But ML estimators deal with missing data better using Full information maximum likelihood (FIML) method. But comparison of factor structures from both estimators did not show any different in estimated parameters. For this reason, the results reported here are based on MLR estimation with missing data dealt by FIML. Based on the discussion, I decided to use the two factor model for subsequent analysis. The two factors, which are also strongly correlated are - academic efficacy measured by EMATH and EREAD, and personality efficacy (career self-management) measured by EALONG, ECONTRL and EESTEEM.

4.6.2.2 CFA with predictors - Multiple cause multiple indicator (MIMC) model

The purpose of this section is to investigate predictors of Expectancy of Success (ES). Since ES is composed of ACAD (academic efficacy) and PERS (personality efficacy), latent regressions are estimated on both the latent factors with all the choice determinants as independent variables. In accordance with the CFA analysis, ACAD and PERS are allowed to be correlated. ACAD is measured by EMATH and EREAD, while PERS is measured by EALONG, ECONTRL and EESTEEM. This model has the best model fit and highest internal reliability (Cronbach Alpha was 0.50 for ACAD and 0.70 for PERS).

CFA with covariates (MIMIC) includes models where the relationship between factors and a set of covariates are studied to understand measurement invariance and population heterogeneity. These models can include direct effects, that is, the regression of a factor indicator on a covariate in order to study measurement non-invariance. Structural equation modeling (SEM) includes models in which regressions among the continuous latent variables are estimated (Bollen, 1989; Browne & Arminger, 1995; Joreskog & Sorbom, 1979). In all of these models, the latent variables are continuous. Observed dependent variable variables can be continuous, censored, binary, ordered categorical (ordinal), unordered categorical (nominal), counts, or combinations of these variable types.

Since MIMIC is also a measurement invariance testing procedure, I also checked for measurement invariance in SV and AV to ensure that the regression coefficients of choice determinants on latent variables are unbiased (Guenole and Brown, 2014). Since most of the choice determinants in this study are categorical, I was able to use multi-category CFA (mgCFA) methods. I followed the procedure suggested in the literature (Putnick and Bornstein, 2016) to test for measurement invariance. Unless all three kinds of invariance are satisfied (configural, metric and scalar), we cannot rely on unbiasedness of regression coefficients and standard errors in the latent regression part of MIMIC models (Cieciuch et. al., 2019). I found complete measurement invariance (configural, metric and scalar) in the final MIMIC model being estimated in this study. Therefore, the regression coefficients in the regression results can be interpreted as unbiased differences in the means of the latent variables across different levels of the choice determinants.

4.6.2.3 Factor structure

The factor structure estimated jointly with the latent regression does not change the factor structure of the two-factor model in CFA. The correlation between the two latent variables - ACAD and PERS - is 0.33 after including the latent regressions in the MIMC model. Since the factor structure has not changed after inclusion of covariates, we can rule of direct effects of the choice determinants on measurement indicators.

4.6.2.4 Expected improvement in academic efficacy (ACAD)

Expected improvement in academic efficacy (ACAD) was influenced by individual and household characteristics. Additionally, both attainment and adverse life experiences are also statistically significant predictors of ACAD. The results of the latent regression where ACAD is the dependent variable, and the full set of choice determinants as independent variables are presented below.

Table 23 Estimated coefficients from regressing ACAD on covariates

Predictor	Expected academic benefits (ACAD) (Coeff. $\widehat{\lambda_2}$)	ACAD (z-statistic)	Expected personality benefits (PERS) (Coeff. $\widehat{\lambda_2}$)	PERS (z-statistic)
Male	**-0.171**	-7.930	**-0.070**	-2.797
Black	**0.154**	6.002	**-0.062**	-2.186
Hispanic	**0.277**	9.065	0.011	0.307
Age in years	**0.028**	2.605	**0.033**	2.662
Had father(ly) figure	**0.089**	3.234	**0.130**	4.044
Father had at least HS/GED	**-0.113**	-4.107	**-0.111**	-3.510
Living in (PMSA)	-0.025	-0.872	**-0.178**	-5.415
Living in (MSA)	0.002	0.071	**-0.187**	-6.284
Lived in public housing	**0.067**	2.656	**0.059**	1.979
Prior year work	**-0.063**	-2.202	**-0.111**	-3.365
Prior high school credential	**-0.309**	-11.041	**-0.150**	-4.718
Ever worked	**-0.065**	-1.954	-0.074	-1.880
Prior child	-0.025	-0.859	**-0.106**	-3.142
Prior year welfare receipt	**0.068**	3.046	0.019	0.766
Bad health at randomization	**-0.061**	-2.028	0.032	0.937
Marijuana use	**-0.067**	-2.746	**-0.073**	-2.633
Hard drugs use	**-0.099**	-2.132	-0.005	-0.106

4.6.2.4.1 Individual characteristics

Among the individual characteristics age, race, and gender have a statistically significant effect on ACAD. While race and age have a positive impact, men are more likely to have lower academic self-efficacy among at-risk youth than women. Race seems to have a greater impact on ACAD than age, with Hispanics a significantly more impact in comparison to white or other races, than blacks in comparison to white or other races.

4.6.2.4.2 Household characteristics

Among the household characteristics parental education had a statistically significant impact on ACAD but the direction of impact was not the same. The impact of having a father or fatherly figure was positive on expected success in academic efficacy while it was negative for father having at least a high school degree.

4.6.2.4.3 Life experiences

Among attainment related experiences, having a prior high school credential and full-time or part-time employment in the year before NJCS randomization were both negatively associated with ACAD. Negative experiences such as living in public housing and growing up on welfare benefits as a child were both positively influencing ACAD. Both bad health and drug abuse had a statistically significant negative impact on academic efficacy.

4.6.2.5 Expected improvement in personality efficacy (PERS)

Expected improvement in academic efficacy (PERS) was influenced by individual and household characteristics. Additionally, both attainment and adverse life experiences are also statistically significant predictors of PERS. The results of the latent regression where PERS is the dependent variable, and the full set of choice determinants as independent variables are presented below.

4.6.2.5.1 Individual characteristics

Among the individual characteristics gender, race, age and age fixed effects had a significant influence on PERS. The latent construct was negatively associated with male and also with black in comparison to all the other races. While age had a positive impact on PERS, the fixed effect of being 18 or 19 years seems to decrease PERS in comparison to those who are 16-17 years of age. No such difference was found for those who were 20 years and above. Being separated, widowed or divorced also seems to have a negative impact on PERS.

4.6.2.5.2 Household characteristics

Among the household characteristics parental education had a statistically significant impact on ACAD but the direction of impact was not the same. Similar to ACAD having a father or fatherly figure positively impacted PERS but was negatively impacted by father's education attainment of high school credential or more. Living in metropolitan statistical areas (MSA) or primary MSA (PMSA) were both negatively associated with PERS.

4.6.2.5.3 Life experiences

Among attainment related experiences, having a prior high school credential had a negative impact on PERS. Negative experiences such as living in public housing, having a child at the time of NJCS randomization (teen or young parents) and marijuana usage in the past year were all significantly impacting PERS. While living in public housing had a positive impact on the expected improvements in personality efficacy, it was negative for having a child in youth and marijuana usage.

4.7 Conclusion

4.7.1 Situational task value (STV)

In the beginning all the indicators were assumed to represent the underlying latent STV. Theory suggested a two-factor structure where first factor is formed by motivations to leave home, community and other personal reasons. The second factor is formed by motivations to join JC due to need for training, and career aspirations (goals). The first factor captures the motivational importance of JC since participation reduces the risk exposure in a person's current life situations. For at-risk youth, this factor does not strongly correlate with the second factor which appeals more to the vocational identity exploration benefits of participating in JC. Therefore, despite finding empirical support for the two-factor structure, a single factor focusing on situational value of JC due to current risk exposure seems to be a more relevant construct for the application of SETV to the context of JC.

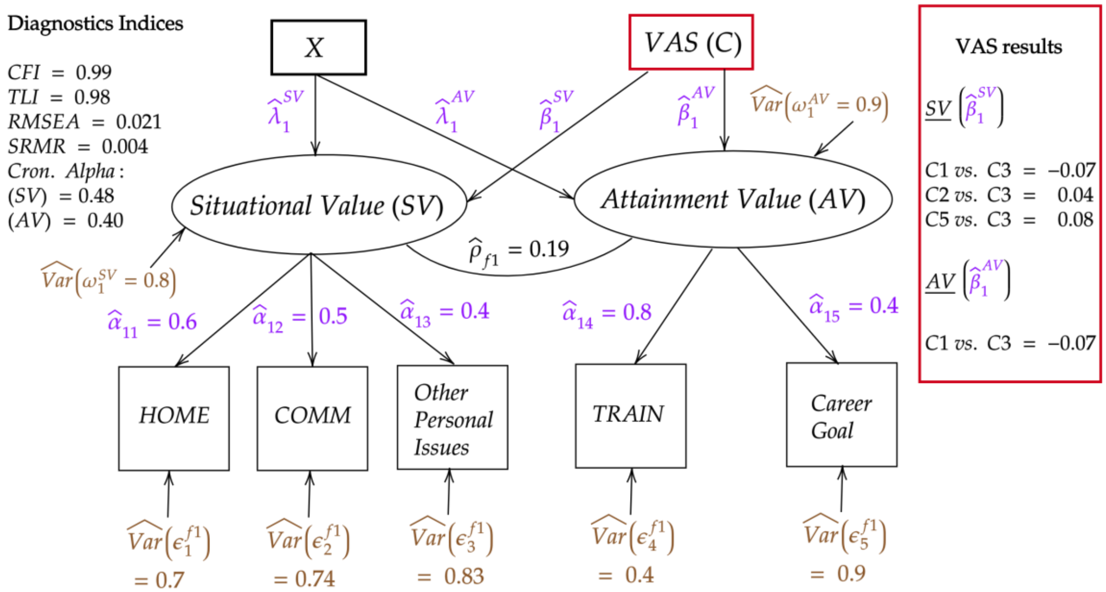

Figure 6 Graphical representation of the final factor structure of STV (all variables are standardized)

In this study, a reliable and valid measure of the subjective motivation to join JC was identified and estimated. Due to the multidimensional nature of STV, this study also clarified that the motivation for at-risk youth to enroll in job training arises primarily due to life situations with high-risk exposure in their existing ecosystems. While there are situations in which STV might not be an influential choice determinant (Tang et. al., 2022), it can still help us understand variation in treatment choices for those who look similar on observable attributes. The significance of STV in the choice analysis could imply that at-risk youth might already be highly motivated for job training due to their life circumstances. Therefore, interventions can focus on leveraging this motivation to ensure persistence and completion in JC and not just enrollment.

4.7.2 Expectations of Success (ES)

There is evidence that all the proxy measures plausibly represent a univariate latent construct for the purposes of modeling. In alignment with theory, the multidimensional nature of the ES construct is explained by how it is composed of expected successes in academic skills and career-self management skills involving personality traits such as positive peer relationships, self-esteem and self-control. The univariate construct also seems relatively more representative of the expected improvements in personality efficacy than academic efficacy.

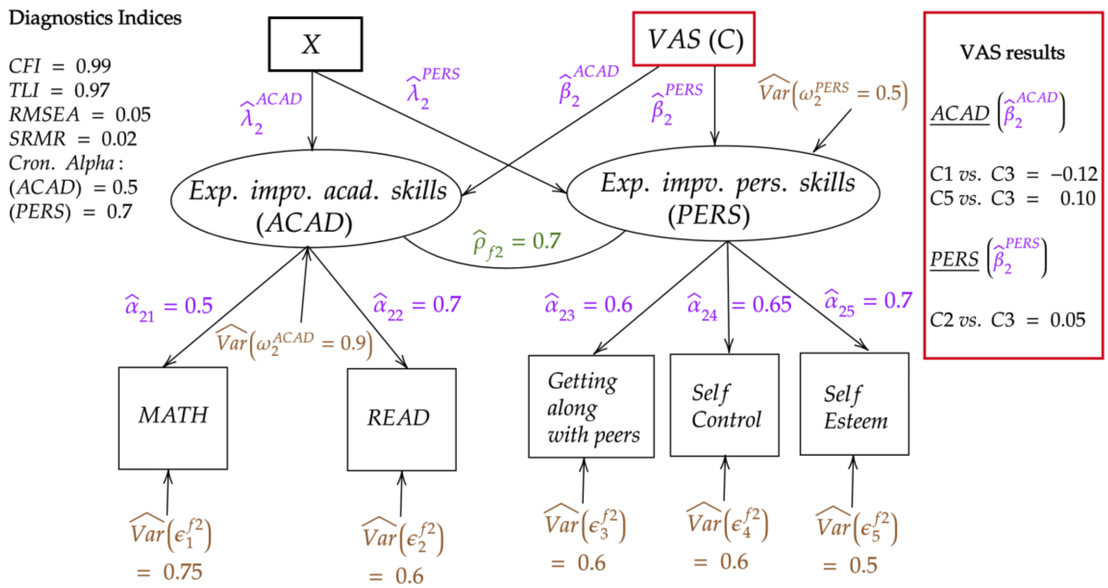

Figure 7 Graphical representation of the final factor structure of ES (all variables are standardized)

When making a vocational education and training choice, a rational youth will expect to improve in skills required to succeed in subsequent occupational trajectory. Since labor market success depends on both cognitive and non-cognitive abilities, expecting improvement in both is rational. But understanding the compositions of these expectations can help in changing the design features of a job training program to serve the youth expectations than policymaker preferences. For example, various studies have found that the earnings impact of Job Corps diminishes in the long term. Despite the participant expectations to succeed in executive functions, the endline survey did not measure any psychological constructs related to EF. Therefore, it is entirely possible that we are underestimating the importance of Job Corps to the at-risk youth population by looking at labor market impact than on identity development.

5. Choice and treatment effect analysis

5.1 Introduction

In the earlier chapters I validated and estimated the univariate latent constructs representing an individual's motivation to participate in Job Corps (STV) and how much improvement in various cognitive domains is expected through participation in Job Corps (ES). I also characterized patterns of information acquisition about Job Corps (Vocational Aspirational Socialization - VAS), as latent categories of an underlying latent construct representing profiles of VAS done by eligible participants. Together, all three latent constructs form the private information set of the agent (eligible participant assigned to program and now has to decide between participation vs. non-participation in Job Corps). The purpose of this study is to explore strategies to resolve three issues. Firstly, how to incorporate latent variables in estimating choice probabilities? Secondly, does the estimation method satisfy required assumptions about the structure of the choice set? Thirdly, how to estimate Average Treatment Effect (ATE) after obtaining the required choice probabilities?

For the purpose of estimating choice probabilities, how to incorporate the agent's private information set with the analyst's (sometimes referred to as economist) information set that consists of only the observed attributes of the agent? The augmented information set now contains information observed by the economist and agent's private information set. In other words, it is also the full information set of the agent containing both attributes observable to the analyst and private agent information set.[GH2] The first approach is sequential estimation of choice probabilities. In this approach, the factor models are estimated first to obtain estimated latent values, of the underlying latent constructs. Then these estimated values are augmented with the economist information to provide the augmented information set. This is the standard approach by which information is added to any of the three primary parametric methods to estimate choice probabilities – logit, conditional logit and mixed logit.

Logit behavior choice model implemented through logistic regression assumes independence of irrelevant alternatives (IIA) between the choice alternatives of participation vs. non-participation in Job Corps. These are the two choice alternatives when the agent is making the compliance decision. This is ex-ante choice. When I analyzed the choice patterns in the endline, agents had used Job Corps and non-JC training programs as close substitutes and thus violating IIA. In such situations, logistic or multinomial models may not capture these substitution effects.

