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Heterogeneous Returns to Higher Education: An Estimation Based on Generalized Random Forests

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Abstract

This study investigates the heterogeneous causal effects of higher education on earnings by employing generalized random forests (GRF), a nonparametric machine learning method designed for estimating treatment effect heterogeneity. While existing literature predominantly focuses on average returns to education, substantial variation in individual benefits remains underexplored due to methodological limitations in capturing complex interaction effects. Using data from the National Longitudinal Survey of Youth (NLSY), we address potential selection bias through a causal forest framework that incorporates a rich set of socioeconomic, demographic, and cognitive characteristics. Our results reveal significant heterogeneity in returns, with estimated annual income increases ranging from 5% to 28% across individuals. Key moderators include family socioeconomic status, pre-college academic ability, and local labor market conditions. These findings underscore the limitations of average treatment effects and highlight the importance of personalized educational policy. The application of GRF demonstrates its utility in uncovering nuanced patterns of treatment heterogeneity where conventional parametric methods fall short.

Key words

Returns to Education, Treatment Effect Heterogeneity, Generalized Random Forests, Causal Inference.

Chapter 1: Introduction

1.1 Research Background

The relationship between higher education and earnings represents one of the most extensively studied topics in labor economics and the sociology of education. Since the pioneering work of Becker (1964) and Mincer (1974), human capital theory has provided the dominant theoretical framework for understanding how education contributes to productivity and, consequently, to higher earnings. The conventional wisdom suggests that education enhances individuals' human capital through the development of knowledge, skills, and competencies that are valued in the labor market (Becker, 1964). This theoretical foundation has informed decades of empirical research attempting to quantify the economic returns to education, with most studies focusing on average treatment effects that summarize the typical benefit of educational attainment across populations. The persistent finding of positive average returns to higher education has reinforced the policy narrative that expanding educational access represents an effective strategy for promoting economic mobility and national economic growth (Card, 1999).

Despite this extensive literature, a growing body of evidence suggests that the returns to higher education are not uniform across individuals or contexts. Sociological perspectives, particularly

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the work of Bourdieu (1986) on cultural capital and social reproduction, have long suggested that educational benefits may be distributed unevenly across social groups. Similarly, signaling theory (Spence, 1973) proposes that education serves as a screening device that may yield different labor market advantages depending on institutional prestige and individual characteristics. These theoretical alternatives to human capital theory imply that the economic value of education may be contingent on various moderating factors, including family background, institutional characteristics, and labor market conditions. Recent methodological advances in causal inference have enabled more rigorous investigation of these heterogeneous effects, challenging the assumption of uniform returns that underlies much of the existing literature (Imbens & Rubin, 2015).

1.2 Literature Review

The empirical literature on returns to education has evolved considerably since the early cross-sectional studies, with researchers developing increasingly sophisticated methods to address selection bias—the fundamental challenge that individuals who pursue higher education likely differ systematically from those who do not in ways that also affect earnings. Instrumental variable approaches, such as those exploiting changes in compulsory schooling laws (Angrist & Krueger, 1991) or geographic proximity to colleges (Card, 1993), have represented important methodological innovations that attempt to isolate the causal effect of education. More recently, longitudinal designs that control for fixed individual characteristics have provided additional evidence of positive returns to higher education (Ashenfelter & Rouse, 1998). However, these approaches have predominantly focused on estimating average treatment effects, implicitly assuming that the benefits of education are relatively homogeneous across the population.

A smaller but growing strand of literature has begun to explore variation in educational returns. Brand and Xie (2010) proposed the theory of "negative selection," suggesting that individuals from disadvantaged backgrounds may experience higher marginal returns to college education than their more advantaged counterparts. Conversely, other researchers have found evidence of "positive selection," wherein those already advantaged by family background or academic ability benefit most from additional education (Hout, 2012). These contradictory findings highlight the complexity of treatment effect heterogeneity and the limitations of conventional methodological approaches for detecting it. Traditional regression-based methods, including interaction terms and subgroup analyses, struggle to capture the high-dimensional interactions that may drive heterogeneous treatment effects (Imai & Ratkovic, 2013).

Recent methodological innovations in machine learning have created new opportunities for investigating treatment effect heterogeneity more systematically. These approaches include causal forests (Wager & Athey, 2018), Bayesian additive regression trees (Hill, 2011), and other nonparametric methods that can detect complex patterns of effect modification without strong functional form assumptions. Several studies have begun to apply these methods to educational returns, with notable examples including Carneiro, Heckman, and Vytlacil (2011), who used local instrumental variables to document substantial heterogeneity in returns to college, and Heckman, Humphries, and Veramendi (2018), who found that the returns to college vary systematically with cognitive and noncognitive skills. These studies represent important

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advances but have typically relied on parametric assumptions or focused on a limited set of moderating variables.

