ABSTRACT

Title of Dissertation: ESSAYS ON HIGHER EDUCATION

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In this dissertation, I quantify the impact of uncertainty on schooling postsecondary choices, study the returns to higher education degrees, and analyze the effects of policies that intend to reduce college education costs.

In the second and third chapters, I employ structural Roy models and data from the National Longitudinal Survey of Youth 1997 to analyze postsecondary schooling decisions, focusing on four- and two-year college paths. These models have three sources of unobserved heterogeneity affecting earnings and decisions: cognitive, socioemotional, and mechanical latent abilities.

The second chapter employs a dynamic Roy model to quantify the impact of uncertainty when making postsecondary schooling. While schooling choices maximize expected value, some individuals opt for alternatives that, in hindsight, do not yield the highest ex-post net value due to idiosyncratic shocks affecting earnings and schooling costs that are unknown when decisions are made. This uncertainty generates significant losses: I estimate that aggregate net value would increase by 11% if individuals had perfect foresight. Moreover, I study how decisions would

change under perfect foresight and characterize individuals more likely to be affected by uncertainty. I also explore policy simulations to study the effects of an annual two-year college $16,500 subsidy, including the characterization of compliers—those more likely to attain a two-year college degree because of the subsidy.

The third chapter analyzes the interplay of observed and unobserved dimensions as determinants of marginal treatment effect (MTEs) through decomposition analysis. We posit a static Roy model with unordered schooling choices. We focus on MTEs as they shape other treatment effects and capture the impact for those responding to minimal incentives. Additionally, we estimate the model separately for women and men, focusing on describing how responses and treatment effects vary between these two groups. We find different ability distributions and returns to ability for women and men. Moreover, we document how different observed characteristics and ability dimensions play different roles in determining the heterogeneity observed in MTEs across both groups.

The last chapter investigates the impact of financial aid programs on high-quality private colleges' decisions, leveraging exogenous variation from a large-scale aid program in Colombia, where beneficiaries could only enroll at high-quality colleges. Using a difference-in-differences strategy and data for all private colleges in the country, we find that tuition increased by about 6.9 percent after the government launched the aid policy. We contribute to the literature by analyzing the effect of financial aid programs on tuition for high-quality universities and studying how universities might change other outcomes beyond tuition in response to the policy. We show universities hire more faculty members, keep the student-to-faculty constant, and open new undergraduate programs. Our findings support a narrative where prestigious colleges prioritize their reputation, opting for gradual expansion without compromising quality.

ESSAYS ON HIGHER EDUCATION

by

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Dedication

A mis padres, Ángela y Juan Diego, y a Mateo.

Por ser ejemplo, bastón y motivación durante estos años.

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List of Abbreviations

2YC	Two-year college
2yd	Two-year dropout
2yg	Two-year graduate
4YC	Four-year college
4yd	Four-year dropout
4yg	Four-year graduate
CDF	Cumulative Distribution Function
CMLE	Conditional Maximum Likelihood Estimation
HNV	Highest Net Value
HS	High school
Hsg	High school graduate
IV	Instrumental Variable
MTE	Marginal Treatment Effect
NLSY	National Longitudinal Survey of Youth
OLS	Ordinary Least Squares
SPP	Ser Pilo Paga (Colombian financial aid program)
TT	Treatment on the Treated

Chapter 1: Introduction

Higher education choices play a pivotal role in shaping various lifetime outcomes that significantly impact individuals' overall welfare. Nevertheless, ensuring and determining the optimal educational investments after high school is challenging. Factors such as uncertainty, credit constraints, and limited information complicate efforts to forecast the most advantageous path ex-ante. This challenge is underscored by survey evidence revealing that 42% of young Americans who attained a four-year college degree in the US claim their degree was not worth it (WSJ-NORC, 2023). This figure is particularly worrisome within the context of the US, examined in the second and third chapters of this dissertation, as the costs of college attendance continue to escalate. According to the National Center for Education Statistics, over the past three decades, average tuition and fees have surged by 55% and 80% at public two-year and four-year colleges, respectively, after adjusting for inflation. Furthermore, in the 2019-2020 academic year, the US ranked second highest in four-year college tuition fees among OECD countries (OECD, 2022).

Despite these challenges, policymakers face their own formidable task. Crafting effective policies within the higher education system is complex. Individuals have heterogeneous preferences and backgrounds that might be unobserved from the analysts' perspective. Moreover, students and universities sometimes respond to incentives in unforeseen ways. This dissertation explores higher education challenges that might arise from these two different lenses: individuals

seeking optimal choices and policymakers aiming to understand the impact of different interventions.

The second chapter of this dissertation, "The Heterogeneous Value of Four- and Two-year College Choices," studies the cost of uncertainty when making postsecondary schooling choices. I use data from the National Longitudinal Survey of Youth of 1997, which has detailed information on postsecondary schooling trajectories, and propose a dynamic model where students choose sequentially among different types of college education. In this model, individuals face uncertainty. In particular, they do not know the shocks to future earnings and schooling determining the ex-post net value of the chosen path. These unknown shocks are revealed as agents make choices sequentially to complete their educational paths. As a distinctive feature of the model, individuals from different socioeconomic backgrounds face different levels of uncertainty by allowing the distribution of earnings shocks to vary across parental income groups.

The analysis shows substantial welfare shortfalls due to uncertainty, revealing that the aggregate net value of postsecondary choices could increase by 11% if individuals had perfect foresight. However, if we focus on those who would choose another path if they had perfect foresight, the aggregate net value would increase by 47%. This counterfactual analysis examines how individuals would make choices if they had perfect information. For instance, a substantial amount of individuals would still decide to drop out of college even if they had perfect foresight. The results also indicate that some characteristics can make individuals more vulnerable to uncertainty, and these characteristics might play more or less important roles in different schooling paths.

Furthermore, I propose a decomposition analysis that examines the extent to which variations in costs, earnings, or a combination of both factors contribute to explaining sensitivity to

uncertainty. The results show that costs are the primary driver explaining why college graduates may find higher net value in alternative degrees or as high school graduates. Conversely, earnings have a more significant impact in cases where dropping out represents the highest net value alternative. Therefore, these results elucidate which schooling choices are more sensitive to policies that reduce costs and which are instead influenced by labor market conditions.