Conditional logit models accommodate this violation by using extreme value distributions for error component of each choice alternative in the utility model (McFadden, 1981). This results in difference in errors to be distributed as logistic. This is also called the McFadden's model. Mixed logit models further generalized the conditional logit models by allowing random coefficients on choice attribute variables to reflect taste heterogeneity among agents for the same choice attribute level. The second approach to incorporate latent variable information is to estimate the latent and choice models together labeled as hybrid choice models (HCM) or integrated choice and latent variable models (ICLV). Such models can be estimated jointly as a complete structural equation model (SEM) with all the dependencies between variables explicitly modeled. Another approach to estimation of ICLV models is simulation- based methods. If the purpose of the analysis is to estimate the choice probabilities alone then there may not be a relative advantage between the sequential and joint estimation. But the joint approach is known to be better than the sequential approach to obtain appropriate standard errors or to empirically analyze an integrated conceptual choice model such as SEVT etc. (Vij and Walker, 2016).

Once the choice probabilities are obtained the next step is to estimate ATE. The inverse of the choice probabilities is used as weights in an inverse probability weighting estimator called ICSW (Aronow and Carnegie, 2013). The authors also suggest the weighted two-stage least squares estimator (W-2SLS) with inverse probabilities as weights to be an equivalent estimator for ATE. This is also confirmed by Small and Tan (2017) in which they show that the conventional 2SLS estimator actually identifies a strength of IV-weighted ATE (SIV_WATE) where the weights correspond to how much the instrument (assignment) influenced the endogenous participation choice. This strength is captured by the identified choice probabilities (compliance scores). Therefore, a weighted 2SLS with inverse of compliance score as weights, will unweight the SIV-WATE to recover ATE.

5.2 Data

5.2.1 NJCS sample

In this study sample there are N = 10718 individuals. The original sample consisted of N = 10779. These individuals are those who have completed baseline and endline (48 month) surveys. They are also not currently enrolled in the Job Corps program. After removing observations with missing data in all measurement indicators (as used in the latent variable analysis) we have N = 10718. In the table below, descriptive statistics of the variable used in choice analysis are displayed. All the covariates are discrete and binary except age in years and the grand-mean centered age in years. Since the factor scores estimated in the previous chapter are standardized, I also centered the only continuous variable in the data – age in years. In addition to age in years, there are also age dummies for the age group. The reference group consists of those in the age group of 16-17 years. The `age2` dummy refers to age group of 18-19 years and finally the `age3` dummy refers to those who are 20 years and above in age. The purpose of adding the dummies in addition to age in years is to capture the developmental fixed effect of being in that age group in adolescence. Research on adolescence development has shown that in each of these age groups, the developmental processes vary and therefore, there are specific developmental changes which happen in each of these age groups (Steinberg and Morris, 2001). The variables pertaining to motivation and expected benefits are the measurement indicators used in the latent variable analysis of STV and ES in the earlier chapters. The reason for their inclusion in this study is because in the hybrid choice model the entire model is jointly estimated as a SEM (Temme et. al., 2008). I do not describe these indicator variables further since they were discussed in the earlier chapters.

I checked whether the covariates used in this study are balanced across the experimental treatment and control groups. For the binary variables in the data, weighted chi-square tests were conducted with the survey sampling weights provided in the NJCS data. The null hypothesis that the variable being tested is balanced between the experimental groups could not be rejected for any variable. ANOVA tests with sampling weights were used to check for covariate balance in age variable. That was also found to be balanced since we could not reject the null hypothesis of no difference in variable's means across the experimental groups. In Table 2 these results are tabulated along with information on proportion of missing data among all the variables. It should be noted that the covariates to be used in the choice analysis have complete data. This is because the data for these variables was obtained from the `milestone` dataset in the NJCS study. To construct this data project staff consulted multiple data records to fill the values missing from eligible participant surveys. The missing information is mostly observed in the indicators for motivation. Since this is relevant only for the joint choice model estimation, it does not affect the sequential analyses. For sequential analyses this is not a concern because we are using the estimated factor scores from the previous chapters, as if they are observed covariates.

For the purpose of choice modeling only those in the experimental treatment group are used for analysis (n=6536). This is because only they faced the choice problem of participation vs. non-participation in JC. Those in the control group at the time of decision-making did not have participation in JC as a choice. Prior studies have estimated choice models for treatment group and the estimated model is then used to predict choice probabilities for the entire sample (Follman, 2000).

5.2.2 Demographic indicators

The choice determinants in this study can be divided into observable and latent attributes of individual and choice. All the attributes except the latent variable for ES are considered to be individual attributes. But ES was modeled based on questions about expected benefits of the program or in other words, perceived value for the features of the Job Corps program. The assumption made in this study is that the survey questions implicitly asked about expected benefits of JC participation over the non-participation in JC. So, the expected benefits are relative to non-JC option(s) (working or other vocational training programs). If this assumption is valid then we can initialize the values of expected benefits for non-participation in JC to zero.

In the random utility models for choice behavior, the concern is about only differences in utilities under alternate choices. So, fixing expected benefits for non-participation in JC (non-JC) to zero is to make it a reference level. So, the estimated latent values for expected benefits represent the relative difference in expected benefits between JC vs. non-JC choices. So, at the time of decision-making, the expected benefits of JC due to its features are in relation to the non-JC alternatives. It is still possible that after the participation decision is made, an individual might find other programs.

Similar to expected benefits of JC participation, it is possible to envisage the latent construct of motivations for JC participation (STV) also as a choice attribute. Similar to the expected benefits, fixing motivation for non-JC to zero is to make it a reference level. The estimated motivation value represents relative motivation between JC vs. non-JC choices. So those who are more motivated to choose non-JC to be close to home would have responded with the code 0 on the question - Was moving away from home an important reason for you to join Job Corps? Then keeping all other item responses constant, the person who is motivated to stay close to home will have a lower predicted motivation (factor score) or closer to preferring the non-JC option, than one motivated to join JC to be away from home.

The observable choice determinants are individual attributes pertaining to age, gender, race, household characteristics, education attainment, characteristics of marriage and cohabitation, prior history with employment, criminal justice, substance abuse, marital relationships, and urbanicity of the individual's region of habitation. Nearly 80 percent of the sample had worked full time or part time in the year before randomization. Approximately, 50 to 60 percent of the sample (experimental treatment group, N = 6536) are men (55 percent), black (49 percent), had a father or a fatherly figure at home (62 percent), lived in a Metropolitan Statistical Area (MSA, 46 percent) and availed welfare benefits in the last year (59 percent). Less than 50 percent of the sample had a father with a high school credential (43 percent), lived in primary metropolitan statistical areas (PMSA, 32 percent). Nearly 20-25 percent of the sample are white (26 percent), already had a child at baseline (21 percent), had used marijuana in the year before randomization with marijuana usage more prevalent (24 percent). A similar proportion lived in public housing and had been arrested before in their lives. Nearly 13 percent of the sample had bad health at the baseline. Less than 10 percent of the sample had taken hard drugs (6 percent), taken drug treatment before (5 percent), and married/living with spouse or separated or divorced (2-7 percent).

In earlier chapters I described how STV can be composed of two different but related dimensions – situational value (SV) of participating in JC and attainment value (AV) of participating in JC. The situational value arises from the life experiences – distal and proximal – such as barriers to identity (including vocational) at home, community and other contexts or stakeholders in the typical developmental ecosystem of an at-risk youth. The attainment value of participating in JC is based on how lack of training and satisfactory employment could be addressed by improving one's vocational skills through JC. Situational and attainment value components can overlap to varying degrees depending on the context and the distinction is subtle (Eccles and Wigfield, 2020). Since the situational value is not related to JC features and since the situational value cannot be considered orthogonal to attainment value, I treat STV more as a latent attribute of the individual than the choice.

It is also possible that the unobserved component of utility functions still contains components of ES and STV that were not measured due to lack of appropriate measurement indicators or proxy measures. There are existing computational methods to partition the latent space into observed and unobserved components (Salzmann et. al., 2010). But these methods are beyond the scope of the current study. So, I assume in this analysis that components of STV and ES unmeasured by the latent variable analysis are orthogonal to the latent constructs accepted at the end of confirmatory factor analysis in the previous chapters. But to keep it simple, the orthogonality is ensured by the orthogonal rotation algorithms in factor analysis.

5.3 Analytical procedure

5.3.1 Generalized stochastic random utility model (GSRUM)

5.3.1.1 Ex-ante choice process - a specific model

Let Y_1 be an indicator (in four years from randomization) of violent crime victimization if the individual attends the Job Corps and Y_0 if they do not. The decision to participate may be made on the expected probability of victimization under both choices: $E[Y_1|H]$, $E[Y_0|H]$ and expected costs $E[Q|H]$. The expectations are those of the relevant decision maker or agent (at-risk youth eligible and with an offer to participate in Job Corps). These expectations are formed under the agent's information set $H \equiv H_{ea}^* = \{X, X^*\}$.

From an analyst's point of view the data generation process or the counterfactual generation process for outcome $Y = y$ under participation $D = d$ and observed information $X = x$ and unobserved information $U = u$, $y_d = g_d(d, x, u)$, and the latent propensity to participate under encouragement level z , $d_z^* = g_z(z, x, u)$.

The analyst's information set contains only the observable attributes of the individual, $H_e = \{X\}$. The agent's private information set H_a^* contains information known only to the agent and usually unmeasurable such as latent psychological perceptions and attitudes X^*. In this study the latent constructs of interest are situational task value (STV) of participating in Job Corps denoted by X_1^* and expectations of success by participating in Job Corps denoted by X_2^*. According to SEV theory (SEVT), the sufficient set of predictors of participation choice in JC or a relevant information set to predict choice is $\tilde{X} = \{X, X_1^*, X_2^*\}$ (Heckman, 2008). So, the sufficient latent information set for predicting choice is $H_a^* = U = X^* = (X_1^*, X_2^*)$. Here U is the unobserved component of random utility not observed by the analyst. It is also the unobserved common causes of D and Y.

The full information available to the agent, $H \equiv H_{ea}^* = H_e \cup H_a^* = (X, X^*)$. For an analyst to use this full information set, they have to jointly model (joint estimation) both the participation choice and the latent constructs influencing the decision. In this study the joint estimation is achieved with structural equation models (SEM).

5.3.1.2 Random utility theory

Individuals derive utility such as achieving a desired outcome by choosing an alternative. In the case of social programs, individuals participate when they expect the program to provide them a net gain on a desired outcome (adjusting for cost of making the participation choice). The latent index of preference D^* is a manifestation of the underlying utilities. The utilities are functions of observed explanatory variables X about the individuals and choice alternatives, and other unobserved variables U. For all individuals $i \in \{1, \ldots N\}$, Let

$$Y = \beta X + U$$

$$Y_1 = \beta_1 X + U_1$$

$$Y_0 = \beta_0 X + U_0$$

Here Y is the indicator variable denoting whether an individual was a victim of violent crime in the time since they applied to Job Corps program. The information observable to the analyst is X and not observed by the analyst but known to the agent is U.

Let U contain information about the latent constructs suggested as choice determinants from the Situational Expectancy Value Theory (SETV). The Subjective Task Value of Job Corps participation (STV) is denoted by X_1^* and Expectations of Success (ES) denoted by X_2^*. Therefore, the SEVT determinants, $X^* = \{X_1^*, X_2^*\} \subset U$. According to SEVT the most proximal choice determinants of JC participation are $\{X, X^*\}$. Therefore, once this information is controlled for, the unexplained variation in participation is considered orthogonal to the covariate space spanned by this information set.

$$U = \lambda X^* + \epsilon;$$

$$Y = \beta X + \lambda X^* + \epsilon; \epsilon \sim distr(\theta_\epsilon)$$

$$X^* = \gamma X + \omega; \omega \sim distr(\theta_\omega)$$

But as defined earlier, X_1^* and X_2^* are latent constructs representing STV and ES respectively. The assumption here is that individuals indicate their underlying STV (X_1^*) through indicator variables or proxy measures $I^{X_1^*}$. Similarly, ES (X_2^*) through indicator variables or proxy measures $I^{X_2^*}$.

The latent constructs X^* are perceptions and attitudes which are also informed by the information individuals acquire about JC experiences (VAS or IAC).

The latent classes of Vocational Anticipatory Socialization (Powers and Myers, 2016) denoted by C. In the context of NJCS, the VAS construct is interchangeably referred to as VAS or Information Acquisition Context (IAC). Indicators $I = \{I^C, I^{X_1^*}, I^{X_2^*}\}$ corresponding to indicator sets for each of the three latent factors of VAS, STV and ES, respectively. The total number of indicators is denoted respectively by $L = \{L^C, L^{X_1^*}, L^{X_2^*}\}$.

For example, indicator $I_l^C : l = 1, \ldots, L^C$ denotes the l^{th} indicator or item for latent class C and total number of indicators is L^C. Similarly, $I_l^{X_1^*}$ and $I_l^{X_2^*}$ are the l-th indicators for X_1^* and X_2^*.

The latent variables can be decomposed into a factor structure that explains the common variance (f) and unique variance (Γ), such that:

$$X^* = F + \Gamma$$

Both ES and STV do not have a well-defined test to extract the underlying X^*. So I used factor analysis to extract the common factor structure (F). The measurement equations for X^* can be written as:

Under joint estimation - Integrated choice and latent variable (ICLV) model

Measurement equations

For STV:

$$I_m^{X_1^*} = \alpha_{1m} X_1^* + \nu_m^{X_1^*} : m = \{1, \ldots, L^{X_1^*}\}$$

For ES:

$$I_m^{X_2^*} = \alpha_{2m} X_2^* + \nu_m^{X_2^*} : m = \{1, \ldots, L^{X_2^*}\}$$

In joint estimation with SEM, the structural equations are expressed as below:

Structural equations

$$X_1^* = \Sigma_{k=1}^{K} \eta_{1k} X_k + \kappa_1 C + \tau_1$$

$$X_2^* = \Sigma_{k=1}^{K} \eta_{2k} X_k + \kappa_2 C + \tau_2$$

Where K represents the total number of observed covariates included in the model and C represents the latent class of VAS (IAC) the individual has been assigned at the end of latent class analysis (Weller, 2020). The individual is usually assigned the latent class to which they have the maximal posterior probability of belonging.

From the point of view of the agent the expected utility or value of participation is $E[Y_1|H]$ and not participating is $E[Y_0|H]$. The expected net value is

$$E[Y_1|H] - E[Y_0|H]$$

Then for agents who choose to participate based on maximum gain, the decision to participate is taken as

$$D = \begin{cases} 1, & \text{if } E[Y_1|H] - E[Y_0|H] \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

This is the generalized Roy model (Cunha et. al., 2005; Heckman, 2007).

Let i denote an individual belonging to the target population of at-risk youth denoted by i. Then H_i represents the information set of the agent i. The agent evaluates participation in JC over non-participation (non-JC) using information H_i. Then the proportion of people who prefer participating in JC over non-participation in JC (non-JC) are given as (dropping subscript i for simplicity):

$$P(D = 1|H) = P(E[Y_1|H] - E[Y_0|H] \geq 0)$$

So, the unconditional probability of participation in JC for each individual is obtained by integrating over the uncertainty inherent in their information set H. The unconditional probability is the probability of choosing JC given the two alternatives of JC and non-JC. It is given as

$$P_i(JC|JC, non-JC) = \int \mathbb{1}(E[Y_1|H = h] \geq E[Y_0|H = h])f(h)dh$$

here, $f(h)$ is the distribution of H in the population (at-risk youth) whose preferences over outcomes are being studied.

5.3.1.2.1 Estimating choice probabilities - joint estimation

Given the above formulation of joint estimation, the conditional probability of participation is

$$P(D = 1|X, X^*; \beta, \theta_\epsilon)$$

But to get the unconditional probability $P(D = 1|X; \Theta)$ we have to integrate over X^*. Using the structural equations for X^* given above, we can get the density $\mathbb{f}(X^*|X; \eta, \kappa, \theta_\tau)$, where $\tau \sim distr(\theta_\tau)$. Since X^* is latent, measurement indicators I are required to model it. So given the measurement equations above for the relationship between I and X^*, we can obtain the density $\mathbb{f}(I|\alpha, \theta_\nu)$, where $\nu \sim distr(\theta_\nu)$.