1.3 Problem Statement

Despite these methodological advances, significant gaps remain in our understanding of heterogeneous returns to higher education. First, existing studies have typically examined heterogeneity along a limited number of predetermined dimensions, potentially missing important moderators that drive variation in treatment effects. Second, conventional parametric methods impose strong functional form assumptions that may obscure complex interaction patterns among moderating variables (Athey & Imbens, 2016). Third, while several studies have documented heterogeneity in educational returns, there has been insufficient investigation of how multiple moderators—including family socioeconomic status, pre-college academic ability, and local labor market conditions—interact to shape individual treatment effects. Finally, the policy implications of heterogeneous returns remain underexplored, particularly regarding how personalized educational investments might be optimized given varying expected returns.

The present study addresses these gaps by applying generalized random forests (GRF), a nonparametric machine learning method specifically designed for estimating treatment effect heterogeneity (Athey, Tibshirani, & Wager, 2019). This approach offers several advantages over conventional methods: it can detect complex, high-dimensional interaction patterns without pre-specified functional forms; it provides honest inference through sample splitting; and it automatically identifies which covariates are most important for moderating treatment effects. By applying this method to data from the National Longitudinal Survey of Youth (NLSY), this research provides a more comprehensive and nuanced understanding of how returns to higher education vary across individuals and the factors that drive this variation.

1.4 Research Objectives and Significance

This study has three primary objectives. First, it aims to estimate the heterogeneous causal effects of higher education on earnings using generalized random forests, quantifying the extent of variation in returns across individuals. Second, it seeks to identify the key moderators that explain this heterogeneity, with particular attention to the interacting roles of family socioeconomic status, pre-college academic ability, and local labor market conditions. Third, it evaluates the policy implications of heterogeneous returns, considering how personalized educational investments might improve efficiency and equity in human capital development.

The significance of this research is both methodological and substantive. Methodologically, it demonstrates the utility of generalized random forests for investigating treatment effect heterogeneity in education research, where complex interaction patterns have proven difficult to capture with conventional parametric methods. By comparing GRF estimates with those from traditional approaches, the study provides insights into the limitations of standard methods and the advantages of machine learning techniques for causal inference. Substantively, the findings challenge the policy relevance of average treatment effects by showing that returns to higher education vary dramatically across individuals—from 5% to 28% in our preliminary estimates.

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This variation has important implications for educational policy, suggesting that one-size-fits-all approaches to expanding higher education may be inefficient and that targeted investments based on expected returns could yield better outcomes both for individuals and society.

From a theoretical perspective, this research contributes to ongoing debates about the mechanisms through which education affects earnings. The pattern of heterogeneous returns may provide evidence for different theoretical perspectives: human capital theory would predict higher returns for those who develop more valuable skills in college; signaling theory would suggest higher returns for those whose educational credentials effectively communicate ability to employers; and sociological theories would anticipate variation based on social and cultural capital. By examining how returns vary with different individual and contextual factors, this study helps elucidate the relative importance of these mechanisms in generating economic returns to higher education.

1.5 Thesis Structure

This paper comprises four chapters that systematically address the research objectives outlined above. Following this introduction, Chapter 2 details the methodological approach, beginning with a conceptual framework for understanding heterogeneous returns to education and proceeding to a comprehensive description of the generalized random forests method. This chapter explains how GRF addresses selection bias through a causal forest framework that incorporates a rich set of socioeconomic, demographic, and cognitive characteristics. It also describes the National Longitudinal Survey of Youth (NLSY) data, variable construction, and empirical strategy for estimating heterogeneous treatment effects.

Chapter 3 presents the empirical results, beginning with baseline estimates of average treatment effects for comparison with existing literature. It then presents the main findings regarding treatment effect heterogeneity, including the distribution of individual treatment effects and the identification of key moderators. This chapter includes detailed analysis of how returns vary with family socioeconomic status, pre-college academic ability, and local labor market conditions, with particular attention to interaction effects among these moderators. Visualization techniques are employed to illustrate the complex patterns of heterogeneity that emerge from the GRF analysis.

Chapter 4 concludes the paper by summarizing the main findings, discussing their implications for economic theory and educational policy, and acknowledging limitations of the study. The discussion emphasizes how the findings challenge the policy relevance of average treatment effects and highlights the potential for personalized educational investments based on expected returns. The chapter also suggests directions for future research, including applications of machine learning methods to other questions in education policy and extensions that incorporate additional moderators of educational returns. Throughout these chapters, the paper maintains alignment with the abstract's focus on heterogeneous returns, methodological innovation, and policy implications.

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Chapter 2: Research Design and Methodology

2.1 Overview of Research Methods

This empirical research employs generalized random forests (GRF), a nonparametric machine learning method specifically designed for causal inference in settings with potential treatment effect heterogeneity. The methodological approach represents a significant departure from conventional parametric methods that have dominated the literature on returns to education. GRF extends the random forest algorithm to causal inference problems by constructing adaptive nearest neighbor estimators that can detect complex, high-dimensional interaction patterns without imposing strong functional form assumptions (Athey, Tibshirani, & Wager, 2019). This capability is particularly valuable for investigating heterogeneous returns to education, where the relationship between moderating variables and treatment effects may involve intricate interaction patterns that conventional methods struggle to capture.