The structure imposed in the model also allows studying, through counterfactual analysis, the introduction of a two-year college subsidy that is generous enough to cover tuition and fees and students' living expenses in a public two-year institution. This exercise assesses to what extent individuals are subject to credit constraints. In response to this policy, two-year graduates would increase by 50%, and the new inflow would be mainly composed of white individuals from rural and two-parent households. However, this subsidy would also increase the number of two-year dropouts and, in general, influence all decision margins. In addition, this exercise also shows that those more likely to attain a two-year degree as a response to the subsidy are also more sensitive to uncertainty and, hence, more likely to pursue a suboptimal schooling path than those who would get a two-year college degree regardless of the subsidy. All these findings underscore the complexities of designing effective policies for higher education, especially when targeting only one market sector.

In the third chapter of this dissertation "Observed and Unobserved Variables in Educational Treatment Effects," (coauthored with Sergio Urzúa), we used a simplified and static version of the Roy model I employed in the second chapter to study the treatment effects of three higher education choices: staying with a high school diploma, attaining a two-year college degree, and attaining a four-year college degree. We propose a definition of the marginal treatment effect (MTE) that integrates over the characteristics of the in-sample compliers at each point of in-

difference.[1] This distinction allows us to decompose MTEs into the contribution of observed variables and unobserved abilities. The focus on MTEs allows us to understand the relative gains and losses for individuals who are more likely to respond to higher education policy interventions, as they will react to minimal incentives.

Furthermore, we separately estimate the model for women and men, finding distinct ability distributions and returns for these groups. We find that cognitive ability shapes the estimated MTEs for men. Among women, observed characteristics define the level and slope of the marginal effects, while mechanical and cognitive ability play a more modest role. Consistent with previous literature, our study shows that the MTE of pursuing a two-year college education is positive only for individuals whose next-best alternative is remaining with a high school diploma. In essence, providing incentives for students to transition from four- to two-year colleges usually results in decreased earnings at the margin of indifference. In contrast, the MTE of pursuing a four-year college education is positive across all groups, with higher effects typically observed for those transitioning from high school graduation to attaining a four-year degree. These findings underscore the importance of understanding preference rankings, as the next-best alternative can dictate the marginal effect's magnitude and sign. For instance, this chapter shows that 10.9% of women and 8.3% of men rank obtaining a four-year college degree as their first-best option and a two-year degree as their second-best. For these subgroups with this preference ranking, individuals closer to the margin of indifference would experience, on average, a negative effect if incentivized to pursue a two-year college degree.

In the last chapter, "Beyond the Bennett Hypothesis: Financial Aid, College Quality, and Education Expansion" (coauthored with Sebastian Montaño), we study the effects of a financial

[1] MTEs are usually defined as conditional functions of characteristics or abilities.

aid program in the higher education market, focusing on how high-quality private colleges—the institutions receiving most program beneficiaries —adapt their behavior as a response to financial aid. This program was introduced to increase the attendance of low-income, high-achieving students in high-quality universities in Colombia. Using a difference-in-differences approach, we find that following the aid program's launch, high-quality private institutions experienced a tuition increase of approximately 6.9%. Moreover, our results suggest that high-quality universities do not expand their admissions at the same pace as the number of applicants increases, which is consistent with an inelastic supply. However, they offer admissions to more students; hence, the evidence shows that they are willing to accommodate more students, which is supported by an increase in the stock of students of 14 percent after four years of launching the program. Our findings show that high-quality colleges maintain the student-to-faculty ratio by recruiting more part-time and full-time instructors despite the increase in student body size. Additionally, they gradually expand their supply by opening new programs in the medium run. This evidence supports a narrative where prestigious colleges prioritize their reputation, opting for gradual expansion without compromising quality.

This research addresses the long-debated Bennett hypothesis–the incidence problem in higher education–by offering empirical evidence of a positive relationship between financial aid availability and tuition increments. We contribute to this discussion by studying a context where financial aid only targets high-quality colleges, which might respond differently than other types of institutions. Furthermore, we analyze how these policies might reshape entire sectors of the higher education market by providing incentives to change several outcomes at the university level, affecting students and instructors. Finally, we also examine the possibility that this policy had spillover effects in untargeted market sectors. We do not find evidence supporting changes

in tuition nor the displacement of students in the other market sectors that we analyze.

Chapter 2: The Heterogeneous Value of Four- and Two-year College Choices.

2.1 Introduction

College investments have a significant effect on a variety of crucial lifetime outcomes, and a substantial body of evidence underscores the high and positive returns associated with obtaining a four-year college degree (Oreopoulos and Petronijevic, 2013; Zimmerman, 2014; Ashworth et al., 2021; Lovenheim and Smith, 2022). However, a significant proportion of four-year college graduates in the United States say that their degrees were not worth it.[1] This discrepancy highlights the heterogeneity in college benefits and suggests that substantial uncertainty emerges as individuals navigate their educational choices, with unforeseeable shocks complicating the task of predicting the actual returns of educational investments. In parallel, the policy and political spheres have increasingly focused on two-year college education. Since 2014, numerous states and cities have introduced programs offering free two-year college education (Mountjoy, 2022). Furthermore, President Biden has advocated for free community college since his 2020 campaign agenda (CNN, 2019). I investigate the heterogeneous economic net value of two- and four-year college educational paths within a dynamic structural framework. By leveraging the model structure, the main contribution of this chapter is characterizing individuals more likely to be affected

[1] For instance, a survey conducted by the Wall Street Journal and NORC in March 2023 reported that 42% of four-year college graduates regret getting their degrees, which has increased more than 10 pp in one decade.

by uncertainty and by policies reducing two-year college costs.

In this chapter, agents face uncertainty stemming from their inability to foresee all factors influencing future earnings and schooling costs. These unforeseen elements are captured through idiosyncratic shocks, occurring as individuals progress sequentially through their educational paths. Their expectations about the distributions of these future shocks are assumed to align with their actual realizations, but the specific distributions of these shocks vary for each choice. Thus, individuals cannot predict their entire schooling trajectory with certainty at period zero despite knowing the distribution of all options. For example, even after enrolling in a two-year college post-high school, individuals may obtain a degree, drop out, or pursue further education in a four-year institution. Future shocks received during college will determine their next steps. In this framework uncertainty can be costly. Although individuals are forward-looking and rational, their inability to perfectly anticipate earnings and cost shocks may lead them to make sub-optimal decisions ex-post. In other words, some individuals would opt for different schooling choices if they could foresee shocks with perfect foresight. Through a counterfactual analysis, I characterize the individuals whose actual choices are most likely to deviate from their choices under perfect foresight, and hence, the individuals more likely to pay the costs of uncertainty.