Let $i = 1, \ldots, N$ denote the index for individuals in the research sample. Under joint estimation and using these densities, the unconditional probability of participation in JC can be estimated as

$$P(D_i, I_i|X_i; \beta, \eta, \kappa, \alpha, \theta_\epsilon, \theta_\tau, \theta_\nu) = \int P(D_i|X_i, X_i^*; \beta, \theta_\epsilon) * \mathbb{f}(I_i|X^*, \alpha, \theta_\nu) * \mathbb{f}(X^*|X_i; \eta, \kappa, \theta_\tau)dX^*$$

Given the structural model for X^* we can substitute it into the equation above and get the unconditional choice probability (compliance score) of participation in JC:

$$\pi(\tilde{x}) = P(D_i, I_i|X_i; \beta, \eta, \kappa, \alpha, \theta_\epsilon, \theta_\tau, \theta_\nu) = \int P(D_i|X_i, X_i^*; \beta, \theta_\epsilon) * \mathbb{f}(I_i|X^*, \alpha, \theta_\nu) * \mathbb{f}(\tau|\theta_\tau)d\tau$$

Here $\tilde{x} = \{x, x^*\}$ denoted for ease of representation in later analysis.

5.3.1.2.2 Sequential estimation

But under sequential estimation, the economist's augmented set, $H_{ea} = H_e \cup H_a = (X, F)$. But as discussed earlier $F \neq \Gamma$. Therefore, including the estimated factor scores as choice determinants is prone to bias. The literature suggests the use of plausible values rather than factor scores (Wu, 2005). Plausible values are multiple imputations of the unobservable latent variables X^* for each individual. But this is not a widely adopted practice yet and therefore, the same has not been used in this analysis. It nevertheless offers a possible extension for future work.

Measurement equations

For STV:

$$I_m^{f1} = \alpha_{1m} f_1 + v_m^{f1} : m = \{1, \ldots, L^{f1}\}$$

For ES:

$$I_m^{f2} = \alpha_{2m} f_2 + v_m^{f2} : m = \{1, \ldots, L^{f2}\}$$

Structural equations

For STV:

$$f_1 = \Sigma_{k=1}^{K} \eta_{1k} X_k + \kappa_1 C + \tau_1$$

For ES:

$$f_2 = \Sigma_{k=1}^{K} \eta_{2k} X_k + \kappa_2 C + \tau_2$$

5.3.3 Compliance scores

5.3.3.1 Joint estimation compliance scores - from ICLV

Under general compliance behavior, the compliance score can be defined as

$$\pi(x, x^*) = \pi(\tilde{x}) = E[D = 1 | Z = 1, X = x, X^* = x^*] - E[D = 1 | Z = 0, X = x, X^* = x^*]$$

Since those in the control group did not get access to Job Corps, $E[D = 1|Z = 0, X = x, X^* = x^*] = 0$. So, in this case, the compliance score is the same as the propensity score (compliance score, henceforth). If the control group members could have also participated in JC, then propensity and compliance scores would be different. For this reason, I will continue using the term compliance score $(\pi(\tilde{x}))$.

$$\hat{\pi}(\tilde{x}) = P(D = 1|Z = 1, X = x, X^* = x^*)$$

The estimated compliance score model is used to estimate compliance scores for the control group members as well so that, $\exists \hat{\pi}_i(\tilde{x}) \forall i \in \{1, \dots, N\}: 0 < \hat{\pi}(\tilde{x}) < 1$. There is a non-negative compliance score for every individual in the sample.

5.3.3.2 Sequential estimation compliance scores - Logit and Conditional logit models

Under general compliance behavior, the compliance score can be defined as

$$\pi(\tilde{x}) = \pi(x, f) = E[D = 1|Z = 1, X = x, F = f] - E[D = 1|Z = 0, X = x, F = f]$$

Since those in the control group did not get access to Job Corps, $E[D = 1|Z = 0, X = x, F = f] = 0$. So, in this case, the compliance score is the same as the propensity score (compliance score, henceforth). If the control group members could have also participated in JC then propensity and compliance scores would be different. For this reason, I will continue using the term compliance score $(\pi(\tilde{x}))$.

$$\hat{\pi}(\tilde{x}) = P(D = 1|Z = 1, X = x, F = f)$$

The estimated compliance score model is used to estimate compliance scores for the control group members as well so that, $\exists \hat{\pi}_i(\tilde{x}) \forall i \in \{1, \dots, N\}: 0 < \hat{\pi}(\tilde{x}) < 1$. There is a non-negative compliance score for every individual in the sample.

In the conventional logistic regression used for propensity score estimation,

$$\pi(\tilde{x}) = \frac{1}{1 + e^{-\tilde{x}\beta}}$$

In this case, the error distribution is assumed to follow the standard logistic distribution. In this study, the ex-ante choice set has only two alternatives – to participate or not in JC. The agents might be aware of non-JC VET programs as a third alternative to be used with either ex-ante choice alternative. For example, ex-post choice patterns show that among the experimental program group there were those who (a) enrolled only in JC (b) enrolled in Job Corps and another non-JC program (c) Did not enroll in any VET program. In the experimental control group, JC was not an option so there were individuals who (a) enrolled in a non-JC program and (b) did not enroll in any VET program. Such choice substitution patterns violate the IIA assumption. Such a violation implies that there is conditional dependency among choice alternatives. Conditional logit models with GEV error distributions for individual error components are flexible in accommodating various substitutions patterns. Mixed logit models provide the maximum flexibility in specification of individual error distributions and their covariance structure (McFadden and Train, 2000). Due to computational issues, mixed logit models were not used in this dissertation work but earmarked for future research.

Even if unobserved utility in each choice alternative is GEV, their difference is distributed as logistic. Therefore, in a binary choice setting, the difference between unobserved utilities under each alternative is distributed as logistic function. In other words, both logit and conditional logit assume that the unobserved utility (errors) under each choice alternative is extreme value distributed. That is why the difference in errors, or the net unobserved utility is distributed as logistic in both cases. Conditional logit allows GEV family of distributions for errors while logistic model assumes GEV Type-1 or Gumbel distribution for independent errors. The difference between logit and conditional logit lies in the former assuming that the unobserved utility (errors) of each choice alternative is independent of each other while conditional logit allows for them to be correlated, as it is natural when there is selection on gains. Since vocational choices, under the generalized Roy model, are assumed to be made based on unobserved expected gains, conditional logit models are natural tools for estimating choice probabilities especially when there are more than two alternatives with complex substitution patterns. This complexity is not addressed well in logistic or multinomial models used in treatment effect literature.

5.3.4 Average treatment effect (ATE)

5.3.4.1 Weighted-2SLS (W-2SLS)

Initially I considered using the inverse compliance score weighted (ICSW) estimator for ATE (Aronow and Carnegie, 2013). But the approach required standard errors be computed by bootstrapping each step of the choice probability estimation. But this was not possible for latent class analysis, and choice model analysis (in STATA) because when using sampling weights bootstrapping is no feasible. Therefore, I chose the weighted- two stage least squares (W-2SLS) estimator (Aronow and Carnegie, 2013; Small and Tan, 2017). Identification of ATE by weighting the 2SLS IV estimand was suggested under deterministic compliance by Aronow and Carnegie (2013). But the identification under stochastic compliance relies on the result of Small and Tan (2017) where they find that under a stochastic compliance class (SCC) framework, the conventional 2SLS IV estimand identifies a strength-of-IV weighted ATE (SIV-WATE). It is a weighted average of individual ATE. The weights correspond to the extent to which the IV (random assignment Z) encourages an individual to participate. They are given as

$$w(x,u) = P(D = 1|Z = 1, X = x, U = u) - P(D = 1|Z = 0, X = x, U = u)$$

where U is the sufficient set (relevant information set) of unmeasured common causes of D and Y. In SEVT the $\{X, X^*\}$ are sufficient common causes of D (choice) and Y(performance or outcome). Therefore,

$$w(x,u) = w(x,x^*) = P(D = 1|Z = 1, X = x, X^* = x^*) = \pi(x,x^*) = \pi(\tilde{x})$$

So, inverse weighting with estimated compliance scores $\hat{\pi}(\tilde{x})$ should recover the ATE. The assumptions required for this identification are:

IV-1: Consistency of stochastic counterfactuals.

The second assumption of randomized encouragement IV (Z) is satisfied as in the deterministic compliance.

IV-2: Random assignment:

- IV 2(a): If H_{ea} was obtained before random assignment: $\{Y_1, Y_0, D_1, D_0\} \perp Z$

Exclusion restriction is not required in stochastic compliance since every individual's degree of ex-ante compliance is estimated (Esterling et. al., 2011).

IV-3': Exclusion restriction: Required to identify causal effects of unobserved compliance behavior. Not required in stochastic compliance since every individual's degree of ex-ante compliance is estimated (Esterling et. al., 2011).

The fourth assumption is that encouragement is a relevant IV with non-trivial impact on participation. This is assumed to be true since offer to enroll in JC is a strong encouragement to participate.

IV-4: Relevance of instrument for participation (non-trivial encouragement): $E[D_i(z=1) - D_i(z=0)] \neq 0$.

The fifth assumption is that of stochastic monotonicity originally discussed by Small and Tan (2017) and generalized here to stochastic behavior.

IV -5: Stochastic monotonicity: $E[D_{1i}|H_i] - E[D_{0i}|H_i] \geq 0$

- IV-5(a) Small and Tan (2017) describe the same effectively as: $P\left(D=1|Z=1,\tilde{X}=\tilde{x}\right) \geq P\left(D=1|Z=0,\tilde{X}=\tilde{x}\right)$

Under these assumptions W-2SLS consistently identifies ATE.

5.3.4.2 g-computation

In the case of one-sided noncompliance, compliance scores are the same as propensity scores. How would the estimated ATE differ if we assumed strong ignorability (no unmeasured confounders and non-negative propensity scores) and used the compliance scores as propensity scores? g-computation methods consistency estimate ATE given propensity scores estimated from a choice model with no unmeasured confounders. The g-computation has the lowest bias and variance in the context of a binary treatment, outcome, and baseline confounders (Chatton et. al., 2020) and outperforms alternative methods even in the presence of an unobserved confounding indirectly affecting assignment through measured baseline covariate (Ren et. al., 2023).

To identify ATE with g-computation, three assumptions have to be satisfied.

1. Consistency in counterfactuals: This assumption as stated in the deterministic compliance class requires SUTVA to be satisfied. But since SUTVA is violated under stochastic choice, the consistency is established with the stochastic consistency assumption discussed earlier.
2. Exchangeability: This assumption requires no unmeasured confounding after controlling for the observed information. The assumption is satisfied if the information observed is a relevant information set H_R such that all the choice determinants are contained in it. Based on the SEVT theory and discussions so far, I assumed that $H_R = \{X, STV, ES\} = \{X, X^*\} = H$. This implies that the information set used by the analyst is the relevant information set when X^* is incorporated into the estimation of choice probabilities either under sequential or joint estimation of the choice and latent variable models.
3. Positivity: This assumption is satisfied when the covariates are balanced across the participation and non-participation group after weighting with the compliance scores. Balance checking procedures were conducted to confirm this assumption.

Under the satisfaction of the three assumptions (assumptions 2 + 3 = strong ignorability), and since Y is binary, the ATE is the absolute risk difference,

$$ATE = E[Y_1 - Y_0] = E[Y_1 - Y_0 | \pi(\tilde{x})]\pi(\tilde{x})$$

This estimation is conducted to compare with estimated ATE from the weighted 2SLS estimator. Simulation studies will be required to test the sensitivity of the difference between W-2SLS and g-computation under varying levels of unconfoundedness.

5.3.5 Choice Models

In the following analysis, we want to test the relevance of using agent information set over the economist information set in estimating choice probabilities. We will also estimate ATE using choice probabilities from each of the models.

5.3.5.1 Model 1

In this model we assume that the IIA (irrelevance of independent alternatives) assumption is satisfied. This allows the use of logistic regression under a logit model of binary choice to estimate the required choice probabilities. In this model we will use only the economist information set $I_e = \{X\}$.

5.3.5.2 Model 2

In this model we replace the economist information set with agent information set. This augmented set has information on the latent factors X^* estimated latent variable values (common factor scores), $\hat{F} = \{\hat{f}_1, \hat{f}_2\}$. Therefore, the full information used here is $\{X, \hat{\theta}_1, \hat{\theta}_2\}$. We use the logistic regression to estimate the choice probabilities.

5.3.5.3 Model 3

In both cases above, the propensity score model was estimated with all the theoretically identified choice determinants under the relevant information set. Since many subsequent analyses involves

SEM modeling, I wanted to reduce the number of variables to be included in the model and account for uncertainty in this model selection process. To identify the influential set of choice determinants, under model uncertainty, I used Bayesian Model Averaging (BMA) (Hoeting et. al., 1999; Hinne et. al., 2020; Porwal and Rafterty, 2022). This model uses the BMA-identified set of variables in the logistic regression model.

5.3.5.4 Model 4

In this model I used conditional logit model with only X. In models 1-3 we assumed IIA to hold good. In ex-ante participation choice, IIA is satisfied when the binary choice alternatives are mutually exclusive of each other. But in ex-post participation choice, agents have access to a third alternative, non-JC job training programs. IIA would still be satisfied if introducing this third alternative does not alter the proportion of substitution among the other two alternatives. But this can be violated if there are situations where introducing a third alternative can alter the substitution proportions. This seems to happen when we include non-JC as an alternative in the urban vs. rural contexts. Additionally, many of those who enrolled in JC also enrolled in a non-JC training program. Therefore, even the ex-ante choice alternatives are not mutually exclusive since they have a nested structure. 1. In the first step, an agent chooses between participating in JC or not participating in JC. In the second step, they can choose to participate in a non-JC job training program or choose to work. So, the ex-post choice set has a nested structure. 2. In urban areas (PMSA and MSA) the JC centers offer more variety of courses and are of a higher quality. In urban areas, JC is of higher quality than non-JC programs. So, most of the experimental treatment group in urban areas either go to JC or work. But in rural areas (non-MSA) since JC is of lower quality, it is considered as a closer alternative to non-JC programs. So, even those participating in JC might additionally do a non-JC training program. The proportion of substitution between JC: non-JC and non-JC to work changes between urban and rural areas.

5.3.5.5 Model 5

In model 5, we implement the conditional logit model (GEV relaxes IIA) but with agent information set H_{ea}.

5.3.5.6 Model 6

We do conditional logit with baseline covariaets chosen as influential predictors of choice under possible model uncertainty. The procedure to obtain such influential predictors (with a minimal threshold - ten percent- of inclusion under multiple model specifications) is called Bayesian Model Averaging (Hinne et. al., 2020).

5.3.5.7 Model 7

I estimated the integrated choice and latent variable model jointly to predict the choice probabilities. This was implemented in Mplus as a complete structural equation model (SEM). But due to convergence issues I had to use the single factor models of ES and STV rather than their underlying two-factor structures as identified in the factor analysis conducted in Chapter 3.

Models were not compared using the conventional goodness of fit measures since model validation of the SEVT theory was a better criteria. This has been the latest guidance in the transportation research literature whose use of discrete choice models is the most prevalent (Parady et. al., 2021).

5.4 Results

5.4.1 Choice probabilities

5.4.1.1 Logit

Table-logit below shows the significant predictors of participation choice in JC under different information sets but estimated with logistic regression. The coefficients are marginal effects estimated in STATA. The significant predictors of choice based on only the observable attributes (information set of the economist) are the fixed effects of belonging to age groups 18-19 yrs. and 20 years or above, in comparison to those who are 16-17 years old. Both these fixed effects are negative on the likelihood of JC participation. The likelihood of participation is increased by being male, having a father who is a high school graduate or more, and when household income is greater than USD 18,000. The likelihood of participation is lower for those who are 18 years or above. The likelihood of participation also reduces if there was a prior record of being arrested or having undergone treatment for drug abuse and finally having a child when applying to the JC program. When I added information on latent variables to the model, in addition to all the significant predictors from the analyst information set, expected improvement in academic and personality efficacy through JC also significantly predict the participation choice.