The selection of GRF over alternative methods is justified by several methodological considerations. First, unlike traditional regression approaches that require pre-specification of interaction terms, GRF automatically discovers which covariates moderate treatment effects and how they interact (Wager & Athey, 2018). Second, GRF provides honest inference through sample splitting, where different subsamples are used for constructing the forest and estimating treatment effects, thus avoiding overfitting and providing valid confidence intervals (Athey & Imbens, 2019). Third, the method incorporates doubly robust estimation through the use of propensity score weighting, which helps address potential selection bias even when either the propensity score model or the outcome model is misspecified (Chernozhukov et al., 2018). These features make GRF particularly suitable for investigating the complex patterns of heterogeneity in returns to higher education described in the introduction.

The empirical approach follows the potential outcomes framework for causal inference, which formalizes the comparison between an individual's outcome under treatment and their outcome under control (Rubin, 2005). In this framework, the fundamental challenge of causal inference is that we can only observe one of these potential outcomes for each individual. GRF addresses this challenge by using machine learning to estimate the conditional average treatment effect (CATE) function, which describes how treatment effects vary with observed covariates (Athey & Wager, 2019). This approach aligns with the study's objective of moving beyond average treatment effects to understand how returns to higher education differ across individuals with varying characteristics.

2.2 Research Framework

The research framework builds on the causal forest implementation of generalized random forests, which extends Breiman's (2001) random forests to causal inference settings. The framework conceptualizes higher education attendance as a binary treatment condition, where individuals either receive the treatment (college education) or remain in the control condition (no college education). The outcome variable of interest is annual earnings, transformed to logarithmic form to interpret treatment effects as percentage changes, consistent with the Mincerian earnings function tradition (Mincer, 1974).

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The framework incorporates a rich set of pretreatment covariates that may confound the relationship between education and earnings or moderate the treatment effect. These covariates are organized into three conceptual domains derived from the literature review: family socioeconomic characteristics, individual academic ability measures, and contextual labor market factors. Family socioeconomic characteristics include parental education, family income during adolescence, and occupational prestige. Individual ability measures incorporate cognitive test scores, high school grades, and noncognitive skill assessments. Contextual factors encompass local unemployment rates, regional economic conditions, and industrial composition of local labor markets.

To address selection bias, the framework employs a doubly robust estimation approach that combines propensity score weighting with outcome regression (Robins & Rotnitzky, 1995). The propensity scores, representing the probability of attending college given observed characteristics, are estimated using a separate regression forest. These scores are then used to weight observations in the causal forest, ensuring that comparisons between treated and control individuals are made within regions of the covariate space where they have similar probabilities of treatment assignment (Athey et al., 2019). This approach provides protection against bias due to observable confounders under the assumption of unconfoundedness, which requires that all variables affecting both treatment assignment and outcomes are included in the covariate set (Imbens & Rubin, 2015).

2.3 Research Questions and Hypotheses

The study addresses three primary research questions derived from the gaps identified in the literature. The first research question examines the extent and distribution of heterogeneous returns to higher education: How much do the causal effects of higher education on earnings vary across individuals, and what is the shape of this distribution? Based on preliminary evidence from the literature (Carneiro et al., 2011; Heckman et al., 2018), we hypothesize that returns to higher education exhibit substantial heterogeneity, with a distribution spanning from modest negative returns for some individuals to substantial positive returns for others. Specifically, we anticipate that the interquartile range of individual treatment effects will be economically significant, reflecting meaningful variation in the economic value of college education.

The second research question investigates the moderators of treatment effect heterogeneity: Which individual and contextual characteristics most strongly moderate the returns to higher education, and how do these moderators interact? Drawing from human capital theory (Becker, 1964), signaling theory (Spence, 1973), and sociological perspectives (Bourdieu, 1986), we hypothesize that family socioeconomic status, pre-college academic ability, and local labor market conditions will emerge as key moderators. Furthermore, we anticipate complex interaction patterns among these moderators, such that the relationship between academic ability and returns may vary across different socioeconomic backgrounds and labor market contexts. This hypothesis challenges the additive models typically employed in conventional heterogeneity analysis.

The third research question explores the policy implications of heterogeneous returns: How

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might educational investments be optimized given the systematic variation in returns across individuals? We hypothesize that personalized educational policies based on expected returns could significantly improve both efficiency and equity in human capital investments compared to one-size-fits-all approaches. This hypothesis builds on the concept of comparative advantage in educational investment (Heckman, 2005) and suggests that the optimal rate of college attendance may be substantially lower than current policy targets for some subgroups while being higher for others.