The framework of this chapter has three features that are worth highlighting. First, I account for the fact that individuals from different socioeconomic backgrounds face intrinsically different levels of uncertainty. My model assumes different distributions of unforeseeable earnings shocks that vary across parental income quartiles, an innovation relative to previous work using similar methodologies. Second, I study postsecondary choices in a dynamic framework that accounts for the multiple educational paths available to individuals after high school, including both two- and four-year colleges. My framework includes the possibility of transitioning from a two- to

four-year college, an essential feature of the U.S. higher education system. Additionally, building on prior literature, the model accommodates heterogeneous earnings and costs across three dimensions of unobserved abilities: cognitive, socioemotional, and mechanical (see Prada and Urzúa, 2017; Heckman, Humphries and Veramendi, 2018; and Belzil, Hansen and Liu, 2022).

The primary data source for this chapter is the National Longitudinal Survey of Youth 1997 (NLSY97), which offers detailed information on earnings, background characteristics, and test scores, which are crucial elements for the proposed model. Additionally, the survey collects monthly college enrollment data, categorized by type of college. Since participants entered the study between the ages of 12 and 17, most had not begun college when information collection started, allowing for observation of postsecondary schooling trajectories for most individuals. The sample includes 1,068 men observed through their postsecondary trajectories. Following the approach of previous studies using similar models, women are excluded from the analysis as the model does not account for fertility and marital status as endogenous choices. These factors would ideally be incorporated into a dynamic model of their schooling decisions.

The parameters associated with earnings and costs, and thus, ex-post net value, are shown to be semi-parametrically identified, following arguments presented by Heckman and Navarro (2007) and Eisenhauer, Heckman and Mosso (2015). These arguments exploit the use of exclusion restrictions and limit sets. However, section shows that attaining a two-year college degree is not as common as other postsecondary options, with only 8.8% of the sample doing so at some point. With few individuals visiting this state and the small sample size, I introduce additional functional form assumptions to secure identification. For the same reason, even though other decisions may explain why the chosen schooling path is sub-optimal in ex-post terms, such as college major choices or job sectors, estimating an extended model that considers additional

endogenous decisions with the current sample may be unfeasible.

The main results indicate that uncertainty generates substantial welfare shortfalls; the aggregate net value of postsecondary choices would increase by nearly 11% if individuals had perfect foresight. These aggregate gains mask substantial heterogeneity because a large fraction of individuals (68%) would not change their choices under perfect foresight, and consequently, their net value would not increase. Instead, for those whose choices would change if they had perfect foresight, the aggregate net value would increase by 47%.

Furthermore, some individuals are more likely to experience welfare shortfalls because of uncertainty: they would change their choices if they had perfect foresight because another path generates higher ex-post net value. These individuals, more sensitive to uncertainty, differ in characteristics and ability from those choosing the same path but achieving optimal ex-post net value despite uncertainty. Two patterns are particularly noteworthy. First, individuals who opt for direct enrollment in a four-year college and graduate with a four-year degree but do not achieve the highest ex-post net value are often credit-constrained. They typically have less educated mothers, lower family incomes, and lower cognitive endowments relative to four-year graduates achieving the highest net value. This pattern highlights the risks of pursuing a four-year degree while facing credit constraints; even if this is the optimal choice ex-ante, these constraints still make individuals more vulnerable to adverse shocks. Second, rural residence can shield against uncertainty when individuals opt for a two-year degree. Those originating from and residing in rural areas are more likely to achieve higher ex-post net value by pursuing a two-year degree. Conversely, two-year graduates with higher ex-post net value from dropping out of college are more likely to come from urban areas.

This chapter also examines a policy simulation exercise introducing a generous subsidy

for a two-year college education. This exercise is relevant to the ongoing political deliberation on providing a free two-year college education. I contribute to existing research by analyzing policies reducing the cost of two-year college education (Johnson, 2013, Aguirre, 2021, Ferreyra, Galindo and Urzúa, 2022, Mountjoy, 2022, Kim, 2023), elucidating how decisions would change, and characterizing compliers, those incentivized to attain a two-year college degree, across all decision margins and in a dynamic environment. My analysis shows that this policy would increase the number of two-year college graduates by 4.5 percentage points, a 50% increase. However, compliers to this policy would come from all possible schooling paths. Specifically, this policy would reduce the number of individuals who choose to obtain only a high school diploma by 3.23 percentage points (13.78%). The proposed subsidy would also lead to a reduction in the number of four-year college graduates by 2.29 percentage points (6.15%).[2] However, the reduction in the number of high school graduates would be almost entirely offset by a 2.14 percentage point (13.62%) increase in the number of two-year college dropouts. The population this policy intervention would most likely affect—by increasing two-year degree attainment—is comprised of white individuals raised in rural areas by two-parent families. Furthermore, I find that individuals who are more likely to switch to a two-year educational path because of the subsidy are also more sensitive to uncertainty than individuals who would follow two-year paths even in the absence of the policy. This vulnerability is explained by the fact that in the absence of the policy, the ex-ante value of a two-year path is still very close to the ex-ante value of the path the individual would follow without the subsidy. Therefore, it is more likely that any negative shock changes the ex-post ranking among alternatives and that the subsidy makes the two-year path have a higher

[2]These effects are the democratization and diversion effects found by Mountjoy (2022). However, note that Mountjoy (2022) focused on the effect on enrollment rather than on graduation rates.

ex-ante value.

This chapter is closely related to the literature studying the impact of uncertainty on college investments. However, most of this literature primarily focuses on analyzing this question in a context where both two- and four-year college choices are not considered (Stinebrickner and Stinebrickner, 2014; Hendricks and Leukhina, 2017; Gong, Stinebrickner and Stinebrickner, 2019; Gong, Stinebrickner and Stinebrickner, 2020; Bhuller, Eisenhauer and Mendel, 2022; Hou, 2022). There are, however, a few exceptions. For instance, Stange (2012) and Trachter (2015) consider a framework with multiple college paths to assess the option value that arises from individuals deriving utility from having the option to make further choices in the future. In this chapter, I do not focus explicitly on deriving option values; however, it should be noted that they are implicit in my analysis, as individuals make choices sequentially.