From the latent class analysis in chapter 2, results showed that Class 1 refers to latent group of individuals who do not seek vocational anticipatory guidance from any of the close relationships – family and friends. Class 2 refers to latent group has individuals who are most likely to talk to parents and friends but more importance to friends; find their advice important and receive encouragement to participate in Job Corps. In comparison to those who seek guidance from the parents (class 3), members of classes 1 and 2 seem to have a decreased likelihood of participation in Job Corps.

Bayesian model averaging (BMA) was conducted to identity significant predictors of choice in the logit model assuming there is underlying model uncertainty. The set of significant predictors identified by BMA have at least 10 percent chance of being included in the choice model despite the underlying model uncertainty. These covariates are personality efficacy, IAC classes 1 and 2, age (in years), gender, living with a spouse, arrest, and drug treatment history.

Table 24 Estimated coefficients from logit model – different information sets (PIP=posterior model inclusion probability)

Domain	**Variables**	**LOGITX**	**LOGITXU**	**LOGIT BMA**
		Coeff (se)	Coeff (se)	Mean (se) *PIP
Latent Variables	ACAD		0.047(0.017) ***	
Latent Variables	PERS		0.08(0.015) ***	0.092 (0.015) **
Latent Variables	VAS – Class 1 vs. 3		-.064(0.016) ***	-0.076 (0.015) **
Latent Variables	VAS – Class 2 vs. 3		-.055(0.015) ***	-0.048 (0.027) **
Individual characteristics	Age in years	-0.003(0.005)	-0.005(0.006)	-0.016 (0.002) **
Individual characteristics	Age (18-19 vs. 16-17 years)	-0.053(0.017) ***	-0.052(0.017) ***	
Individual characteristics	Age (> =20 vs. 16-17 years)	-0.051(0.031)	-0.053(0.031) *	
Individual characteristics	Male	0.057(0.113) ***	0.062(0.011) ***	0.07(0.011) **
Individual characteristics	Living with spouse	-0.027(0.039)	-0.024(0.04)	-0.09(0.027) **
Household characteristics	Father HS/GED	0.025(0.014) *	0.032(0.015) **	
Household characteristics	HH income (> 30K/annum)	0.037(0.017) **	0.044(0.017) **	
Prior adverse experiences	Had child at randomization	-0.029(0.015) **	-0.027(0.015) *	
Prior adverse experiences	Ever arrested	-0.043(0.013) ***	-0.044(0.013) ***	-0.027(0.024) ***
Prior adverse experiences	Attended drug treatment	-0.072(0.026) ***	-0.075(0.026) ***	-0.016(0.033) **
	N	6,531	6,509	6,509

5.4.1.2 Conditional logit (McFadden's Logit)

The next table presents the set of significant predictors when different information sets were used in the conditional logit model. The set of significant predictors identified here are similar to logit in comparison to the corresponding information sets. Bayesian model averaging (BMA) also provides similar results between logit and conditional logit models. Results should always be reported in terms of marginal effects without which there is discrepancy in the results between the logit and conditional logit estimations. For example, when the two model results were compared without converting them to marginal effects, the direction of impact of arrest history, drug history and having a child when applying to JC changed from being positive in the logit model to negative in the conditional logit model. But shown below, when using marginal effects, the direction of impact of these variables does not change between logit and conditional logit models. It should also be noted that while in both logit and conditional logit, there is a statistically significant positive impact of father's high school attainment or higher on JC participation, the same variable was not a significant predictor when the dummy variables for latent classes of IAC (VAS) were not included in the model.

Table 25 Estimated coefficients from conditional logit model – different information sets (PIP=posterior model inclusion probability)

Domain	Variable	MLOGITX (Model 4)	MLOGITXU (Model5)	MLOGIT BMA (Model 6)
		Relative Risk Ratio (se)	Coeff(se)	Coeff(se)
Latent Variables – Choice attribute	ACAD		0.047 (0.017) ***	0.26 (0.09) ***
Latent Variables – Choice attribute	PERS		0.08(0.016) ***	0.472 (0.09) ***
Latent Variables	VAS – Class 1 vs. 3	-.079(0.016) ***	-.06(0.016) ***	-.371(.086) ***
Latent Variables	VAS – Class 2 vs. 3	-.053(0.015) ***	-.055(0.015) ***	-.309(.084) ***
Individual characteristics	Age (18-19 vs. 16-17 years)	-0.053(0.017) ***	-0.052(0.017) ***	-0.274(0.096) ***
Individual characteristics	Age (> =20 vs. 16-17 years)	-0.051(0.031)	-0.053(0.031) *	-0.295(0.171) *
Individual characteristics	Male	.057(0.011) ***	0.062(0.011) ***	0.355(0.06) ***
Individual characteristics	Living with spouse	-0.026(0.039)	-0.024(0.04)	-0.454(0.116) ***
Household characteristics	Father HS/GED	0.025(0.015) *	0.032(0.015) **	
Household characteristics	HH income (> 30K/annum)	0.036(0.017) **	0.044(0.017) **	
Prior adverse experiences	Had child at randomization	-0.029(0.015) **	-0.027(0.015) *	
Prior adverse experiences	Ever arrested	-0.043(0.013) ***	-0.044(0.013) ***	
Prior adverse experiences	Attended drug treatment	-0.072(0.026) ***	-0.076 (0.026) ***	
	No of cases	6,531		6,533

5.4.1.3 ESEM

Both of the results above were obtained by sequential estimation approach – estimate the latent variables separately and then include them in the choice model as predictors of choice. The disadvantages of sequential estimation have been documented in earlier research, favoring joint estimation both latent and choice models together (Vij and Walker, 2017; Bouscasse, 2018). But the challenge is that joint estimation is extremely computation intensive and therefore might not be a convenient tool for the analyst. Even though simulation based joint estimation methods such as Simulation based maximum likelihood (MSE) estimators are now being widely used across statistical programming languages (Biogeme library in Python and Apollo library in R), they demand considerable prior statistical knowledge for model specifications. A convenient alternative for the applied researcher is to use SEM software for estimating the joint or hybrid choice model (HCM) or integrated choice and latent variable models (ICLV).

I followed Temme (2008) and use SEM modeling with Mplus software for ICLV modeling. In this study particularly, simulation-based methods in Python or R could not be used since they do not yet support survey sampling weights in their estimation. This is a severe limitation of using these methods with large scale secondary survey data from both experimental and observational studies. Mplus allows sampling weighting in the ICLV estimation along with Full information maximum likelihood method (FIML) for dealing with missing data in measurement indicators. Since the ICLV-SEM modeling can lead to overidentification issues, I perform an Exploratory SEM (ESEM) analysis to identify an ICLV model specification that could converge and be informative about the choice model being studied.

Firstly, increasing the number of factors within each latent construct increases the number of dimensions for integration in simulation-based methods. This significantly increases the computational requirements. Therefore, even though prior analysis of ES and STV confirmed a two factor (2F) structure for both constructs, for ICLV I retain the single factor models (1F) for both constructs – subjective task value (STV) of participating in JC and expected benefits from participation in JC (ES). In the ESEM analysis I use the 2F models since that is strongly supported by theory. Model specification for ICLV was done based on the results of the 2F ESEM. The two factors within each construct are regressed on the full set of covariates used in this study. ESEM also allows cross loading of items across the two factors within each construct - which is an advantage over CFA and more informative for the ICLV model specification purposes. The results of ESEM are tabulated below.

Table 26 Exploratory Factor Analysis results – factor loadings and regression coefficients

Latent Construct	Obs. Var.	Coefficient (std. factor loading)	SE	z	p
sv	rhome	0.402	0.020	20.369	0.000
sv	rcomm	0.707	0.023	30.397	0.000
sv	rother	0.283	0.017	16.233	0.000
av	rhome	0.067	0.020	3.367	0.001
av	rcomm	-0.013	0.002	-5.920	0.000
av	rother	0.090	0.028	3.196	0.001
av	rtrain	0.642	0.093	6.883	0.000
av	rcrgoal	0.441	0.049	9.003	0.000
acad	emath	0.283	0.027	10.452	0.000
acad	eread	0.269	0.020	13.238	0.000
acad	ealong	0.016	0.007	2.322	0.020
acad	eesteem	0.065	0.013	5.137	0.000
acad	econtrl	-0.025	0.005	-5.063	0.000
pers	eread	0.167	0.036	4.595	0.000

Table 26, continued

pers	ealong	0.694	0.024	29.193	0.000
pers	eesteem	0.653	0.026	25.529	0.000
pers	econtrl	0.839	0.025	33.466	0.000
av	male	-0.041	0.018	-2.355	0.019
av	welfkid	0.035	0.014	2.551	0.011
av	bchild	0.035	0.013	2.691	0.007
sv	black	0.290	0.017	17.037	0.000
sv	hisp	0.129	0.016	8.153	0.000
sv	welfkid	0.044	0.014	3.207	0.001
sv	pmsa	0.061	0.018	3.472	0.001
sv	publich	0.068	0.013	5.109	0.000
sv	bhsged	-0.106	0.016	-6.730	0.000
sv	bchild	-0.031	0.016	-1.980	0.048
sv	barrest	0.095	0.013	7.162	0.000
sv	byrwelf	0.035	0.014	2.474	0.013
sv	badhlth	0.050	0.013	3.837	0.000
sv	drugtrt	0.035	0.014	2.521	0.012
sv	potuse	0.060	0.013	4.476	0.000
sv	harduse	0.052	0.015	3.464	0.001
acad	flclass_1	-0.176	0.031	-5.610	0.000
acad	flclass_5	0.133	0.030	4.503	0.000
acad	male	-0.130	0.029	-4.423	0.000

Table 26, continued

acad	hisp	0.129	0.039	3.276	0.001
acad	age	0.199	0.062	3.204	0.001
acad	hadfath	0.121	0.036	3.353	0.001
acad	fathhs	-0.149	0.036	-4.122	0.000
acad	pmsa	-0.105	0.040	-2.630	0.009
acad	msa	-0.110	0.041	-2.662	0.008
acad	publich	0.053	0.026	2.024	0.043
acad	byrwrk	-0.104	0.037	-2.809	0.005
acad	bhsged	-0.261	0.039	-6.641	0.000
acad	evrwrk	-0.077	0.036	-2.157	0.031
acad	potuse	-0.090	0.027	-3.335	0.001
pers	black	-0.085	0.041	-2.085	0.037
pers	pmsa	-0.108	0.037	-2.942	0.003
pers	msa	-0.125	0.037	-3.331	0.001

Based on the results of the ESEM, the ICLV model regressed STV on significant predictors of SV and AV in the ESEM output - **male**, welfkid, bchild, **black, hisp**, **pmsa, publich, bhsged,** bchild, barrest, byrwelf, badhlth, drugtrt, **potuse**, and harduse. Similarly, the model regressed ES on significant predictors of ACAD and PERS – f_class1 and f_class5, **male**, **hisp,** age, hadfath, fathhs, **publich,** byrwrk, **bhsged**, evrwrk, **potuse, black**, **pmsa**, and msa. Among STV and ES, the common predictors were – male, black, hisp, bhsged, publich, pmsa, bhsged, and potuse. The common predictors were included only as predictors of ES and predictors of STV distinct from those of ES alone were included in the STV regression specification. As for the choice variable itself, only those variables which were identified as influential even after including latent variables are specified – age, age2, age3, and livspous.

5.4.1.4 ICLV

Table 27 Estimated coefficients compared across logit, conditional logit and ICLV. Only the information set including factor scores and latent classes is considered for information set

Domain	**Variables**	**LOGITXU**	**MLOGIT**	**ICLV**
		Coeff. (se)	Coeff. (se)	Coeff. (se)
Latent Variables	ACAD (ES)	0.047(0.017) ***	0.047 (0.017) ***	(ES) 0.266 (0.045) ***
Latent Variables	PERS (ES)	0.08(0.015) ***	0.08(0.016) ***	
Latent Variables	VAS – Class 1 vs. 3	-.064(0.016) ***	-.06(0.016) ***	-0.138 (0.034) ***
Latent Variables	VAS – Class 2 vs. 3	-.055(0.015) ***	-.055(0.015) ***	-0.127 (0.035) ***
Individual characteristics	Age (18-19 vs. 16-17 years)	-0.052(0.017) ***	-0.052(0.017) ***	0.137 (0.046) ***
Individual characteristics	Age (> =20 vs. 16-17 years)	-0.053(0.031) *	-0.053(0.031) *	0.130 (0.078)
Individual characteristics	Male	0.062(0.011) ***	0.062(0.011) ***	0.168 (0.032) ***
Household characteristics	Father HS/GED	0.032(0.015) **	0.032(0.015) **	0.087 (0.042)
Household characteristics	HH income (> 30K/annum)	0.044(0.017) **	0.044(0.017) **	0.093 (0.039) ***
Prior adverse experiences	Had child at randomization	-0.027(0.015) *	-0.027(0.015) *	-0.060 (0.032)
Prior adverse experiences	Ever arrested	-0.044(0.013) ***	-0.044(0.013) ***	-0.109 (0.032) ***
Prior adverse experiences	Attended drug treatment	-0.075(0.026) ***	-0.076(0.026) ***	-0.095 (0.031) ***
	N	6,509	6509	6531

5.4.2 Average Treatment Effect (ATE)

The table below reports the mean and standard deviation of choice probabilities estimated under different information sets and choice models. The three information sets are – information set of the economist containing only the observed variables, information set containing the latent variables from the agent information set, and finally the information set containing most influential predictors as predicted by Bayesian model averaging (BMA) to control for model uncertainty.

Table 28 Distributional parameters of estimated compliance scores and corresponding ATE

Model	Mean Choice Probability	Std. dev - Choice Probability	ATE (g-method) Coeff. (se) (victimization)	ATE (W-2SLS) Coeff. (se) (victimization)
Logit X	0.752	0.082	-1.9 (0.009)	-3.9 (0.011)
Logit XU	0.751	0.09	-1.9 (0.009)	-4.0 (0.011)
Logit BMA	0.752	0.078	-1.9 (0.009)	-4.0 (0.011)
MLogit X	0.752	0.083	-1.9 (0.009)	-4.0 (0.011)
MLogit XU	0.752	0.091	-1.9 (0.009)	-4.0 (0.011)
MLogit BMA	0.753	0.086	-1.9 (0.009)	-4.0 (0.011)
ICLV	0.78	0.094	-1.92 (0.009)	-3.8 (0.005)

The distribution of propensity scores looked similar across the sequential estimation methods. While the mean of the propensity score distribution from the joint estimation method (ICLV) was same as the sequential method, there was a difference in the observed standard errors. The figure below graphically shows the distribution of propensity scores from the different models in the table.

The average treatment effect (ATE) was estimated with two estimations – g-computation based method (g-computation) and the weighted two stage least squares (W-2SLS) (Aronow and Carnegie, 2013). Both of them showed a statistically significant impact of participation in Job Corps on reducing the likelihood of becoming a violent crime victim, four years from enrollment. But there is a difference in the magnitude of the treatment effect between the two methods. The ATE estimated with the ICLV choice probability has a lower standard error than the sequential estimation methods. This reduction in the standard error of the ATE could potentially be due to the reasons that ICLV probabilities have a greater coverage of the [0,1] interval as shown in the graph below.

5.4.2.1 Distribution of choice probabilities

The distribution of propensity scores looked similar across the sequential estimation methods. While the mean of the propensity score distribution from the joint estimation method (ICLV) was same as the sequential method, there was a difference in the observed standard errors. The figure 7 below graphically shows the distribution of propensity scores from the different models in the table.