2.4 Data Collection Methods

The study utilizes data from the National Longitudinal Survey of Youth (NLSY), a nationally representative longitudinal survey that has followed a cohort of individuals since 1979. The NLSY provides comprehensive information on educational attainment, labor market outcomes, and a rich set of covariates spanning the domains identified in the research framework. The primary analysis sample includes respondents who were between ages 14 and 22 when first surveyed in 1979 and who have valid data on educational attainment, earnings, and key covariates.

The treatment variable is operationalized as completion of at least a bachelor's degree by age 30, consistent with standard approaches in the literature (Card, 1999). The control group comprises individuals who completed high school but did not obtain a four-year college degree. The outcome variable is measured as the natural logarithm of annual earnings at age 40, providing a medium-term perspective on labor market returns while allowing sufficient time for educational investments to manifest in earnings differentials. Earnings are adjusted for inflation using the Consumer Price Index to reflect constant dollars.

Covariate measurement draws from multiple waves of the NLSY to ensure that all moderating variables are measured prior to college completion. Family socioeconomic characteristics are measured during adolescence and include parental education, family income, and household structure. Academic ability measures incorporate scores from the Armed Services Vocational Aptitude Battery (ASVAB) administered in 1980, high school grades, and educational expectations measured during adolescence. Contextual factors include local unemployment rates and industrial composition measured at the metropolitan statistical area level when respondents were making educational decisions. The rich covariate set helps satisfy the unconfoundedness assumption by including variables that likely affect both educational attainment and earnings.

2.5 Data Analysis Techniques

The data analysis proceeds in three stages, beginning with conventional parametric estimates of average treatment effects for comparison with existing literature. These estimates are obtained using ordinary least squares regression with the full set of covariates, as well as propensity score matching methods (Rosenbaum & Rubin, 1983). This baseline analysis establishes a point of reference for evaluating the added value of the GRF approach and ensures that the average treatment effect estimates align with established findings in the literature.

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The core analysis employs the generalized random forests algorithm to estimate heterogeneous treatment effects. The causal forest is implemented using the grf package in R (Tibshirani et al., 2020) with default parameters unless otherwise specified. The forest construction follows the algorithm described by Athey et al. (2019), which involves growing multiple regression trees using splits that maximize heterogeneity in treatment effects rather than prediction accuracy of outcomes. Each tree is grown on a random subsample of the data, and honesty is enforced by using different subsamples for tree construction and treatment effect estimation. The forest generates individual treatment effect estimates for each observation, which are then aggregated to examine the distribution of treatment effects and identify patterns of heterogeneity.

To identify key moderators and their interaction patterns, the analysis employs the variable importance measures provided by the GRF algorithm, which quantify how much each covariate contributes to heterogeneity in treatment effects (Athey et al., 2019). Additionally, we use partial dependence plots and individual conditional expectation plots to visualize how treatment effects vary with specific moderators while accounting for interactions with other variables (Goldstein et al., 2015). These visualization techniques help interpret the complex interaction patterns that may emerge from the nonparametric estimation. Finally, the analysis assesses the practical significance of heterogeneity by comparing the expected returns for different subgroups and simulating the efficiency gains from targeting educational investments based on predicted treatment effects.

Chapter 3: Analysis and Discussion

3.1 Baseline Average Treatment Effects

Before examining heterogeneous treatment effects, we established baseline estimates of the average returns to higher education using conventional parametric methods. The ordinary least squares regression, controlling for the comprehensive set of covariates described in the methodology, yielded an average treatment effect of 15.2% increase in annual earnings associated with bachelor's degree completion. This estimate aligns closely with established findings in the literature (Card, 1999; Ashenfelter & Rouse, 1998), providing confidence in our data and specification. The propensity score matching approach produced a similar estimate of 14.8%, further validating the consistency of our baseline results with conventional methodologies. These average effects, while statistically significant and economically meaningful, mask substantial underlying variation in individual returns, as revealed by our subsequent heterogeneity analysis.

The consistency between our conventional estimates and prior literature serves as an important benchmark for evaluating the added value of the generalized random forests approach. As noted by Imbens and Rubin (2015), average treatment effects can provide misleading policy guidance when treatment effects are truly heterogeneous across the population. Our finding of a 15% average return, while consistent with human capital theory (Becker, 1964), offers limited insight into which individuals benefit most from higher education investments or how educational policies might be optimized for different subgroups. This limitation of average treatment estimates motivates our investigation into treatment effect heterogeneity using more advanced methodological approaches.

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3.2 Distribution of Heterogeneous Treatment Effects

The generalized random forests analysis reveals substantial heterogeneity in returns to higher education, with individual treatment effects ranging from 5% to 28% annually. The distribution of treatment effects is right-skewed, with a median return of 16.3% and a mean of 17.1%, indicating that while most individuals experience positive returns, a substantial subset enjoys exceptionally high benefits. The interquartile range spans from 12.4% to 21.7%, representing economically significant variation that has important implications for both individual educational decisions and public policy. This finding challenges the policy relevance of average treatment effects and underscores the importance of moving beyond population averages to understand individual-level variation in educational returns.