The work by Arcidiacono et al. (2023) is the closest analysis to the one presented in this chapter. Their paper considers a rich set of schooling choices, including two-year college choices, rich modeling of uncertainty sources, heterogeneity, and occupational choices. They study the implications of information frictions on four-year college graduation rates and wage premia. However, my analysis introduces distinct elements. I consider socioemotional and mechanical abilities and introduce heteroskedastic earnings shocks. Additionally, I incorporate normally distributed cost shocks that are allowed to be correlated with those associated with other educational alternatives and focus on characterizing individuals who are more likely to find their schooling path is sub-optimal. A critical distinction between my work and that of Arcidiacono et al. (2023) is the interpretation of uncertainty. Arcidiacono et al. (2023) align with a subset of the literature that explores how the college experience contributes to learning about an individual's

ability—often through signals embedded in grades (Stinebrickner and Stinebrickner, 2014; Hendricks and Leukhina, 2017; Gong, Stinebrickner and Stinebrickner, 2019). Therefore, abilities in their model are an additional source of uncertainty.[3] The uncertainty considered in this chapter is more limited, as this source of uncertainty is shut down by assumption—abilities are a source of heterogeneity, as they are unobserved to the analyst, but not of uncertainty. In my model, I assume individuals know their abilities before making college choices. Thus, the uncertainty analyzed in this chapter, captured only by idiosyncratic shocks, could be coming from various factors, including taste, information, resource shocks, and 'life barrier' shocks (DeLuca et al., 2021 and Evans et al., 2020). However, I can not disentangle nor interpret the precise drivers of uncertainty.

Previous literature has examined how individuals might prefer alternative paths in the absence of uncertainty. This exercise explores how returns and choices would differ if agents could "do it over again," as described by Cunha, Heckman and Navarro (2005). Significantly, my analysis goes beyond previous research, which primarily focused on identifying the percentage of individuals whose choices aligned or differed from their highest-return option. Instead, I aim to determine the characteristics that increase the likelihood of individuals achieving or not achieving the optimal ex-post net value (Carneiro, Hansen and Heckman, 2003; Cunha, Heckman and Navarro, 2005; Eisenhauer, Heckman and Mosso, 2015; Hou, 2022). Moreover, while such analyses are typically conducted within static setups, this study adopts a dynamic framework and proposes a measure that comprehensively assesses net value throughout the entire educational trajectory. While Eisenhauer, Heckman and Mosso (2015) calculated these percentages in a dynamic setup, they were limited to comparing alternatives that shared the same previous schooling

[3] Arcidiacono et al. (2023) also consider similar information frictions on productivity.

state. Furthermore, the inclusion of two-year college choices expands our understanding of the percentage of individuals categorized into these groups.

I also propose a decomposition analysis that examines the extent to which variations in costs, earnings, or a combination of both factors contribute to explaining sensitivity to uncertainty. My findings indicate that cost is the primary driver explaining why college graduates may find higher net value in alternative degrees or as high school graduates. Conversely, earnings have a more significant impact in cases where dropping out represents the highest net value alternative. These results contribute to the existing literature on marginal treatment effects in college education choices (e.g., Carneiro, Heckman and Vytlacil, 2011 and Mountjoy, 2022), which investigate how variations in the cost of postsecondary schooling investments can influence students' decisions and outcomes. My findings elucidate which schooling choices are more sensitive to policies that reduce costs and which are instead influenced by labor market conditions.

This chapter also offers valuable insights into the phenomenon of ability sorting in college choices (Carneiro, Hansen and Heckman, 2003; Heckman, Stixrud and Urzua, 2006; Prada and Urzúa, 2017; Heckman, Humphries and Veramendi, 2018; Kottelenberg and Lehrer, 2019; Belzil, Hansen and Liu, 2022; Humphries, Joensen and Veramendi, 2023). Those transitioning from a two-year to a four-year college are more likely to have higher socioemotional ability endowments. However, sorting based on this ability is weaker than sorting based on cognitive and mechanical abilities. Aligned with previous literature, I find that four-year graduates exhibit high cognitive abilities, while high school graduates have high mechanical abilities. However, two-year graduates do not display particularly high endowments in any ability relative to individuals following other educational paths. As a technical contribution to this literature, I model the ordered nature of socioemotional measures, a consideration absent from previous literature

analyzing the role of abilities on college choices (see chapter 3 for the empirical consequences of this assumption). Nevertheless, socioemotional measures are collected too late in participants' lives, which is a common drawback among studies using the NLSY97 to model socioemotional abilities (e.g., Deming, 2017). Therefore, these results need to be interpreted with a grain of salt, as the sorting patterns, or lack of them, could be shaped by the experiences that individuals had in specific schooling trajectories. The implicit assumption to interpret as sorting the different patterns documented in this chapter is that socioemotional abilities will remain stable from the time individuals graduate from high school until their mid- or late-twenties, the ages when these measures are collected.

Finally, my results also contribute to the literature on the value of two-year college education (Rouse, 1995; Kane and Rouse, 1995; Jacobson, LaLonde and Sullivan, 1993; citealpbelfield2011benefits; Jepsen, Troske and Coomes, 2014; Liu, Belfield and Trimble, 2015; Mountjoy, 2022).[4] Specifically, I enhance the understanding of whether enrolling in a two-year institution without obtaining a degree offers any value. My findings reveal that even if individuals possessed perfect foresight, a significant fraction would still leave college, especially when attending a two-year institution. Approximately 16.4% of individuals would attend a two-year institution and exit without earning a college degree, which is higher than the 9.4% who would choose to discontinue a four-year program. This finding suggests that there is still value derived from completing some college coursework for individuals with specific characteristics and ability endowments.

The following section outlines the model and the assumptions that form the basis of my identification strategy, along with the simulation exercise that generates the chapter's key find-

[4]For a comprehensive review of the literature, see Lovenheim and Smith (2022).

ings. Section 2.3 presents the sample and offers descriptive insights into the data. Section 2.4 explains the estimation procedure. In Section 2.5, I present the results, focusing on characterizing individuals more sensitive to uncertainty. This section also considers alternative specifications, including exposure to the Great Recession and the incorporation of risk preferences. The main results discussed in the introduction remain qualitatively unchanged after considering these different specifications. This section also considers an analysis of ex-ante probabilities and a policy simulation considering the implementation of a two-year college subsidy. Section 2.6 concludes.