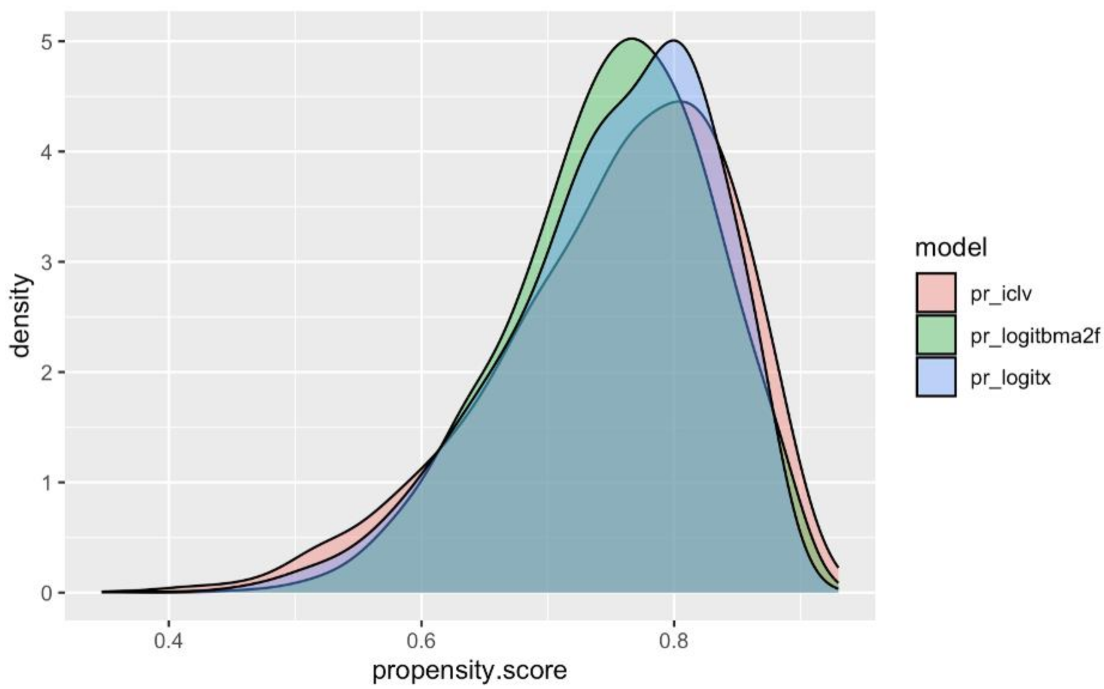

Figure 8 Distribution of estimated compliance scores - LogitX vs. Logit BMA vs. ICLV

The ATE estimated with the ICLV choice probability has a lower standard error than the sequential estimation methods. This reduction in the standard error of the ATE could potentially be due to the reasons that ICLV probabilities have a greater coverage of the [0,1] interval as shown in Fig. 8.

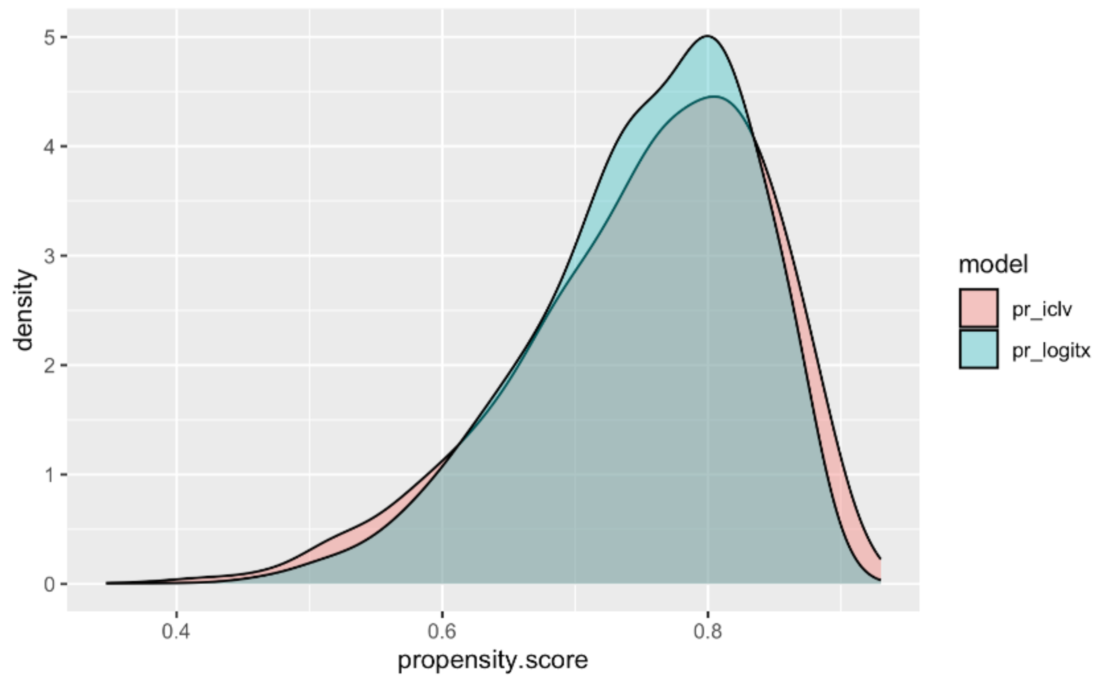

Figure 9 Distribution of estimated compliance scores - LogitX vs. ICLV

5.5 Conclusion

The estimated latent class memberships of vocational socialization, and factor scores of STV and ES constructs were included in a logistic model of binary choice. The model analysis was conducted only among those assigned to the treatment group and then extrapolated to obtain compliance scores for the control group also. Since the randomly selected groups are balanced on pretreatment confounders, it is assumed that if the group assignment were inverted for everyone in the sample, the parametric structure of the estimated choice model would not be significantly different from the model before inverting assignment statuses.

The three logit models in the table below were estimated with different information sets. LogitX used only information observed by the analyst or the baseline covariates. LogitXU augmented the information set with estimated factor scores of the latent constructs modeled earlier. While factors of success expectancy increased the likelihood of participation, factors of subjective value were statistically insignificant. This is plausible when STV and ES are conceptually overlapping.

The other comparison is regarding the validity of Independence of Irrelevant Alternatives (IIA assumption). The logistic or multinomial models - typically used in statistical treatment effects literature assume IIA. But the assumption fails under a variety of conditions when the choice structure is complex and especially if individuals treat different choice alternatives as close substitutes.

In Job Corps this happens between MSA and non-MSA settings. The quality of JC centers is poor in rural areas and therefore, endline data shows that many in rural areas attended both Job Corps and other VET programs by treating them as complementary goods. The estimated choice probabilities can vary when IIA is satisfied and when it is not. McFadden's conditional logit models or Mlogit model relaxes the IIA assumption. There was no difference between logit and mlogit with information set containing both the observed covariates and estimated factor scores.
The integrated choice and latent variable model (ICLV) is the joint estimation alternative to sequential estimation discussed so far. The key difference between ICLV and sequential methods in the choice model structure is that in the joint method only ACAD factor or success expectancy significantly predicts choice and not the expected personality skills improvement. The other difference is the higher marginal effect of the significant predictors under ICLV than other methods. The direction of impact changed for some variables between sequential and joint methods too.

The Average Treatment Effects were estimated using all the estimated choice probabilities from various models discussed above. Since the estimated compliance score is also the propensity score, I used two estimators to show the difference between identifying ATE under strong vs. latent ignorability conditions. The g-method estimator assumes strong ignorability while the weighted 2SLS assumes latent ignorability. The results show that choosing the wrong estimator can lead to a 100 percent improvement in ATE from a 2 percent reduction in victimization probability under g-estimation to nearly 4 percent in weighted 2SLS.

5.5.1 Discussion

The influential predictors of choice did not vary much between different choice models or information sets. But at the same time, the latent expectations of success were a strong influence on participation choice even after controlling for all the observable individual characteristics. The motivational aspect of Job Corps was hypothesized to be a significant predictor of participation choice. But its insignificance could simply be due to the fact that there is an overlap between ES and STV. But the distributions of estimated choice probabilities show that even though the mean and variance under different information sets and sequential vs. joint estimation could be similar, the ICLV probabilities have a fatter tail and are able to pick up variation in likelihood of participation due to incorporating the latent constructs directly without using the factor scores as done in the sequential estimation. The efficiency of ICLV approach is also seen in the reduced standard errors on the regression coefficients of the choice models. With additional information on the attributes of different choice alternatives, it might be possible to derive greater utility from the joint estimation approach. Moreover, it also acts as a validation tool for testing various behavioral theories of adolescent decision making. While I did not test mixed logit models of choice due to computational restrictions, they offer an extremely flexible framework to model complex individual heterogeneity as random coefficients with an appropriate error structure. Moreover, Bayesian methods can be employed at every level of the analysis to incorporate expert knowledge via appropriate priors. Therefore, despite the similarity in results between the joint and sequential choice modeling approaches, there is a great advantage to using sequential methods to systematically constructs theories of behavior in addition to studying treatment effect heterogeneity.

Finally, the disagreement between ATE from g-computation and weighted 2SLS was due to the difference in the ignorability assumptions between the two methods. The latent ignorability assumption made for W-2SLS is more plausible and relatively easier to satisfy under noncompliance. While the ATE under strong ignorability from g-computation is significantly different from W-2SLS, future simulation studies are required to decompose the nature of this discrepancy. A big limitation of this study is that while eligible participants wanted to succeed in skills relevant for their vocational identity development, the endline surveys did not measure any of these skills as outcomes. Therefore, it is plausible despite the well analyzed diminishing long term returns to labor market outcomes from Job Corps participation, there might be significant long-term effects in vocational identity related constructs. A positive youth development-based intervention has to consider vocational skill development as the primary outcome rather than a mediator of the impact of job training on observable employment or earnings. An important limitation is that NJCS was a multisite RCT. Therefore, it is plausible that there are site characteristics that are strong predictors of compliance but cannot be observed. Simulation studies will also be required to analyze the sensitivity of ATE estimates from W-2SLS to site-level unobserved confounders.

6. Conclusion

6.1 Introduction

The purpose of this dissertation was to estimate the average effect (ATE) of choosing a treatment in a randomized experiment with noncompliance. This required modeling noncompliance as a hybrid choice model or an integrated choice and latent variable model (ICLV). The identification of ATE required an econometric model of noncompliance choice under inherent uncertainty (ex-ante choice) as an ICLV model. The situated expectancy value theory (SEVT) provided a model for the cognitive process underlying individual noncompliance behavior. SEVT provided a plausible model of vocational education and training choice (VET choice) among at-risk youth. SEVT helped in identifying the pretreatment covariates – observed and unobserved – which constitute a sufficient information set to fully describe the noncompliance behavior. These are also a sufficient set of confounders which can be adjusted with to obtain unbiased ATE of a job-training program (Job Corps) participation on the risk of violent crime victimization among at-risk youth. I estimated a four percent reduction in the risk of violent crime victimization by participating in the Job Corps program.

There are many methodological limitations in using the ICLV framework. Modeling individual choice with ICLV requires a strong theory of the underlying socio-cognitive process – how choices behavior can be explained by the nature of individuals' interaction with their environment over space and time. SEVT was such a theory used to model the ex-ante noncompliance choice using ICLV. But latent constructs in such well-defined theories could be contextual and multidimensional. Clearly defining the dimensions relevant for a study's context and availability of corresponding data are important to satisfy the identification assumptions for ATE. Future work will consist of sensitivity analyses for the identification assumptions and simulation studies to test the robustness of ICLV model for multiple underlying data generating processes.

6.2 Main findings and discussion

In the second chapter, noncompliance behavior was modeled within a theoretical and econometric framework. This resulted in the ICLV model of compliance choice. This posited compliance as a stochastic choice that violated the deterministic nature of choice counterfactuals in the potential outcomes' framework. Therefore, stochastic consistency assumptions were proposed to define stochastic counterfactuals. Such counterfactuals formed the statistical counterpart of the ex-ante econometric compliance choice model. SEVT provided a theoretically sufficient confounder (information) set required to satisfy econometric identification assumptions. This required explaining which elements of the Job Corps context formed different components of SEVT. An important feature of this model is the influence of negative life circumstances of at-risk youth - as a motivation factor - on VET choice. Another important feature was explaining the relevant dimensions of the latent constructs in at-risk youths' noncompliance behavior. Under the assumptions made, choice probabilities of the ICLV model are consistently estimated. These probabilities are theoretically equivalent to a balancing score called the compliance score in one-sided noncompliance (control group has no access to treatment). These compliance scores are used as inverse weights to identify ATE with weighted two-stage least square estimator.

In the third chapter, the first latent construct of SEVT was analyzed. It describes how individuals in the Job Corps study acquired information and guidance about program experiences and enrollment, referred to as vocational aspirational socialization (VAS). Five latent classes of VAS were identified based on binary (yes or no) indicators of VAS behavior - whether they spoke to parent, relative or peer, found their guidance important and received explicit encouragement to enroll. One of the salient findings are that talking to a source is strongly and positively correlated with both perceived importance of guidance and encouragement received. This could be indicative of youth seeking guidance from sources who inherently act as mentors (Dappen and Isernhagen, 2010). This is because youth intrinsically value guidance from supportive mentors (Anda, 2001; Spencer, 2006; Scheel et. al., 2009). Secondly, talking to parents first about JC seems to increase the likelihood of talking to all close relationships than just parents. Thirdly, in the fifth chapter, only those latent classes with no guidance from parents negatively influence participation probability. These findings support the existing empirical evidence for the importance of parental involvement as a strong predictor of academic and vocational motivation for at-risk youth (Ginsburg and Bronstein, 1993; Gonzalez-DeHaas et. al., 2005; Schmid and Garrels, 2021; Boonk et. al., 2021).

In the fourth chapter, the second and third latent constructs of SEVT were analyzed – subjective task value of participation in Job Corps (STV), and expectancy of success by participating in Job Corps (ES). The subjective value was theoretically composed of the situational value from current life circumstances and the attainment value from job training and achieving career progress. Confirmatory factor analysis supported the theoretical factorization with the available indicators data. Negative life circumstances increased the situational value while aspirational value was not strongly influenced by any observable attributes of the individual. These findings are plausible because the residential feature of Job Corps reduces exposure to risk factors (US report, 2014) and most of the individual responses had positive response on attainment value indicators. The latter result could be due to perceived importance of VET for vocational identity development and resilience enhancement among vulnerable youth (Fuller and MacFayden, 2011; Guo and Wang, 2020; Keijzer et. al., 2021). The other latent construct ES was theoretically composed of expected improvement in academic skills and expected improvement in personality skills. Both sets of skills are considered as positive youth development skills (Lerner, 2006). Confirmatory factor analysis supported the theoretical factorization with the available indicators data. The most racially salient findings were that compared to white students, black students had greater expectations for academic improvement and lower expectations for improvement in self-regulation. For black students, racially discriminatory incidents are known to negatively affect self-regulation (Gibbons et. al., 2012). Therefore, they may not expect improvement in personality skills due to the high likelihood of discriminatory incidents in their developmental ecosystem even after job training. Another salient finding was that having a father or fatherly figure increased both expectations while having prior high school credential or work experience decreased both expectations (East et. al., 2006; Richardson Jr., 2009).

In the fifth chapter, the primary finding was that enrolling in Job Corps reduced the risk of violent crime victimization by 4 percent among the study population (representativeness of target population? Plausibility of assumptions? CITE). The compliance scores used as inverse weights in ATE estimation did not vary among different models used to estimate it. The models differed along sequential or joint estimation procedure, but also whether latent variables were included or excluded in the model. Both observed individual attributes and latent constructs of SETV were statistically significant predictors of compliance or participation choice among those assigned to Job Corps. But in the final choice model, only ES factors are significant predictors of choice and not STV (strongly correlated and complex interaction of underlying factors; LCA to identify interaction complexity). One of the most interesting observations is that individuals were likely to participate if their household income was at least 30k per annum. While prior arrest and drug treatment experience also reduced likelihood of participation. Among different model specifications, there was no change in the choice likelihood for participation in Job Corps between sequential and joint estimation. Similarly, no change in choice likelihood was observed when including or excluding latent variable information in sequential models. The marginal effect of latent constructs was small. But the marginal effects were higher in joint estimation with the ICLV model than in sequential estimation with reduced form model. This was due to relatively greater variance reduction in the ICLV than in the reduced form models.