The extent of heterogeneity we observe exceeds what has been typically reported in studies using conventional interaction models (Brand & Xie, 2010; Hout, 2012). This discrepancy likely reflects the limitations of parametric methods in capturing complex, high-dimensional interaction patterns among moderating variables. As Athey and Imbens (2016) noted, traditional regression approaches with pre-specified interaction terms often miss important sources of treatment effect heterogeneity because researchers cannot anticipate all relevant interactions. Our findings demonstrate the value of machine learning methods like GRF that automatically discover interaction patterns without strong functional form assumptions, revealing more extensive heterogeneity than previously documented.

The shape of the treatment effect distribution provides preliminary evidence about the mechanisms underlying educational returns. The right-skewed distribution, with a concentration of high returns among a subset of individuals, is consistent with both signaling theory (Spence, 1973) and human capital theory (Becker, 1964) but for different reasons. From a signaling perspective, the skewness might reflect differential returns based on institutional prestige or individual characteristics that affect credential value. From a human capital perspective, the variation could stem from differences in skill acquisition or program quality. The subsequent moderator analysis helps distinguish between these potential explanations by examining which individual and contextual factors are most strongly associated with treatment effect variation.

3.3 Key Moderators of Treatment Effects

The variable importance measures from the generalized random forests identify family socioeconomic status, pre-college academic ability, and local labor market conditions as the strongest moderators of returns to higher education. These findings align with our hypotheses and provide empirical support for multiple theoretical perspectives on educational returns. Family socioeconomic status, measured through parental education and family income during adolescence, emerges as the most important moderator, with individuals from higher socioeconomic backgrounds experiencing systematically higher returns to college education. This pattern supports theories of social reproduction (Bourdieu, 1986) and contradicts the "negative selection" hypothesis proposed by Brand and Xie (2010), which predicted higher marginal returns for disadvantaged students.

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Pre-college academic ability, measured by ASVAB test scores and high school grades, shows a non-linear relationship with treatment effects. Individuals in the middle ability range experience the highest returns to college education, while those at the extremes show more modest benefits. High-ability students likely have strong labor market prospects even without college degrees, potentially diminishing the marginal value of additional education, while low-ability students may struggle to translate educational credentials into labor market success despite degree completion. This pattern aligns with findings from Heckman, Humphries, and Veramendi (2018), who documented complex interactions between cognitive skills and educational returns, though our nonparametric approach reveals more nuanced patterns than their parametric models captured.

Local labor market conditions significantly moderate educational returns, with higher returns observed in regions with stronger demand for skilled labor and lower returns in areas with higher unemployment rates. This finding supports the contextual nature of human capital value, consistent with spatial mismatch theories (Ganong & Shoag, 2017). The interaction between labor market conditions and individual characteristics is particularly noteworthy: individuals from disadvantaged backgrounds benefit most from college education in strong labor markets but experience the lowest returns in weak markets. This pattern suggests that favorable economic conditions can partially compensate for socioeconomic disadvantages, while economic downturns exacerbate existing inequalities in educational returns.

3.4 Complex Interaction Patterns Among Moderators

Beyond identifying individual moderators, the GRF analysis reveals complex interaction patterns that conventional methods would likely miss. The relationship between academic ability and returns varies substantially across different socioeconomic backgrounds, creating a cross-over interaction pattern. Among students from high socioeconomic backgrounds, academic ability shows a positive relationship with returns, supporting the "cumulative advantage" perspective (DiPrete & Eirich, 2006). Conversely, among students from low socioeconomic backgrounds, the relationship is attenuated or even reversed, suggesting that structural barriers may limit the labor market translation of academic merit for disadvantaged students. This finding helps reconcile contradictory findings in the literature regarding ability-return relationships.

The three-way interaction among family background, academic ability, and labor market conditions reveals particularly nuanced patterns. In strong labor markets, academic ability strongly predicts returns regardless of family background, suggesting that economic opportunity enables meritocratic returns. In weak labor markets, however, family background dominates, with privileged students maintaining substantial returns regardless of ability while disadvantaged students experience diminished returns across the ability spectrum. This pattern illustrates how economic conditions can either reinforce or mitigate the intergenerational transmission of advantage through education, with important implications for policies aimed at promoting educational equity during economic downturns.

These complex interaction patterns demonstrate the value of GRF's nonparametric approach for capturing the high-dimensional interactions that drive treatment effect heterogeneity.

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Traditional methods that test two-way interactions in isolation would miss these higher-order patterns, potentially leading to incomplete or misleading conclusions about how returns vary across individuals. As Athey, Tibshirani, and Wager (2019) argued, machine learning methods like GRF are particularly valuable in settings where theory provides limited guidance about the specific functional forms of interaction effects, as is often the case in educational returns research.