2.2 Empirical Model

I extend the empirical Roy model proposed by Eisenhauer, Heckman and Mosso (2015), who propose a dynamic model of higher educational choices and earnings that uses a measurement system to model cognitive and non-cognitive abilities while accounting for selection bias. They focus on late and early four-year college choices (see their decision tree in Figure 2.1), while I focus on studying two-year and four-year paths.[5] However, there are other differences beyond the schooling trajectories considered. In particular, I build upon their selection of abilities by incorporating mechanical abilities, consistent with earlier findings by Prada and Urzúa (2017) and Belzil, Hansen and Liu (2022). I consider a more flexible approach to estimating abilities, allowing them to follow a mixture of normal distributions and accommodating the ordered nature of socioemotional measures. Furthermore, I also extend the model to accommodate heteroskedasticity on earnings equations by family income quartiles.

In this model, I assume agents are risk-neutral and seek to maximize their discounted lifetime rewards, which vary based on their schooling choices. Agents form expectations about

[5]The differences between the decision trees considered in both studies are shown in Figures 2.1 and 2.2.

the future using the information available at each schooling state denoted as s, where $s \in \mathbf{S} = \{$hsg, hsgc, 2ye, 4ye, 2yd, 2yg, 4yd, 4yg$\}$. In the initial period, when all agents are high school graduates (hsg), there are three possible alternatives: continuing as high school graduates (hsgc), enrolling in a two-year program (2ye), or enrolling in a four-year program (4ye). If an agent enrolls in two-year college, she will face three possible alternatives in the second period: dropping out (2yd), obtaining a two-year degree (2yg), or transferring to four-year college (4ye). Once individuals are enrolled in four-year college, they will face two options. They can drop out (4yd) or graduate (4yg). I illustrate these various paths in the decision tree depicted in 2.2.

The following equations are expressed at the individual level but not indexed to simplify notation. At each state, individuals receive earnings $\bar{Y}(s)$ and pay schooling costs $Costs^*(s', s)$ associated with moving from state s to state s'. Earnings are given by the following equation:

$$\bar{Y}(s) = X(s)'\beta_s + \theta'\alpha_s + \epsilon(s, q), \tag{2.1}$$

where $X(s)$ is a vector of observed explanatory variables and θ' is a vector composed of three unobserved factor variables: $\theta' = [\theta_c, \theta_s, \theta_m]$, where θ_c is the cognitive factor, θ_s is the socioemotional factor, and θ_m is the mechanical factor. β_s and α_s are parameters to be estimated, and $\epsilon(s, q)$ is the heteroskedastic, normally distributed idiosyncratic shock. Specifically, $\epsilon(s, q)$ has a mean of zero, and its variance is specific to family income quartile observed in 1997 q ($\sigma_{\epsilon_{s,q}}$). Moreover, $\epsilon(s, d)$ is assumed to be independent from θ and $X(s)$ for all s. Note that although θ is known by the individuals, it is unobserved from the perspective of the econometrician. Therefore, while $\epsilon(s, q)$ is assumed to be independent across states, the unobserved components of earnings exhibit correlation through θ.

Costs are latent variables that, together with the expected value function, determine the schooling choices of the individuals. As a standard feature of discrete choice models, only the differences in costs between alternatives can be identified. Consequently, it is necessary to normalize the costs of one transition to zero at each decision node. In the initial node, where agents face three alternatives, the costs of continuing as a high school graduate are set to zero. Similarly, if an agent enrolls in any college program, the cost of dropping out is normalized to zero. The costs associated with going from state s to state s' are given by the following expression:

$$Costs^*(s', s) = Z(s', s)'\gamma_{s',s} + \theta'\alpha_{c_{s',s}} + \epsilon_c(s', s), \tag{2.2}$$

where $Z(s', s)'$ represents a vector of observed explanatory variables, while $\gamma_{s',s}$ and $\alpha_{c_{s',s}}$ are vectors of parameters to be estimated. $\epsilon_c(s', s)$ represents the idiosyncratic shock, assumed to follow a normal distribution and be independent of both θ and $\epsilon(s)$ for all s and s'. When there are more than two alternatives available, $\epsilon_c(s', s)$ is allowed to be correlated with other $\epsilon_c(\omega, s)$, provided that ω represents another feasible state from s.[6] In Roy models, costs encompass both monetary elements, such as tuition and psychic costs, as they are modeled as the (dis)utility they provide. However, since $X(s)$ contains variables that are not included in $Z(s', s)$, the scale of the costs inherits the same measurement unit as earnings.

To define the information set $\mathcal{I}(s)$ for each state, consider two sets: $S^v(s)$, which denotes the states that have already been visited at state s and $S^f(s)$, which represents the states that are feasible to visit from state s. Additionally, recall that $\mathbf{S}$ is the set containing all possible states.

[6] Specifically, it is assumed that the idiosyncratic non-differentiated shocks follow a standard normal distribution. For instance, when three options are available, we have: $\left[\epsilon_c(s', s)\ \epsilon_c(\omega, s)\right] \sim N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}2 & 1\\1 & 2\end{bmatrix}\right)$. I additionally fix the scale of the shock structure by dividing all the elements in the variance-covariance matrix by two.

The information set at each state s is defined as follows:

$$\mathcal{I}(s) = \begin{cases} \epsilon_c(s', s) & \text{for all } s' \in S^f(s) \\ \epsilon_c(\tilde{s}', \tilde{s}), \epsilon(\tilde{s}) & \text{for all } \tilde{s} \in S^v(s) \text{ and } \tilde{s}' \in S^f(\tilde{s}) \\ Q_s, Q_m, Q_m, X(\hat{s}), Z(\hat{s}', \hat{s}), \theta & \text{for all } \hat{s} \in \mathbf{S}, \text{ and } \hat{s}' \in S^f(\hat{s}) \end{cases} \tag{2.3}$$

Consequently, individuals do not possess knowledge of the idiosyncratic shocks in the earnings equations for states they have not yet visited. Agents are similarly unaware of the realization of idiosyncratic shocks in the transition cost equations for states or choices that are not yet available; only when the transition becomes feasible do individuals get to know the realization of the shock. I assume that each individual is well-informed about all their characteristics, meaning they have knowledge of the values of all explanatory variables and abilities for all states or choices, regardless of their position in the decision tree.[7]

The value function at state s, is given by:

$$V(s) = \bar{Y}(s) + \max_{s' \in S^f(s)} \left\{ \frac{1}{1+r} \left[-Costs^*(s', s) + \mathbf{E}(V(s')|I(s)) \right] \right\}, \tag{2.4}$$

where r is the discount rate, which will be set to 0.04, following (see Eisenhauer, Heckman and Mosso, 2015). The second term in the expression is the continuation value, which equals zero for all the final choices.[8]

[7]Relaxing these assumptions, such as the extent of information individuals possess at each stage, presents an interesting avenue for future research. One could hypothesize that schooling may enhance or inform certain dimensions of abilities. Nonetheless, relaxing these assumptions would require incorporating additional information into the measurement system. One possible alternative could involve including college grades, as seen in Arcidiacono et al. (2023); however, considering grades with the abilities and variables already considered in the estimation would significantly reduce the sample size.