6.3 Robustness of identification assumptions

To ensure internal validity of ATE, the identification assumptions have to be satisfied. For the assumptions that are not empirically verifiable, simulation studies are required. Observed data can establish of plausibility of the remaining assumptions. Firstly, the expected SUTVA assumption for stochastic counterfactuals is a priori assumed to be true in the case of ex-ante noncompliance behavior. This is because due to inherent uncertainty deterministic choice counterfactuals are not plausible representations of actual choice behavior under uncertainty. The randomization of IV assumption is satisfied in noncompliance settings because random assignment is the IV. This assignment is a non-trivial encouragement because it offers enrollment to a job training program which the at-risk youth are motivated to join. The sensitivity of ATE obtained from weighted 2SLS depends on strength of the IV and similarity of treatment effects between those who satisfy and violate the stochastic monotonicity assumption. Since 77 percent of those assigned to treatment participated in Job Corps, this study has a strong IV. Those who violate stochastic monotonicity would have negative compliance scores because the likelihood of participation without an offer is greater than with an offer. Since the likelihood of participating without an offer is zero in one-sided noncompliance, compliance scores are always non-negative. Therefore, stochastic monotonicity is plausibly satisfied. Even in the case of two-sided noncompliance, stochastic monotonicity boils down to asking if there is anybody who would do the opposite of what the IV encourages. It is unlikely when the study sample is drawn from motivated applicants to the program. In such cases, the expected behavior is not to act contrary to the IV encouragement. Finally, the stochastic latent ignorability assumption states that the ATE for the target population is the same as the ATE for those who are expected to be compliers. In other words, after adjusting for the observed and latent confounders, the treatment effect is independent of the compliance choice because all common causes have been controlled for. The plausibility of this assumption relies on the confounding set being a sufficient set to adjust for common causes of participation and outcome based on SEVT. Therefore, it can be sensitive to the richness of data characterizing latent constructs in SEVT.

6.4 Limitations and Future Research Agenda

In this dissertation work, I have proposed an integrated framework to identify, and estimate ATE under one-sided noncompliance. Extending ICLV approach to two-sided noncompliance is an open question. The treatment considered in this study was binary and therefore compliance was all-or-none. Therefore, extending ICLV to deal with partial compliance settings would allow the study of continuous treatments or complex interventions. If partial compliance is modeled as a continuous construct, then it can represent the intensity of the treatment received for continuous treatment. Partial compliance can also be modeled as a categorical latent construct to represent patterns of using different components of a complex intervention. Such categorical modeling can be achieved with latent class choice models. Bayesian formulation of all the variations discussed above would offer a systematic way to study various sources of uncertainties and incorporate prior knowledge. A major limitation to this dissertation was the cross-sectional nature of the data. Extending the ICLV method to dynamic choice contexts with longitudinal data can help in modeling adolescent decision-making from a life-course perspective (Elder et. al., 2003; Bynner, 2007; Benson and Elder, 2011).

A major theoretical limitation in this dissertation is that the existing literature is insufficient to fully characterize the latent constructs in SEVT. The two-dimensional factor structure of the latent variables STV and ES was supported by theory and empirical analyses. But it was not possible to identify other potential dimensions with existing theoretical progress. Future qualitative interviews with at-risk youth about factors motivating their vocational education and training choice are essential in improving the rigor of SEVT models. Such qualitative interviews can be used to develop discrete choice experiments. Stated choice experiments can be conducted with at-risk youth to analyze how attributes of VET choice alternatives can influence the final decision (Hawke et. al., 2020; Cost and Surrocks, 2007; Klojgaard et. al., 2012). Data from stated choice experiments help in realizing the full potential of ICLV framework as shown in the transportation model choice literature (Ben-Akiva et. al., 2002). This is because the repeated measurements help to decompose the intra-individual and inter-individual sources of variations.

Finally, Testing the sensitivity of the identification assumptions and relative efficiency of modeling and estimation choices can be achieved via simulation studies. Simulation studies can also help in studying the impact of various data generating mechanisms and missing data patterns on the estimated results. Complex ICLV models require a lot of computational resources. Therefore, reducing the number of parameters to be estimated using semi-parametric and non-parametric methods can greatly improve the feasibility of simulating complex ICLV model specifications. There are many machines learning augmented approaches in choice modeling that can analyzed with such simulation work (Cranenburgh et. al., 2021).

6.5 Looking forward

This dissertation showed how the ICLV framework can systematically identify, and estimate ATE under noncompliance. But the framework has empirical applications in any context of adolescent or youth decision-making. More importantly, it mandates theory building as a necessary step to characterize choice heterogeneity in program evaluation settings. Future work will improve the statistical rigor of each component step of this framework and identify necessary gaps in theory and data for the widespread use of empirical researchers in adolescence and causal sciences.

References

Aakvik, Arild, James J. Heckman, and Edward J. Vytlacil. "Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs." *Journal of Econometrics* 125, no. 1-2 (2005): 15-51.

Abbring, Jaap H., and James J. Heckman. "Econometric evaluation of social programs, part III: Distributional treatment effects, dynamic treatment effects, dynamic discrete choice, and general equilibrium policy evaluation." *Handbook of econometrics* 6 (2007): 5145-5303.

Adkisson, Hailey Anne. """ It's all about that piece of paper": Vocational anticipatory socialization messages received by first generation college students." PhD diss., North Dakota State University, 2013.

Aley, Melinda R., and Kenneth J. Levine. "From whom do young adults actively seek career information? An ego-network analysis of vocational anticipatory socialization." *Communication Studies* 71, no. 2 (2020): 351-367.

Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. "Identification of causal effects using instrumental variables." *Journal of the American statistical Association* 91, no. 434 (1996): 444-455.

Armstrong, J. Scott. "Derivation of theory by means of factor analysis or Tom Swift and his electric factor analysis machine." *The American Statistician* 21, no. 5 (1967): 17-21.

Aronow, Peter M., and Allison Carnegie. "Beyond LATE: Estimation of the average treatment effect with an instrumental variable." *Political Analysis* 21, no. 4 (2013): 492-506.

Ashforth, Blake E., Spencer H. Harrison, and David M. Sluss. "Becoming: The interaction of socialization and identity in organizations over time." In *Current issues in work and organizational psychology*, pp. 316-339. Routledge, 2018.

Asparouhov, Tihomir, and Bengt Muthén. "Auxiliary variables in mixture modeling: Three-step approaches using M plus." *Structural equation modeling: A multidisciplinary Journal* 21, no. 3 (2014): 329-341.

Asparouhov, Tihomir, and Bengt Muthén. "Random starting values and multistage optimization." *Mplus* (2019): 1-8.

Asparouhov, Tihomir, and Bengt Muthén. "Using Bayesian priors for more flexible latent class analysis." In *proceedings of the 2011 joint statistical meeting, Miami Beach, FL*. American Statistical Association Alexandria, VA, 2011.

Bandura, A. "Self-efficacy: The exercise of control." *New York: Freeman* (1997).

Bandura, Albert. "Self-efficacy: toward a unifying theory of behavioral change." *Psychological review* 84, no. 2 (1977): 191.

Bandura, Albert. "Social foundations of thought and action." *Englewood Cliffs, NJ* 1986, no. 23-28 (1986).

Banerjee, Abhijit V., and Andrew F. Newman. "Occupational choice and the process of development." *Journal of political economy* 101, no. 2 (1993): 274-298.

Bartlett, Jennifer, and José F. Domene. "The vocational goals and career development of criminally involved youth: Experiences that help and hinder." *Journal of Career Development* 42, no. 3 (2015): 229-243.

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., & Polydoropoulou, A. (2002). Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges, 2002*, 431-470.

Ben-Akiva, Moshe, Daniel McFadden, Kenneth Train, Joan Walker, Chandra Bhat, Michel Bierlaire, Denis Bolduc et al. "Hybrid choice models: Progress and challenges." *Marketing Letters* 13 (2002): 163-175.

Benson, Janel E., and Glen H. Elder Jr. "Young adult identities and their pathways: a developmental and life course model." *Developmental psychology* 47, no. 6 (2011): 1646.

Berlin, Kristoffer S., Natalie A. Williams, and Gilbert R. Parra. "An introduction to latent variable mixture modeling (part 1): Overview and cross-sectional latent class and latent profile analyses." *Journal of pediatric psychology* 39, no. 2 (2014): 174-187.

Berry, Jane M. "Cognitive efficacy across the life span: Introduction to the special series." *Developmental Psychology* 25, no. 5 (1989): 683.

Blotnicky, Karen A., Tamara Franz-Odendaal, Frederick French, and Phillip Joy. "A study of the correlation between STEM career knowledge, mathematics self-efficacy, career interests, and career activities on the likelihood of pursuing a STEM career among middle school students." *International journal of STEM education* 5 (2018): 1-15.

Boat, Ashley A., Alejandra Miranda, and Amy K. Syvertsen. "Enhancing education and career pathways through peer and near-peer social capital." *Journal of Youth and Adolescence* (2022): 1-18.

Bolck, Annabel, Marcel Croon, and Jacques Hagenaars. "Estimating latent structure models with categorical variables: One-step versus three-step estimators." *Political analysis* 12, no. 1 (2004): 3-27.

Bollen, K. A. (1989). A new incremental fit index for general structural equation models. *Sociological methods & research*, *17*(3), 303-316.

Bong, Mimi, and Richard E. Clark. "Comparison between self-concept and self-efficacy in academic motivation research." *Educational psychologist* 34, no. 3 (1999): 139-153.

Boonk, Lisa M., Henk Ritzen, Hieronymus JM Gijselaers, and Saskia Brand-Gruwel. "Stimulating parental involvement in vocational education and training (VET): A case study based on learning histories of teachers, principals, students, and their parents." *Teaching and Teacher Education* 100 (2021): 103279.

Borchert, Michael. "Career choice factors of high school students." (2002).

Bouscasse, Hélène. "Integrated choice and latent variable models: A literature review on mode choice." (2018).

Britner, Shari L., and Frank Pajares. "Sources of science self-efficacy beliefs of middle school students." *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching* 43, no. 5 (2006): 485-499.

Bronfenbrenner, Urie. "Human development, bioecological theory of." (2001).

Brown, Timothy A. *Confirmatory factor analysis for applied research*. Guilford publications, 2015.

Browne, Michael W., and Gerhard Arminger. "Specification and estimation of mean-and covariance-structure models." In *Handbook of statistical modeling for the social and behavioral sciences*, pp. 185-249. Boston, MA: Springer US, 1995.

Bruin, J. (2006). A practical introduction to factor analysis: exploratory factor analysis.

Bynner, John. "Rethinking the youth phase of the life-course: The case for emerging adulthood?." *Journal of youth studies* 8, no. 4 (2005): 367-384.

Byrd, Christy M., and Dorinda J. Carter Andrews. "Variations in students' perceived reasons for, sources of, and forms of in-school discrimination: A latent class analysis." *Journal of school psychology* 57 (2016): 1-14.

Cabrera, Alberto F., Regina Deil-Amen, Radhika Prabhu, Patrick T. Terenzini, Chul Lee, and Robert E. Franklin, Jr. "Increasing the college preparedness of at-risk students." *Journal of Latinos and Education* 5, no. 2 (2006): 79-97.

Catalano, Richard F., M. Lisa Berglund, Jean AM Ryan, Heather S. Lonczak, and J. David Hawkins. "Positive youth development in the United States: Research findings on evaluations of positive youth development programs." *The annals of the American academy of political and social science* 591, no. 1 (2004): 98-124.

Celeux, Gilles, and Gilda Soromenho. "An entropy criterion for assessing the number of clusters in a mixture model." *Journal of classification* 13 (1996): 195-212.

Chatton, Arthur, Florent Le Borgne, Clémence Leyrat, Florence Gillaizeau, Chloé Rousseau, Laetitia Barbin, David Laplaud, Maxime Léger, Bruno Giraudeau, and Yohann Foucher. "G-computation, propensity score-based methods, and targeted maximum likelihood estimator for causal inference with different covariates sets: a comparative simulation study." *Scientific reports* 10, no. 1 (2020): 9219.

Choi, Bo Young, Heerak Park, Eunjoo Yang, Seul Ki Lee, Yedana Lee, and Sang Min Lee. "Understanding career decision self-efficacy: A meta-analytic approach." *Journal of Career Development* 39, no. 5 (2012): 443-460.

Choi, Su Jung, Jin Chul Jeong, and Seoung Nam Kim. "Impact of vocational education and training on adult skills and employment: An applied multilevel analysis." *International Journal of Educational Development* 66 (2019): 129-138.

Cieciuch, Jan, Eldad Davidov, Peter Schmidt, and René Algesheimer. "How to obtain comparable measures for cross-national comparisons." *Kölner Zeitschrift für Soziologie und Sozialpsychologie* 71, no. S1 (2019): 157-186.

Coast, Joanna, and Sue Horrocks. "Developing attributes and levels for discrete choice experiments using qualitative methods." *Journal of health services research & policy* 12, no. 1 (2007): 25-30.

Cole, Stephen R., and Constantine E. Frangakis. "The consistency statement in causal inference: a definition or an assumption?." *Epidemiology* 20, no. 1 (2009): 3-5.

Collins, Linda M., and Stuart E. Wugalter. "Latent class models for stage-sequential dynamic latent variables." *Multivariate Behavioral Research* 27, no. 1 (1992): 131-157.

Cranenburgh, Sander, Shenhao Wang, Akshay Vij, Francisco Pereira, and Joan Walker. "Choice modelling in the age of machine learning-discussion paper." *Journal of Choice Modelling* 42 (2022): 100340.

Cunha, Flavio, and James J. Heckman. "Identifying and estimating the distributions of ex post and ex ante returns to schooling." *Labour Economics* 14, no. 6 (2007): 870-893.

Cunha, Flavio, James J. Heckman, and Salvador Navarro. "The identification and economic content of ordered choice models with stochastic thresholds." *International Economic Review* 48, no. 4 (2007): 1273-1309.

Damaske, Sarah, Adrianne Frech, and Hilary Wething. "The Life Course of Unemployment: The Timing and Relative Degree of Risk." *Work and Occupations* (2023): 07308884231162949.

Dappen, Leon D., and Jody C. Isernhagen. "Developing a student mentoring program: Building connections for at-risk students." *Preventing School Failure: Alternative Education for Children and Youth* 49, no. 3 (2005): 21-25.

Davey, A., and J. Savla. "Power Analysis with Missing Data." *A Structural Equation Modeling Approach* (2010).

Dawid, Philip. “Decision-theoretic foundations for statistical causality.” *Journal of Causal Inference* 9, no. 1 (2021): 39-77.

De Anda, Diane. “A qualitative evaluation of a mentor program for at-risk youth: The participants’ perspective.” *Child and adolescent social work journal* 18, no. 2 (2001): 97-117.

DeLuca, Christopher, Lorraine Godden, Nancy L. Hutchinson, and Joan Versnel. “Preparing at-risk youth for a changing world: revisiting a person-in-context model for transition to employment.” *Educational Research* 57, no. 2 (2015): 182-200.

Depaoli, Sarah, Yuzhu Yang, and John Felt. “Using Bayesian statistics to model uncertainty in mixture models: A sensitivity analysis of priors.” *Structural Equation Modeling: A Multidisciplinary Journal* 24, no. 2 (2017): 198-215.

Depaoli, Sarah. “Mixture class recovery in GMM under varying degrees of class separation: frequentist versus Bayesian estimation.” *Psychological methods* 18, no. 2 (2013): 186.

DiClemente, Ralph J., John S. Santelli, and Richard Crosby, eds. *Adolescent health: Understanding and preventing risk behaviors*. John Wiley & Sons, 2009.