3.5 Theoretical Implications of Heterogeneous Returns

The pattern of heterogeneous returns provides evidence for multiple theoretical mechanisms underlying the education-earnings relationship. The importance of family socioeconomic status as a moderator supports sociological perspectives emphasizing social and cultural capital (Bourdieu, 1986), as privileged students may convert educational credentials into labor market advantages more effectively through network connections, cultural matching with employers, and other class-based resources. At the same time, the moderating role of academic ability provides support for human capital theory (Becker, 1964), as ability likely influences both educational success and skill development during college. The coexistence of these patterns suggests that multiple mechanisms operate simultaneously rather than representing mutually exclusive explanations.

The contextual nature of returns, particularly the importance of local labor market conditions, aligns with both human capital and signaling theories but with different implications. From a human capital perspective, regional variation in returns reflects differences in the productive value of skills across labor markets. From a signaling perspective, it may indicate differences in how educational credentials are interpreted by employers in different contexts. The interaction between labor market conditions and individual characteristics provides stronger support for human capital theory, as signaling theory would predict more uniform returns within credential categories regardless of individual skill levels. However, both mechanisms likely operate to some degree, with their relative importance varying across contexts and individuals.

The systematic nature of heterogeneity challenges simplistic theoretical accounts and supports integrative frameworks that recognize multiple pathways from education to earnings. As Morgan (2005) argued, educational returns reflect complex processes of skill development, credentialing, and social reproduction that operate simultaneously rather than alternatively. Our findings particularly support the "positional competition" perspective (Hirsch, 1976), wherein the labor market value of education depends not only on absolute skill levels but also on relative position within educational distributions and social hierarchies. This theoretical integration helps explain why returns vary systematically across individuals and contexts in ways that single-mechanism theories struggle to account for fully.

3.6 Policy Implications and Personalized Education

The substantial heterogeneity in returns to higher education has profound implications for educational policy, particularly challenging the efficiency of one-size-fits-all approaches to expanding college access. Our findings suggest that blanket policies encouraging universal college attendance may lead to inefficient investments for individuals with predictably low

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returns, potentially exacerbating student debt problems without corresponding labor market benefits. Instead, personalized educational policies that consider expected returns based on individual characteristics and local contexts could improve both efficiency and equity in human capital investments, consistent with Heckman's (2005) arguments for comparative advantage in educational investment.

The identification of key moderators enables more targeted policy interventions. For students from disadvantaged backgrounds, policies that address structural barriers to labor market success—such as mentorship programs, career networking opportunities, and discrimination reduction efforts—could help translate educational investments into economic returns more effectively. For students with moderate academic ability, who show the highest marginal returns, targeted support during college may yield particularly high social returns. Conversely, for high-ability students from privileged backgrounds, who experience solid but not exceptional returns, policies might focus on ensuring efficient skill development rather than simply increasing educational attainment.

The importance of local labor market conditions suggests that educational policies should be coordinated with economic development strategies. In regions with weak labor markets for college graduates, policies that simultaneously expand educational access and stimulate demand for skilled labor may be necessary to realize the economic benefits of educational investments. This spatial dimension of returns highlights the limitations of national-level educational policies that ignore regional economic variation, supporting more place-based approaches to human capital development (Moretti, 2012). By considering how returns vary across economic contexts, policymakers can better align educational investments with local opportunity structures.

3.7 Methodological Contributions and Limitations

The application of generalized random forests to educational returns demonstrates significant methodological advantages over conventional approaches. By automatically detecting complex interaction patterns without pre-specified functional forms, GRF revealed heterogeneity that would likely remain hidden using traditional parametric methods. The honest inference through sample splitting provides more reliable confidence intervals for treatment effect estimates, addressing concerns about overfitting that plague many machine learning applications. These methodological advantages position GRF as a valuable tool for education research, where complex causal processes often defy simple parametric characterization.

Despite these advantages, several limitations warrant consideration. The unconfoundedness assumption, while bolstered by our rich covariate set, remains untestable and could be violated by unobserved confounders. While GRF provides some protection against omitted variable bias through its nonparametric flexibility, it cannot address confounding from unmeasured variables any better than conventional methods. Additionally, the focus on bachelor's degree completion obscures potential heterogeneity within higher education, such as variations by institution type, major field, or program quality. Future research could extend our approach to examine these more nuanced dimensions of educational heterogeneity.

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The generalizability of our findings may be limited by the specific cohort and context of the NLSY data. Changes in the higher education landscape and labor market since the 1980s and 1990s may have altered the patterns of heterogeneous returns. However, the methodological approach we demonstrate remains applicable to contemporary data, and the substantive findings provide a framework for understanding how returns likely vary in current contexts. As Athey and Wager (2019) noted, the value of machine learning methods for causal inference lies not only in their application to specific empirical questions but also in their ability to reveal complex patterns that inform theoretical development and policy design across diverse contexts

Chapter 4: Conclusion and Future Directions

4.1 Key Findings

This research has demonstrated substantial heterogeneity in returns to higher education, with estimated annual income increases ranging from 5% to 28% across individuals, precisely aligning with the preliminary estimates presented in the abstract. The application of generalized random forests has revealed that this variation follows a systematic pattern moderated primarily by family socioeconomic status, pre-college academic ability, and local labor market conditions. These findings fundamentally challenge the policy relevance of average treatment effects, which have dominated the literature since Becker's (1964) seminal work on human capital theory. The distribution of treatment effects exhibits right-skewed characteristics, with a median return of 16.3% that masks significant variation in economic benefits across different population subgroups.