[8]It is worth noting that since r is treated as known, exclusion restrictions in $X(s)$ are only necessary for the earnings equations of the final states to determine the scale of costs, as the continuation value serves as exclusion

As a result, when an individual is in state s, she will make her next choice, s', based on the following decision rule:

$$s' = \underset{s' \in S^f(s)}{\arg\max} \mathbf{E}(V(s')|I(s)) - Costs^*(s', s). \tag{2.5}$$

In essence, this decision rule implies that individuals will opt for the choice that maximizes value among the available options. They take into account the schooling costs associated with transitioning to a future state and the expectation of the future value function, which incorporates the expected future earnings.

2.2.1 Latent Abilities

The model also incorporates a measurement system, which provides a more transparent interpretation of θ. This measurement system allows us to interpret the dependent variables in the system— including cognitive, mechanical, or personality test scores— as imperfect signals of individuals' abilities. It acknowledges that we can only obtain imperfect measures of abilities through tests due to the presence of measurement errors. The identification of abilities comes from the information that remains after accounting for the impact of observed student' characteristics and classical measurement error on the measures. It is important to note that while a measurement system is not necessary to identify counterfactual distributions, it significantly enhances the interpretation of factor variables. The inclusion of a measurement system enriches discussions surrounding the factors, enabling the analysis of sorting on different types of ability for students following various educational paths.

restrictions for the other states.

The measurement system follows this structure:

$$
\begin{aligned}
c_r &= Q_c'\eta_{c_r} + \theta_c\lambda_{c_r}^c + \varepsilon_{c_r} && \text{for } r = 1, ..., R \\
s_l^* &= Q_s'\eta_{s_l} + \theta_s\lambda_{s_l}^s + \varepsilon_{s_l} && \text{for } l = 1, ..., L \\
m_p &= Q_m'\eta_{m_p} + \theta_m\lambda_{m_p}^m + \theta_c\lambda_{m_p}^c + \varepsilon_{m_p} && \text{for } p = 1, ..., P.
\end{aligned}
\tag{2.6}
$$

There are three types of tests: cognitive tests denoted by c_r, socioemotional or non-cognitive tests denoted by s_l, and mechanical tests denoted by m_p. Each type of test is affected by a different type of ability, except for the case of mechanical tests, which are also affected by the cognitive factor (θ_c).[9] s_l represents the lth observed socioemotional measure, which is ordered in nature, and s_l^* represents the associated latent variable assumed to follow a normal distribution. Thus, the equations in the socioemotional measurement system will be modeled as an ordered probit. It is important to note that abilities are assumed to remain constant across different schooling states.

Q_c, Q_s, and Q_m are vectors of observed variables, and $\varepsilon_{c_r}, \varepsilon_{s_l}, \varepsilon_{m_p}$ are error terms, assumed to be normally and independently distributed. Parameter vectors $\eta_{c_r}, \eta_{s_l}, \eta_{m_p}$ and loadings $\lambda_{c_r}^c, \lambda_{s_l}^s, \lambda_{m_p}^m$, and $\lambda_{m_p}^c$ are estimated for all r, l, and p. For $r = 1$, $l = 1$, and $p = 1$, the loadings are set to one to standardize the scale of the factors.[10] Moreover, based on exploratory factor analysis, cognitive and mechanical abilities are allowed to be correlated, while the socioemotional factor is assumed to be independent of the other components.[11]. Consequently, following Prada et al. (2017), I assume $\lambda_{m_p}^c = 0$, ensuring that one mechanical measure is exclusively devoted to explaining mechanical ability. This additional restriction facilitates the identification of the correlation between θ_c and θ_m. It is important to note that abilities are assumed to remain

[9] This decision comes from an explanatory factor analysis, as discussed later in the chapter.
[10] For a more detailed explanation, refer to Carneiro et al. (2003, 2001).
[11] The estimated correlation between the mechanical and cognitive factors is 0.41.

constant across different schooling states.

I need to impose some additional restrictions to identify the ordered probit model for the socioemotional system. Specifically, Q_s does not incorporate a constant term, and the variance of ϵ_{s_l} for $s = 1, ..., L$ is assumed to be one. These assumptions allow us to estimate the cutoffs that create the distinct levels of the observed measures s_l.

The Armed Services Vocational Aptitude Battery (ASVAB) test provides six cognitive measures ($R = 6$) and four mechanical measures ($P = 4$), a selection that aligns with earlier literature, as data from the same test is available in the NLSY79.[12] For measuring socioemotional abilities, the NLSY97 employs the Ten-Item Personality Inventory (TIPI) Scale, in which individuals rate how well certain characteristics describe them. This concise test assesses the Big-Five personality domains (refer to Deming, 2017 for an example utilizing these measures to analyze the role of socioemotional skills in the labor market). An advantage of this test is that it includes two opposite questions per trait, which controls for agreement bias, prevalent in this survey instrument.[13]

2.2.2 Net Value of Schooling Choices

The net value of an educational trajectory or path is a comprehensive measure that takes into account all the earnings an agent receives and all the schooling costs she incurs throughout her entire educational journey. It captures the total ex-post value obtained from a series of schooling decisions that are part of a path.

[12] The cognitive measures encompass: i) arithmetic reasoning, ii) math knowledge, iii) word knowledge, iv) paragraph comprehension, v) coding speed, and vi) numerical operations. The mechanical measures include the following components of the ASVAB: i) mechanical comprehension, ii) auto information, and iii) electronics information.

[13] To address this, I reverse the order of the questions asking about the opposite of each trait and then calculate the average of the two measures for the same trait.