DiStefano, Christine, Min Zhu, and Diana Mindrila. “Understanding and using factor scores: Considerations for the applied researcher.” *Practical assessment, research, and evaluation* 14, no. 1 (2009): 20.

Dvorsky, Melissa R., Michael J. Kofler, G. Leonard Burns, Aaron M. Luebbe, Annie A. Garner, Matthew A. Jarrett, Elia F. Soto, and Stephen P. Becker. “Factor structure and criterion validity of the five Cs model of positive youth development in a multi-university sample of college students.” *Journal of youth and adolescence* 48 (2019): 537-553.

East, Leah, Debra Jackson, and Louise O’Brien. “Father absence and adolescent development: a review of the literature.” *Journal of Child Health Care* 10, no. 4 (2006): 283-295.

Eccles, Jacquelynne S., and Allan Wigfield. “From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation.” *Contemporary educational psychology* 61 (2020): 101859.

Egondi, Thaddaeus, Caroline Kabiru, Donatien Beguy, Muindi Kanyiva, and Richard Jessor. “Adolescent home-leaving and the transition to adulthood: A psychosocial and behavioural study in the slums of Nairobi.” *International journal of behavioral development* 37, no. 4 (2013): 298-308.

Ehrenberg, Andrew SC. “The factor analytic search for program types.” *Journal of Advertising Research* 8, no. 1 (1968): 55-63.

El Zarwi, Feras, Akshay Vij, and Joan L. Walker. “A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services.” *Transportation Research Part C: Emerging Technologies* 79 (2017): 207-223.

Elder, Glen H., Monica Kirkpatrick Johnson, and Robert Crosnoe. *The emergence and development of life course theory*. Springer US, 2003.

Enders, Craig K., and Deborah L. Bandalos. "The relative performance of full information maximum likelihood estimation for missing data in structural equation models." *Structural equation modeling* 8, no. 3 (2001): 430-457.

Finn, Adam, and Luming Wang. "Formative vs. reflective measures: Facets of variation." *Journal of Business Research* 67, no. 1 (2014): 2821-2826.

Fischhoff, Baruch. "Assessing adolescent decision-making competence." In *Judgment and Decision Making*, pp. 300-319. Routledge, 2013.
Fischhoff, Baruch. "Assessing adolescent decision-making competence." In *Judgment and Decision Making*, pp. 300-319. Routledge, 2013.
Frangakis, Constantine E., and Donald B. Rubin. "Principal stratification in causal inference." *Biometrics* 58, no. 1 (2002): 21-29.

Fuller, Carol, and Tony MacFadyen. "'What with your grades?'Students' motivation for and experiences of vocational courses in further education." *Journal of Vocational Education & Training* 64, no. 1 (2012): 87-101.

Gecas, Viktor. "The social psychology of self-efficacy." *Annual review of sociology* 15, no. 1 (1989): 291-316.

George, Jennifer M., and Gareth R. Jones. "Organizational spontaneity in context." *Human performance* 10, no. 2 (1997): 153-170.

Gibbons, Frederick X., Ross E. O'Hara, Michelle L. Stock, Meg Gerrard, Chih-Yuan Weng, and Thomas A. Wills. "The erosive effects of racism: reduced self-control mediates the relation between perceived racial discrimination and substance use in African American adolescents." *Journal of personality and social psychology* 102, no. 5 (2012): 1089.

Ginsburg, Golda S., and Phyllis Bronstein. "Family factors related to children's intrinsic/extrinsic motivational orientation and academic performance." *Child development* 64, no. 5 (1993): 1461-1474.

Gonzalez-DeHass, Alyssa R., Patricia P. Willems, and Marie F. Doan Holbein. "Examining the relationship between parental involvement and student motivation." *Educational psychology review* 17 (2005): 99-123.

Government Accountability Office (GAO). "Job Corps: Better Targeted Career Training and Improved Pre-enrollment Information Could Enhance Female Residential Student Recruitment and Retention. Report to Congressional Committees". GAO-09-470 (2009).

Goza, Franklin, and Igor Ryabov. “Adolescents’ educational outcomes: Racial and ethnic variations in peer network importance.” *Journal of youth and adolescence* 38 (2009): 1264-1279.

Guo, Dong, and Anyi Wang. “Is vocational education a good alternative to low-performing students in China.” *International Journal of Educational Development* 75 (2020): 102187.

Gupta, Arpana, SinHui Chong, and Frederick TL Leong. “Development and validation of the vocational identity measure.” *Journal of Career Assessment* 23, no. 1 (2015): 79-90.

Hafferty, Frederic William. “Socialization, professionalism, and professional identity formation.” *Teaching medical professionalism* 2 (2016): 54-67.

Hawke, Lisa D., Em Hayes, Srividya Iyer, Eóin Killackey, Gina Chinnery, Geneviève Gariépy, Lehana Thabane et al. “Youth-oriented outcomes of education, employment and training interventions for upcoming youth: Protocol for a discrete choice experiment.” *Early Intervention in Psychiatry* 15, no. 4 (2021): 942-948.

Heckman, James J. “Econometric causality.” *International statistical review* 76, no. 1 (2008): 1-27.

Heckman, James J., and Jeffrey A. Smith. “The determinants of participation in a social program: Evidence from a prototypical job training program.” *Journal of Labor Economics* 22, no. 2 (2004): 243-298.

Heckman, James J., and Rodrigo Pinto. “The Econometric Model for Causal Policy Analysis.” *Annual Review of Economics* 14 (2022): 893-923.

Higgins, E. Tory. “Value.” (2007).

Higgins, George E. “Digital piracy: An examination of low self-control and motivation using short-term longitudinal data.” *CyberPsychology & Behavior* 10, no. 4 (2007): 523-529.

Hinne, Max, Quentin F. Gronau, Don van den Bergh, and Eric-Jan Wagenmakers. “A conceptual introduction to Bayesian model averaging.” *Advances in Methods and Practices in Psychological Science* 3, no. 2 (2020): 200-215.

Hinojosa, Ramon, Jenny Nguyen, Kyle Sellers, and Heba Elassar. “Barriers to college success among students that experienced adverse childhood events.” *Journal of American college health* 67, no. 6 (2019): 531-540.

Hirschi, Andreas. “Career adaptability development in adolescence: Multiple predictors and effect on sense of power and life satisfaction.” *Journal of vocational behavior* 74, no. 2 (2009): 145-155.

Hlad′ o, Petr, Lucia Kvasková, Stanislav Ježek, Andreas Hirschi, and Petr Macek. "Career adaptability and social support of vocational students leaving upper secondary school." *Journal of Career Assessment* 28, no. 3 (2020): 478-495.

Hoeting, Jennifer A., David Madigan, Adrian E. Raftery, and Chris T. Volinsky. "Bayesian model averaging: a tutorial (with comments by M. Clyde, David Draper and EI George, and a rejoinder by the authors." *Statistical science* 14, no. 4 (1999): 382-417.

Hoffman, Bobby. "Cognitive efficiency: A conceptual and methodological comparison." *Learning and Instruction* 22, no. 2 (2012): 133-144.

Hu, Y., Cai, Y., Wang, R., Gan, Y., & He, N. (2023). The relationship between self-esteem and aggressive behavior among Chinese adolescents: A moderated chain mediation model. *Frontiers in Psychology*, *14*, 1191134.

Humburg, Martin, and Rolf Van der Velden. "Skills and the graduate recruitment process: Evidence from two discrete choice experiments." *Economics of Education Review* 49 (2015): 24-41.

Husman, Jenefer, and Willy Lens. "The role of the future in student motivation." *Educational psychologist* 34, no. 2 (1999): 113-125.

Ivzori, Yonat, Dalia Sachs, Shunit Reiter, and Naomi Schreuer. "Transition to employment program (SUPER) for youth at risk: A conceptual and practical model." *International journal of environmental research and public health* 17, no. 11 (2020): 3904.

Jahn, Jody LS, and Karen K. Myers. "Vocational anticipatory socialization of adolescents: Messages, sources, and frameworks that influence interest in STEM careers." *Journal of Applied Communication Research* 42, no. 1 (2014): 85-106.

Jiang, Zhou. "Core self-evaluation and career decision self-efficacy: A mediation model of value orientations." *Personality and Individual Differences* 86 (2015): 450-454.

Jöreskog, Karl G., Dag Sörbom, and Jay Magidson. "Advances in factor analysis and structural equation models." *(No Title)* (1979).

Keijzer, Rineke, Roeland van der Rijst, Erik van Schooten, and Wilfried Admiraal. "Individual differences among at-risk students changing the relationship between resilience and vocational identity." *International Journal of Educational Research* 110 (2021): 101893.

King, Zella. "Career self-management: Its nature, causes and consequences." *Journal of vocational behavior* 65, no. 1 (2004): 112-133.

Kirchknopf, Sebastian. "Career adaptability and vocational identity of commercial apprentices in the German dual system." *Vocations and Learning* 13, no. 3 (2020): 503-526.

Kløjgaard, Mirja Elisabeth, Mickael Bech, and Rikke Søgaard. "Designing a stated choice experiment: the value of a qualitative process." *Journal of Choice Modelling* 5, no. 2 (2012): 1-18.

Klotz, Viola Katharina, Stephen Billett, and Esther Winther. "Promoting workforce excellence: formation and relevance of vocational identity for vocational educational training." *Empirical research in vocational education and training* 6 (2014): 1-20.

Kremer, Stefanie, and Louise den Uijl. "Studying emotions in the elderly." In *Emotion measurement*, pp. 537-571. Woodhead Publishing, 2016.

LaLonde, Robert J. "Employment and training programs." In *Means-tested transfer programs in the United States,* pp. 517-586. University of Chicago Press, 2003.

Lee, Yuyoung, Youngjae Kim, Sojeong Im, Eunbi Lee, and Eunjoo Yang. "Longitudinal associations between vocational identity process and career goals." *Journal of Career Development* 49, no. 3 (2022): 569-584.

Lent, R. W. "A Social Cognitive View of Career Development and Counseling." (2005) Retrieved from http://psycnet.apa.org/psycinfo/2004-21312-005

Lent, Robert W., and Gail Hackett. "Career self-efficacy: Empirical status and future directions." *Journal of vocational Behavior* 30, no. 3 (1987): 347-382.

Lent, Robert W., and Steven D. Brown. "Social cognitive model of career self-management: toward a unifying view of adaptive career behavior across the life span." *Journal of counseling psychology* 60, no. 4 (2013): 557

Lent, Robert W., Ijeoma Ezeofor, M. Ashley Morrison, Lee T. Penn, and Glenn W. Ireland. "Applying the social cognitive model of career self-management to career exploration and decision-making." *Journal of Vocational Behavior* 93 (2016): 47-57.

Lerner, Richard M., Jason B. Almerigi, Christina Theokas, and Jacqueline V. Lerner. "Positive youth development a view of the issues." *The journal of early adolescence* 25, no. 1 (2005): 10-16.

Liu, Qin, Michael A. Charleston, Shane A. Richards, and Barbara R. Holland. "Performance of Akaike Information Criterion and Bayesian Information Criterion in Selecting Partition Models and Mixture Models." *Systematic Biology* 72, no. 1 (2023): 92-105.

Lo, Yungtai, Nancy R. Mendell, and Donald B. Rubin. "Testing the number of components in a normal mixture." *Biometrika* 88, no. 3 (2001): 767-778.

Lubke, Gitta H., and Justin Luningham. "Fitting latent variable mixture models." *Behaviour research and therapy* 98 (2017): 91-102.

Luyckx, Koen, Luc Goossens, and Bart Soenens. “A developmental contextual perspective on identity construction in emerging adulthood: change dynamics in commitment formation and commitment evaluation.” *Developmental psychology* 42, no. 2 (2006): 366.

Masyn, Katherine E. “Latent class analysis and finite mixture modeling.” (2013).

McDonald, Catherine C., Janet A. Deatrick, Nancy Kassam-Adams, and Therese S. Richmond. “Community violence exposure and positive youth development in urban youth.” *Journal of community health* 36 (2011): 925-932.

McEwen, Craig A., and Bruce S. McEwen. “Social structure, adversity, toxic stress, and intergenerational poverty: An early childhood model.” *Annual Review of Sociology* 43 (2017): 445-472

McFadden, Daniel, and Kenneth Train. “Mixed MNL models for discrete response.” *Journal of applied Econometrics* 15, no. 5 (2000): 447-470.

McLachlan, Geoffrey J., and David Peel. “Mixtures of factor analyzers.” In *Proceedings of the seventeenth international conference on machine learning*, pp. 599-606. 2000.

Meeus, Wim, Jurjen Iedema, Marianne Helsen, and Wilma Vollebergh. “Patterns of adolescent identity development: Review of literature and longitudinal analysis.” *Developmental review* 19, no. 4 (1999): 419-461.

Mellard, Daryl F., Kari L. Woods, and Linette McJunkin. “Literacy components model for at-risk young adults enrolled in career and technical education.” *Journal of Research in Reading* 38, no. 3 (2015): 249-271.

Metheny, Jennifer, and Ellen Hawley Mcwhirter. “Contributions of social status and family support to college students’ career decision self-efficacy and outcome expectations.” *Journal of Career Assessment* 21, no. 3 (2013): 378-394.

Metzler, Marilyn, Melissa T. Merrick, Joanne Klevens, Katie A. Ports, and Derek C. Ford. “Adverse childhood experiences and life opportunities: Shifting the narrative.” *Children and youth services review* 72 (2017): 141-149.

Morgan, Stephen L., and Christopher Winship. *Counterfactuals and causal inference*. Cambridge University Press, 2015.

Muthén, Bengt O. “Mplus Discussion>> What is a good value of entropy.” (2008).

Muthen, Bengt O., and Linda K. Muthen. “The development of heavy drinking and alcohol-related problems from ages 18 to 37 in a US national sample.” *Journal of studies on alcohol* 61, no. 2 (2000): 290-300.

Muthén, Bengt. “Statistical and substantive checking in growth mixture modeling: comment on Bauer and Curran (2003).” (2003): 369.

Newsome, E. Bryan. “The Cognitive Ability Requirements of Vocational Education: A Role for Elementary Industrial Arts.” (1978).

Nguyen, Trang Quynh, and Elizabeth A. Stuart. “Propensity score analysis with latent covariates: measurement error bias correction using the covariate’s posterior mean, aka the inclusive factor score.” *Journal of Educational and Behavioral Statistics* 45, no. 5 (2020): 598-636.

Nylund-Gibson, Karen, and Andrew Young Choi. “Ten frequently asked questions about latent class analysis.” *Translational Issues in Psychological Science* 4, no. 4 (2018): 440.

Nylund-Gibson, Karen, and Katherine E. Masyn. “Covariates and mixture modeling: Results of a simulation study exploring the impact of misspecified effects on class enumeration.” *Structural Equation Modeling: A Multidisciplinary Journal* 23, no. 6 (2016): 782-797.

Nylund-Gibson, Karen, Ryan Grimm, Matt Quirk, and Michael Furlong. “A latent transition mixture model using the three-step specification.” *Structural Equation Modeling: A Multidisciplinary Journal* 21, no. 3 (2014): 439-454.

Nylund, Karen L., Tihomir Asparouhov, and Bengt O. Muthén. “Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study.” *Structural equation modeling: A multidisciplinary Journal* 14, no. 4 (2007): 535-569.

O’Donnell, Meaghan L., Ingo Schaefer, Tracey Varker, Dzenana Kartal, David Forbes, Richard AA Bryant, Derrick Silove et al. “A systematic review of person-centered approaches to investigating patterns of trauma exposure.” *Clinical psychology review* 57 (2017): 208-225.

Osborne, JASON W., ANNA B. Costello, and J. THOMAS Kellow. “Exploratory factor analysis (EFA) is rightly described as both an art and a science, whereresearchers follow a series of ana-lytic steps involving judgments more reminis-cent of qualitative inquiry, an interesting irony given the mathematical sophistication underly-ing EFA models’.” *Best Practices in Quantitative Methods* 86 (2008).