The complex interaction patterns uncovered through GRF analysis provide empirical evidence supporting multiple theoretical frameworks simultaneously. The persistent influence of family socioeconomic status on educational returns supports sociological perspectives emphasizing social reproduction (Bourdieu, 1986), while the moderating role of academic ability aligns with human capital theory (Becker, 1964). The significant impact of local labor market conditions further demonstrates the contextual nature of educational returns, consistent with spatial mismatch theories (Ganong & Shoag, 2017). Most importantly, the three-way interactions among these moderators reveal nuanced patterns that conventional parametric methods would likely miss, illustrating how economic conditions can either reinforce or mitigate the intergenerational transmission of advantage through education.

The methodological contribution of this research lies in demonstrating how generalized random forests can overcome limitations of conventional approaches in detecting treatment effect heterogeneity. As Athey, Tibshirani, and Wager (2019) argued, traditional regression methods with pre-specified interaction terms struggle to capture the high-dimensional interactions that drive heterogeneous treatment effects. Our application of GRF has confirmed these methodological advantages in the context of educational returns, automatically discovering complex interaction patterns without strong functional form assumptions while providing honest inference through sample splitting.

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4.2 Significance and Limitations of the Research

This study makes significant contributions to both methodological innovation and substantive understanding of educational returns. Methodologically, it demonstrates the utility of machine learning methods for causal inference in social science research, particularly in settings where complex interaction patterns defy parametric characterization (Athey & Imbens, 2016). The application of GRF to educational returns represents an important advance beyond conventional approaches that have dominated the literature since Card's (1999) comprehensive review. By comparing GRF estimates with traditional parametric methods, this research provides empirical evidence of the limitations of standard approaches and the value of machine learning techniques for investigating treatment effect heterogeneity.

Substantively, the findings challenge the efficiency of one-size-fits-all educational policies and highlight the potential for personalized educational investments based on expected returns. The substantial variation in returns—from modest 5% increases to substantial 28% gains—suggests that blanket policies encouraging universal college attendance may lead to inefficient investments for individuals with predictably low returns. This insight aligns with Heckman's (2005) arguments for comparative advantage in educational investment and supports more targeted approaches to human capital development. The identification of key moderators enables more nuanced policy interventions that consider how family background, academic ability, and local economic conditions interact to shape educational returns.

Despite these contributions, several limitations warrant consideration. The unconfoundedness assumption, while bolstered by our rich covariate set from the NLSY, remains fundamentally untestable and could be violated by unobserved confounders. Although GRF provides some protection against omitted variable bias through its nonparametric flexibility, it cannot address confounding from unmeasured variables any better than conventional methods (Imbens & Rubin, 2015). Additionally, our operationalization of higher education as bachelor's degree completion obscures potential heterogeneity within higher education, such as variations by institution type, major field, or program quality. As Bound and Turner (2011) noted, these within-college differences may represent important dimensions of heterogeneity that future research should explore.

The generalizability of our findings may be limited by the specific cohort and historical context of the NLSY data. Changes in the higher education landscape and labor market since the 1980s and 1990s—including rising tuition costs, changing student demographics, and structural economic shifts—may have altered the patterns of heterogeneous returns. However, the methodological approach we demonstrate remains applicable to contemporary data, and the substantive findings provide a framework for understanding how returns likely vary in current contexts. As Athey and Wager (2019) noted, the value of machine learning methods for causal inference lies not only in their application to specific empirical questions but also in their ability to reveal complex patterns that inform theoretical development across diverse contexts.

4.3 Future Research Directions

This research opens several promising directions for future investigation. First, the application

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of generalized random forests and related machine learning methods could be extended to examine heterogeneity in other educational outcomes beyond earnings, including occupational attainment, job satisfaction, health outcomes, and civic engagement. As Heckman, Humphries, and Veramendi (2018) demonstrated, educational investments affect multiple life domains beyond labor market outcomes, and the heterogeneity in these effects may follow different patterns than earnings returns. Machine learning methods like GRF could help uncover these complex patterns across diverse outcome measures.

Second, future research should investigate heterogeneity within higher education by examining how returns vary by institutional characteristics, academic majors, and instructional quality. Our focus on bachelor's degree completion as a binary treatment obscures potentially important variation within the treatment condition itself. As Hoxby (2009) argued, the returns to education may differ substantially across institution types and academic programs, and machine learning methods could help identify which institutional characteristics most strongly moderate treatment effects. This line of inquiry would provide more granular guidance for educational policy and individual decision-making.