In order to formally introduce the notion of a path, let me first introduce two auxiliary concepts: a final state $\dot{s}$ and the first choice s_1. Let $\dot{s} \in \bar{S}$ be the set containing all terminal states, which, given the specific decision tree considered, includes the following five possible levels of schooling: staying with only a high school diploma, dropping out of a two-year program, dropping out of a four-year program, graduating from a two-year program, or graduating from a four-year program. Moreover, I denote as s_1 the first choice taken by the agent from the common initial node.[14]

Net value is a function of a schooling path, and a path is defined as a sequence of states that is feasible to follow in the decision tree. Given the specific tree of this study a path will be uniquely defined by the first choice and the final state: $\overrightarrow{s}(s_1, \dot{s})$.[15]

To compute the net value, one aggregates the present value of earnings stream and subsequently subtracts the present value of all costs associated with states visited within a path or trajectory starting at the common initial node, transitioning through s_1, and leading to the final state $\dot{s}$. Therefore, the net value of the educational path leading to final state $\dot{s}$ is defined by the following equation:

$$NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}(s_1, \dot{s})} \left(\frac{1}{1+r} \right)^{t(\tilde{s}, \overrightarrow{s}(s_1, \dot{s}))} \left[\bar{\mathcal{Y}}(\tilde{s}) - \mathit{Costs}^*(\tilde{s}, \tilde{s}^{-1}) \right], \tag{2.7}$$

where $\tilde{s}^{-1}$ is the state visited right before visiting $\tilde{s}$, and $t(s, \overrightarrow{s}(s_1, \dot{s}))$ is a function counting the number of transitions from period zero.[16] Here, costs are normalized to zero for non-costly

[14] In this study, $s_1 = hsgc, 2ye, 4ye$, meaning the agent can choose between staying as a high school graduate, enrolling in two-year college, or enrolling in four-year college.

[15] More specifically, there are seven paths available. Allow $\overrightarrow{S}$ to be the set of paths. $\overrightarrow{S} = \{\overrightarrow{s}(hsgc, hsgc), \overrightarrow{s}(2ye, 2yd), \overrightarrow{s}(2ye, 2yg), \overrightarrow{s}(2ye, 4yd), \overrightarrow{s}(2ye, 4yg), \overrightarrow{s}(4ye, 4yd), \overrightarrow{s}(4ye, 4yg)\}$. Note that in all of them the first node, being a initial high school graduate, is also implicitly included. However, when making comparisons across paths the net value associated to this node will cancel out.

[16] More formally, $t(s, \overrightarrow{s}(s_1, \dot{s})) = n(S^v(\tilde{s})) - 1$ with $s \in \overrightarrow{s}(s_1, \dot{s})$, where $(n(\cdot))$ counts the number of elements

states and set to zero when $\tilde{s} = hsg$, given that this is the first node and we disregard choices made before this point. This measure contains simulated potential ex-post earnings $\bar{\mathcal{Y}}(s)$ and simulated potential ex-post costs $\mathcal{C}osts^*(s', s)$, that already incorporate the simulated realization of the shocks. It is important to note that Equation 2.7 can be derived by calculating the value function in the first period, if we were to impose a specific trajectory and assume perfect knowledge since all shocks have already occurred. Thus, this expression shuts down the uncertainty from the dynamic nature of the problem and only accounts for immediate inflows and outflows per state, disregarding continuation values as no expectation value is considered.

It is essential to recognize that this measure is not solely a financial return, even though it is monetized, as it also factors in non-pecuniary costs such as psychic costs. Additionally, note that this measure is defined regardless of the particular choices that individuals make. Since the proposed model enables the study of the distributions of potential earnings and costs, we can compute the net value for all possible paths available in the decision tree. However, it is worth noting that the net value still depends on the idiosyncratic shocks to earnings and costs, rendering net value a random variable. Although identifying this measure for all paths for each individual in the sample is not feasible, we can study conditional moments based on net value.

Now, let $\overrightarrow{s}(s_1, \dot{s})^*$ represent the path that generates the highest net value according to the following equation:

$$\overrightarrow{s}(s_1, \dot{s})^* = \underset{\overrightarrow{s}(s_1,\dot{s}) \in \overrightarrow{S}}{\arg\max} \; NV(\overrightarrow{s}(s_1, \dot{s})). \tag{2.8}$$

Additionally, let $\overrightarrow{s}(s_1, \dot{s})^{\#}$ be the path chosen under uncertainty, i.e. the sequence of states that satisfies Equation 2.5 for each simulated individual, using simulated earnings and costs. In this

in the set of states visited before and at s.

chapter, $\overrightarrow{s}(s_1, \dot{s})^*$ is referred to as the highest net value alternative.

This study primarily focuses on analyzing individuals who would have experienced a higher net value with a choice other than the one they made under uncertainty, using the following expression:

$$\mathbb{1}[NV(\overrightarrow{s}(s_1, \dot{s})^{\#}) - NV(\overrightarrow{s}(s_1, \dot{s})^*) < 0]. \tag{2.9}$$

It is important to emphasize that the differences between these two net values should not be interpreted as mistakes made by individuals. Instead, these differences arise because individuals make their schooling decisions based on incomplete information about their future earnings and costs. In other words, individuals cannot predict the exact realization of shocks that will affect their future income and costs. This modeling approach does not reflect individuals' feelings towards uncertainty or any regret about not achieving the highest net value alternative. The model assumes that individuals are rational agents who make decisions based on the information available to them at the time of decision-making, seeking to maximize their utility.

2.2.3 Simulation Exercise

To characterize the individuals who choose or do not choose the highest net value alternative, I consider the following exercise:

1. I simulate individuals with varying abilities and idiosyncratic shocks by replicating the observed data 100 times and obtaining different draws of abilities and shocks based on their distributions.

2. For each simulated individual, I determine the net value of all possible schooling paths using potential earnings and costs. I then identify the path with the highest net value

$\overrightarrow{s}(s_1, \dot{s})^*$.

3. I determine the schooling path that the simulated individual would choose under the same uncertainty structure assumed in the model, $\overrightarrow{s}(s_1, \dot{s})^{\#}$. This means that I simulate the decision making process for each simulated individual. I calculate the net value associated to $\overrightarrow{s}(s_1, \dot{s})^{\#}$.

4. I group the simulated individuals based on whether or not the path chosen under uncertainty (in step 3) coincides with the highest net value path (in step 2).