Parady, Giancarlos, David Ory, and Joan Walker. “The overreliance on statistical goodness-of-fit and under-reliance on model validation in discrete choice models: A review of validation practices in the transportation academic literature.” *Journal of Choice Modelling* 38 (2021): 100257.

Parker, Philip David, Herbert W. Marsh, Joseph Ciarrochi, Sarah Marshall, and Adel Salah Abduljabbar. “Juxtaposing math self-efficacy and self-concept as predictors of long-term achievement outcomes.” In *Noncognitive psychological processes and academic achievement*, pp. 39-58. Routledge, 2017.

Patil, Vivek H., Surendra N. Singh, Sanjay Mishra, and D. Todd Donavan. “Efficient theory development and factor retention criteria: Abandon the ’eigenvalue greater than one’criterion.” *Journal of Business Research* 61, no. 2 (2008): 162-170.

Pierce, B. K. “Do mathematics and reading competencies ıntegrated into career and technical education courses ımprove high school student state assessment scores.” *Yayımlanmamış doktora tezi, University of South Florida, USA* (2013).

Pierce, Kristin B., and Victor M. Hernandez. “Do Mathematics and Reading Competencies Integrated into Career and Technical Education Courses Improve High School Student State Assessment Scores?.” *Career and Technical Education Research* 39, no. 3 (2015): 213-229.

Porfeli, Erik J., Bora Lee, Fred W. Vondracek, and Ingrid K. Weigold. “A multi-dimensional measure of vocational identity status.” *Journal of adolescence* 34, no. 5 (2011): 853-871.

Porwal, Anupreet, and Adrian E. Raftery. “Comparing methods for statistical inference with model uncertainty.” *Proceedings of the National Academy of Sciences* 119, no. 16 (2022): e2120737119.

Powers, Samantha Rae, and Karen K. Myers. “Vocational anticipatory socialization: College students’ reports of encouraging/discouraging sources and messages.” *Journal of Career Development* 44, no. 5 (2017): 409-424.

Powers, Samantha Rae, and Karen K. Myers. “Vocational anticipatory socialization: College students’ reports of encouraging/discouraging sources and messages.” *Journal of Career Development* 44, no. 5 (2016): 409-424.

Pratt, Travis C., and Jillian J. Turanovic. “Lifestyle and routine activity theories revisited: The importance of”risk” to the study of victimization.” *Victims & Offenders* 11, no. 3 (2016): 335-354.

Proitsi, Petroula, Gillian Hamilton, Magda Tsolaki, M. Lupton, M. Daniilidou, Paul Hollingworth, N. Archer et al. “A multiple indicators multiple causes (MIMIC) model of behavioural and psychological symptoms in dementia (BPSD).” *Neurobiology of aging* 32, no. 3 (2011): 434-442.

Putnick, Diane L., and Marc H. Bornstein. “Measurement invariance conventions and reporting: The state of the art and future directions for psychological research.” *Developmental review* 41 (2016): 71-90.

Quílez-Robres, Alberto, Nieves Moyano, and Alejandra Cortés-Pascual. “Executive Functions and Self-Esteem in Academic Performance: A Mediational Analysis.” *International Journal of Psychological Research* 14, no. 2 (2021): 52-60.

Ragelienė, Tija. “Links of adolescents identity development and relationship with peers: A systematic literature review.” *Journal of the Canadian Academy of Child and Adolescent Psychiatry* 25, no. 2 (2016): 97.

Rahmani, Hamed, and Wim Groot. “Risk Factors of Being a Youth Not in Education, Employment or Training (NEET): A Scoping Review.” *International Journal of Educational Research* 120 (2023): 102198.

Raykov, Tenko. “Propensity score analysis with fallible covariates: A note on a latent variable modeling approach.” *Educational and Psychological Measurement* 72, no. 5 (2012): 715-733.

Ren, Jinma, Paul Cislo, Joseph C. Cappelleri, Patrick Hlavacek, and Marco DiBonaventura. “Comparing g-computation, propensity score-based weighting, and targeted maximum likelihood estimation for analyzing externally controlled trials with both measured and unmeasured confounders: a simulation study.” *BMC Medical Research Methodology* 23, no. 1 (2023): 18.

Richardson Jr, Joseph B. “Men do matter: Ethnographic insights on the socially supportive role of the African American uncle in the lives of inner-city African American male youth.” *Journal of Family Issues* 30, no. 8 (2009): 1041-1069.

Richardson, Michelle, Charles Abraham, and Rod Bond. “Psychological correlates of university students’ academic performance: a systematic review and meta-analysis.” *Psychological bulletin* 138, no. 2 (2012): 353.

Romeo, Russell D. “The teenage brain: The stress response and the adolescent brain.” *Current directions in psychological science* 22, no. 2 (2013): 140-145.

Rose, J. M., Antonio Borriello, and Andrea Pellegrini. “Formative versus reflective attitude measures: Extending the hybrid choice model.” *Journal of Choice Modelling* 48 (2023): 100412.

Rose, Theda, Michael A. Lindsey, Yunyu Xiao, Nadine M. Finigan-Carr, and Sean Joe. “Mental health and educational experiences among black youth: A latent class analysis.” *Journal of youth and adolescence* 46 (2017): 2321-2340.

Sabri, Bushra, Jun Sung Hong, Jacquelyn C. Campbell, and Hyunkag Cho. “Understanding children and adolescents’ victimizations at multiple levels: An ecological review of the literature.” *Journal of social service research* 39, no. 3 (2013): 322-334.

Salzmann, Mathieu, Carl Henrik Ek, Raquel Urtasun, and Trevor Darrell. “Factorized orthogonal latent spaces.” In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pp. 701-708. JMLR Workshop and Conference Proceedings, 2010.

Sanders, Jackie, Robyn Munford, Tewaporn Thimasarn-Anwar, Linda Liebenberg, and Michael Ungar. “The role of positive youth development practices in building resilience and enhancing wellbeing for at-risk youth.” *Child abuse & neglect* 42 (2015): 40-53.

Savickas, Mark L. “Career construction theory and practice.” *Career development and counseling: Putting theory and research to work* 2 (2013): 144-180.

Scheel, Michael John, Soumya Madabhushi, and Autumn Backhaus. “The academic motivation of at-risk students in a counseling prevention program.” *The Counseling Psychologist* 37, no. 8 (2009): 1147-1178.

Schmid, Evi, and Veerle Garrels. “Parental involvement and educational success among vulnerable students in vocational education and training.” *Educational Research* 63, no. 4 (2021): 456-473.

Schochet, Peter Z., and John Burghardt. “Using propensity scoring to estimate program-related subgroup impacts in experimental program evaluations.” *Evaluation Review* 31, no. 2 (2007): 95-120.

Schochet, Peter Z., John Burghardt, and Sheena McConnell. “Does job corps work? Impact findings from the national job corps study.” *American economic review* 98, no. 5 (2008): 1864-86.

Schunk, Dale H., and Barry J. Zimmerman. “Modeling and self-efficacy influences on children’s development of self-regulation.” *Social motivation: Understanding children’s school adjustment* (1996): 154-180.

Schunk, Dale H., and Frank Pajares. “Self-efficacy theory.” *Handbook of motivation at school* 35 (2009): 54.

Schunk, Dale H., and Maria K. DiBenedetto. “Self-efficacy theory in education.” *Handbook of motivation at school* 2 (2016): 34-54.

Scotto Rosato, Nancy, and Judith C. Baer. “Latent class analysis: A method for capturing heterogeneity.” *Social Work Research* 36, no. 1 (2012): 61-69.

Seginer, Rachel. “Adolescent future orientation: An integrated cultural and ecological perspective.” *Online readings in psychology and culture* 6, no. 1 (2003): 2307-0919.

Seginer, Rachel. *Future orientation: Developmental and ecological perspectives*. Springer Science & Business Media, 2009.

Shalala, Natasha, Junhao Tan, and Marko Biberdzic. “The mediating role of identity disturbance in the relationship between emotion dysregulation, executive function deficits, and maladaptive personality traits.” *Personality and Individual Differences* 162 (2020): 110004.

Shanahan, Murray, Verner P. Bingman, Toru Shimizu, Martin Wild, and Onur Güntürkün. “Large-scale network organization in the avian forebrain: a connectivity matrix and theoretical analysis.” *Frontiers in computational neuroscience* 7 (2013): 89.

Skorikov, Vladimir, and Fred W. Vondracek. “Positive career orientation as an inhibitor of adolescent problem behaviour.” *Journal of adolescence* 30, no. 1 (2007): 131-146.

Skorikov, Vladimir, and Fred W. Vondracek. “Vocational identity development: Its relationship to other identity domains and to overall identity development.” *Journal of Career Assessment* 6, no. 1 (1998): 13-35.

Slavin, Robert E., and Nancy A. Madden. "What works for students at risk: A research synthesis." *Educational leadership* 46, no. 5 (1989): 4-13.

Small, Dylan S., Zhiqiang Tan, Roland R. Ramsahai, Scott A. Lorch, and M. Alan Brookhart. "Instrumental variable estimation with a stochastic monotonicity assumption." *Statistical Science* 32, no. 4 (2017): 561-579.

Sobel, M. E. (2006). What do randomized studies of housing mobility demonstrate? Causal inference in the face of interference. *Journal of the American Statistical Association*, *101*(476), 1398-1407.

Spencer, Renee. "Understanding the mentoring process between adolescents and adults." *Youth & Society* 37, no. 3 (2006): 287-315.

Spurk, Daniel. "Vocational behavior research: Past topics and future trends and challenges." *Journal of Vocational Behavior* 126 (2021): 103559.

Steinberg, Laurence, and Amanda Sheffield Morris. "Adolescent development." *Annual review of psychology* 52, no. 1 (2001): 83-110.

Stringaris, Argyris, Barbara Maughan, William S. Copeland, E. Jane Costello, and Adrian Angold. "Irritable mood as a symptom of depression in youth: prevalence, developmental, and clinical correlates in the Great Smoky Mountains Study." *Journal of the American Academy of Child & Adolescent Psychiatry* 52, no. 8 (2013): 831-840.

Szcześniak, Małgorzata, Iga Bajkowska, Anna Czaprowska, and Aleksandra Sileńska. "Adolescents' self-esteem and life satisfaction: Communication with peers as a mediator." *International journal of environmental research and public health* 19, no. 7 (2022): 3777.

Tang, Xin, Hye Rin Lee, Sirui Wan, Hanna Gaspard, and Katariina Salmela-Aro. "Situating expectancies and subjective task values across grade levels, domains, and countries: A network approach." *AERA open* 8 (2022): 23328584221117168.

Tate, Kevin A., William Caperton, Dakota Kaiser, Nathan T. Pruitt, Heather White, and Eric Hall. "An exploration of first-generation college students' career development beliefs and experiences." *Journal of Career Development* 42, no. 4 (2015): 294-310.

Tavakol, Mohsen, and Angela Wetzel. "Factor Analysis: a means for theory and instrument development in support of construct validity." *International journal of medical education* 11 (2020): 245.

Temme, Dirk, Marcel Paulssen, and Till Dannewald. "Incorporating latent variables into discrete choice models—a simultaneous estimation approach using SEM software." *Business Research* 1 (2008): 220-237.

Torppa, Minna, Tuija Aro, Kenneth Eklund, Rauno Parrila, Anna-Kaija Eloranta, and Timo Ahonen. "Adolescent reading and math skills and self-concept beliefs as predictors of age 20 emotional well-being." *Reading and Writing* (2023): 1-25.

Train, Kenneth E. *Discrete choice methods with simulation*. Cambridge university press, 2009.

Travis, Wendy J., and Terri Combs-Orme. "Resilient parenting: Overcoming poor parental bonding." *Social Work Research* 31, no. 3 (2007): 135-149.

United States Census Bureau. *2000 Census.*U.S. Census Bureau, 2000.

United States. Department of Labor United States. Department of Commerce; United States. Department of Education; United States. Department of Health and Human Services. "What works in job training: a synthesis of the evidence." (2014).

VanderWeele, Tyler J. "Concerning the consistency assumption in causal inference." *Epidemiology* 20, no. 6 (2009): 880-883.

VanderWeele, Tyler J., and James M. Robins. "Stochastic counterfactuals and stochastic sufficient causes." *Statistica Sinica* 22, no. 1 (2012): 379.

Vermunt, Jeroen K. "Latent class modeling with covariates: Two improved three-step approaches." *Political analysis* 18, no. 4 (2010): 450-469.

Vermunt, Jeroen K., and Jay Magidson. "Latent class cluster analysis." *Applied latent class analysis* 11, no. 89-106 (2002): 60.

Vermunt, Jeroen K., and Jay Magidson. "Upgrade manual for Latent GOLD 5.1." *Belmont, MA: Statistical Innovations* (2016).

Vondracek, Fred W. "Vocational identity development in adolescence." *Adolescence in context: The interplay of family, school, peers, and work in adjustment* (1994): 284-303.

Vuong, Quang H. "Likelihood ratio tests for model selection and non-nested hypotheses." *Econometrica: journal of the Econometric Society* (1989): 307-333.

Wall, Melanie M., and Ruifeng Li. "Comparison of multiple regression to two latent variable techniques for estimation and prediction." *Statistics in medicine* 22, no. 23 (2003): 3671-3685.

Wang, Linbo, James M. Robins, and Thomas S. Richardson. "On falsification of the binary instrumental variable model." *Biometrika* 104, no. 1 (2017): 229-236.

Weden, Margaret M., and Laurie S. Zabin. "Gender and ethnic differences in the co-occurrence of adolescent risk behaviors." *Ethnicity and Health* 10, no. 3 (2005): 213-234.

Weller, Bridget E., and Eusebius Small. “Profiles of risk for HIV/AIDS among young malawian adults: Understanding behavioral intentions.” *Sexuality & Culture* 19, no. 4 (2015): 685-696.

Weller, Bridget E., Natasha K. Bowen, and Gary L. Bowen. “Linking students to appropriate interventions: A typology for social workers based on general strain theory.” *Journal of Social Work* 13, no. 4 (2013): 361-381.

Weller, Bridget E., Natasha K. Bowen, and Sarah J. Faubert. “Latent class analysis: a guide to best practice.” *Journal of Black Psychology* 46, no. 4 (2020): 287-311.

Welsh, Marilyn, and Sarah Schmitt-Wilson. “Executive function, identity, and career decision-making in college students.” *SAGE Open* 3, no. 4 (2013): 2158244013505755.

Whittaker, Tiffany A. “The Comparison of Latent Variable Propensity Score Models to Traditional Propensity Score Models under Conditions of Covariate Unreliability.” *Multivariate Behavioral Research* 55, no. 4 (2020): 625-646.

Wigfield, Allan, and Jacquelynne S. Eccles. “Expectancy–value theory of achievement motivation.” *Contemporary educational psychology* 25, no. 1 (2000): 68-81.

Wilhelm, Francisco, and Andreas Hirschi. “Career self-management as a key factor for career wellbeing.” *Theory, research and dynamics of career wellbeing: Becoming fit for the future* (2019): 117-137.

Woods-Jaeger, Briana, Emily Siedlik, Amber Adams, Kaitlin Piper, Paige O’Connor, and Jannette Berkley-Patton. “Building a contextually-relevant understanding of resilience among African American youth exposed to community violence.” *Behavioral medicine* 46, no. 3-4 (2020): 330-339.

Wu, Margaret. “The role of plausible values in large-scale surveys.” *Studies in educational Evaluation* 31, no. 2-3 (2005): 114-128.

Wurpts, Ingrid C., and Christian Geiser. “Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study.” *Frontiers in psychology* 5 (2014): 920.

Ximénez, Carmen. “Recovery of weak factor loadings in confirmatory factor analysis under conditions of model misspecification.” *Behavior Research Methods* 41, no. 4 (2009): 1038-1052.