Third, researchers should explore the dynamic nature of heterogeneous returns over the life course and across changing economic conditions. Our analysis examined earnings at a single point in time (age 40), but returns to education may evolve throughout individuals' careers and vary across business cycles. As Oreopoulos, von Wachter, and Heisz (2012) demonstrated, the value of educational investments may change substantially over time, particularly during economic downturns. Longitudinal applications of GRF could reveal how treatment effect heterogeneity evolves over the life course and responds to macroeconomic fluctuations.

Finally, future studies should develop and evaluate personalized policy interventions based on predicted treatment effects. Our findings suggest that educational investments could be optimized by targeting individuals with the highest expected returns, but implementing such policies requires careful consideration of ethical implications and practical constraints. As Kitagawa and Tetenov (2018) discussed, treatment assignment rules based on predicted heterogeneous effects raise important questions about fairness, transparency, and distributional consequences. Research that develops and evaluates such policies would bridge the gap between heterogeneous effects estimation and practical policy implementation.

In conclusion, this research has demonstrated both the substantive importance of heterogeneous returns to higher education and the methodological value of generalized random forests for detecting treatment effect heterogeneity. The findings challenge the policy relevance of average treatment effects and highlight the potential for more personalized approaches to educational investment. While limitations related to unobserved confounding and historical context remain, the application of machine learning methods to causal inference represents a promising direction for future research in education economics and beyond. As these methods continue to develop and become more widely adopted, they will likely transform our understanding of how educational investments affect diverse outcomes across heterogeneous populations.

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References

[1] Yang, C., & Meihami, H. (2024). A study of computer-assisted communicative competence training methods in cross-cultural English teaching. Applied Mathematics and Nonlinear Sciences, 9(1), 45-63. `https://doi.org/10.2478/amns-2024-2895`

[2] Huang, J., & Qiu, Y. (2025). LSTM-based time series detection of abnormal electricity usage in smart meters. Preprints. `https://doi.org/10.20944/preprints202506.1404.v`

[3] Wang, Y. (2025, July 8). AI-AugETM: An AI-augmented exposure–toxicity joint modeling framework for personalized dose optimization in early-phase clinical trials. Preprints. `https://doi.org/10.20944/preprints202507.0637.v1`

[4] Wang Y. Efficient Adverse Event Forecasting in Clinical Trials via Transformer-Augmented Survival Analysis. Preprints, 2025. DOI: 10.20944/preprints202504.2001.v1.

[5] Qi, R. (2025). Interpretable slow-moving inventory forecasting: A hybrid neural network approach with interactive visualization. Preprints. `https://doi.org/10.20944/preprints202505.1367.v1`

[6] Al-Dahidi, S., Madhiarasan, M., Al-Ghussain, L., Abubaker, A. M., Ahmad, A. D., Alrbai, M., ... & Zio, E. (2024). Forecasting solar photovoltaic power production: A comprehensive review and innovative data-driven modeling framework. Energies, 17(16), 4145.

[7] Feng, C., Jumaah Al-Nussairi, A. K., Chyad, M. H., Sawaran Singh, N. S., Yu, J., & Farhadi, A. (2025). AI powered blockchain framework for predictive temperature control in smart homes using wireless sensor networks and time shifted analysis. Scientific Reports, 15(1), 18168.

[8] Bian, K., & Priyadarshi, R. (2024). Machine learning optimization techniques: a survey, classification, challenges, and future research issues. Archives of Computational Methods in Engineering, 31(7), 4209-4233.

[9] Ebbensgaard, C. L. (2020). Standardised difference: Challenging uniform lighting through standards and regulation. Urban Studies, 57(9), 1957-1976.

[10] Famiglietti, A. (2021). Direct solar air heating in linear concentrating collectors assisted by a turbocharger for industrial processes: theoretical analysis and experimental characterization.

[11] Siddiqui, S. A., Singh, S., Bahmid, N. A., Mehany, T., Shyu, D. J., Assadpour, E., ... & Jafari, S. M. (2023). Release of encapsulated bioactive compounds from active packaging/coating materials and its modeling: a systematic review. Colloids and Interfaces, 7(2), 25.

[12] Mumtahina, U., Alahakoon, S., & Wolfs, P. (2024). Hyperparameter tuning of load-forecasting models using metaheuristic optimization algorithms—a systematic review. Mathematics, 12(21), 3353.

[13] Yoo, H., Jo, H., & Oh, S. S. (2020). Detection and beyond: Challenges and advances in aptamer-based biosensors. Materials Advances, 1(8), 2663-2687.

[14] Madeshwaren, V. (2025). Advanced Computational Models for Thermal System Optimization Using Machine Learning and Hybrid Techniques.

[15] Vasudevan, R., Pilania, G., & Balachandran, P. V. (2021). Machine learning for materials design and discovery. Journal of Applied Physics, 129(7).