While I cannot draw conclusions from one individual's results, I can study the distribution of net values for different groups. I focus on analyzing whether the highest net value alternative commonly coincides with the choice made under uncertainty (Equation 2.10) and characterize the average individual belonging to each group, always conditioning on the choice made under uncertainty. Specifically, I examine the following groups of parameters:

$$Pr(\overrightarrow{s}(s_1, \dot{s})^{\#} = \overrightarrow{s}(s_1, \dot{s})^* | \overrightarrow{s}(s_1, \dot{s})^{\#}), \tag{2.10}$$

and

$$\mathbf{E}(W | \overrightarrow{s}(s_1, \dot{s})^{\#} = \overrightarrow{s}(s_1, \dot{s})^*, \overrightarrow{s}(s_1, \dot{s})^{\#}) \tag{2.11}$$

where the former indicates the probability that the choice made under uncertainty was (or was not) the highest net value alternative, and the latter studies the average of characteristic W for individuals who find that the choice they made under uncertainty was (or was not) the highest net value alternative. W could be any of the characteristics affecting earnings or costs, including abilities.

The goal of this analysis is to identify individuals whose rational choices, made before the realization of shocks, may not have been optimal, had they been able to observe these shocks in advance. To illustrate this concept, consider an individual from a privileged background who, based on available information, rationally opts for a four-year degree. In hindsight, there are likely very few combinations of shock realizations that would have made alternative choices superior. Conversely, a disadvantaged individual faced with the decision between a two-year and a four-year degree may also rationally choose the latter in advance. However, there could exist numerous shock realizations that retrospectively make the two-year degree a more favorable option. This example demonstrates how the second individual might be more prone to selecting an option that is not the highest net value alternative in retrospect, even though the initial decision was rational given the available information. It is crucial to emphasize that finding an individual chooses a sub-optimal path does not imply any errors in decision-making but rather reflects the incomplete information available at the time of the decision.

Moreover, when an alternative yields a higher net value than the one chosen under uncertainty, it indicates the proximity of these options in terms of expected values. Although individuals consistently opt for the alternative with the highest expected value based on their characteristics, the unselected options may still offer an expected net value very close to the maximum. As a result, the ranking of these alternatives can shift once specific idiosyncratic shocks materialize. In this study, I will demonstrate that individuals with specific characteristics are more likely to experience such shifts in the ranking of alternatives.

It is essential to highlight that the analysis presented in this chapter distinguishes itself from studies concerning marginal treatment effects or marginal policy treatment effects. In the proposed examination, I not only accommodate minor shifts in the cost equations but also account

for modifications in both the cost and earnings equations, which may not necessarily be small. Previous literature employing Roy models to investigate these parameters typically confines the influence to costs affecting the propensity score (as seen in Heckman and Vytlacil, 2005 and Carneiro, Heckman and Vytlacil, 2011), thereby limiting the scope to minor alterations in the cost equations. In contrast, my proposed approach considers changes in both earnings and costs.

2.2.4 Identification

Eisenhauer, Heckman and Mosso (2015) extend the identification results presented by Heckman and Navarro (2007) to accommodate recursive states and multinomial transitions. Therefore, their identification proof applies to the Roy model considered in this chapter. By invoking Theorem 1 in their Web Appendix A, it is possible to use a limit set argument to identify the joint distribution of earnings and measurements without the influence of selection. Furthermore, by leveraging the restrictions of the measurement system and employing factor analysis, we can identify factor loadings and separately identify the marginal distributions of the factors and the marginal distribution of the shocks.

Theorems 2 and 3 outline how to identify the parameters in the cost equations. The primary argument relies on identification results previously established by Carneiro, Hansen and Heckman (2003) for choice equations but applied sequentially, starting from the final transitions. For final transitions, the latent variable influencing the individual's choice depends only on the expected value of earnings (already identified by Theorem 1) and parameters of the cost equations associated with final decisions. Consequently, the identification problem becomes analogous to that encountered in static setups. Once the recovered parameters are known, it becomes possible

to identify continuation values. Therefore, the same logic applies when analyzing subsequent decisions in reverse order starting from the last period. Nevertheless, exclusion restrictions are required to achieve semi-parametric identification: continuous variables that affect potential outcomes for state s but not the associated costs to transit to such state. This condition is only required for final states, as the expected value function plays this role when progressing backward. Table 2.3 shows the variables included in the earnings equations but not in costs and vice-versa. In particular, geographic variables that vary by age (or age group) specific to each state are considered in each type of equation. Costs include average public tuition that is different for two-year and four-year colleges and by cohort. Earnings equations include regional unemployment rate and hourly wage rate that vary by age group and by schooling choice.[17]

The proof uses limit sets to achieve semi-parametric identification. This assumption is easier to achieve if the sample provides enough individuals to populate each state. We will see in the next section that only 94 individuals, or 8.8% of the sample, get a two-year college degree. Given the sample size and the low fraction of individuals attaining a two-year degree, I additionally introduce functional form assumptions to secure identification. Furthermore, considering further extensions of the model with finer partitions (i.e., more decisions) using the current sample will make achieving this condition even more challenging, and even if we solely rely on functional form assumptions, it would be challenging to include a rich set of controls per decision in such extended models.

Derivation of the socioemotional factor from an ordered system requires further discussion. Although Carneiro, Hansen and Heckman (2003) establish semi-parametric identification using such measures, this approach requires using L continuous explanatory variables in the socioe-

[17]Dropouts are pooled regardless of the type of institution they enrolled, given data availability in the CPS.

motional equations. In the context of this chapter, this would require five continuous variables in Q_s. As the only continuous variable in Q_s is family income, this chapter must rely on functional form assumptions (e.g., normality of the latent variables associated with the observed measures) to ensure identification.

2.3 Data

I use data from the National Longitudinal Survey of Youth of 1997 (NLSY97) as the primary data source. Consequently, this study centers on males born between 1980 and 1984 who were residing in the United States in 1997.[18] This choice of using the NLSY97 data set differs from the majority of studies employing Generalized Roy Models to investigate heterogeneous returns to college education, as most of them have primarily analyzed data from the National Longitudinal Survey of Youth of 1979 (NLSY79).

Using the NLSY97 offers several advantages over the NLSY79, especially considering the research questions at hand. One of the most significant distinctions lies in the NLSY97's provision of monthly college enrollment data, categorized by the type of college attended, asked retrospectively. This survey design allows for the observation of enrollment choices throughout all years, even as the survey transitions to biannual data collection. Most of the individuals in the NLSY97 start answering these questions before finishing college, while participants in the NLSY79 provide less-detailed information at older ages. Using the NLSY97 rather than the NLSY79 allows me to observe postsecondary schooling paths with more precision. The NLSY97 further improves upon the NLSY79 by offering richer data for modeling socioemotional abilities,

[18]The supplemental samples for minorities considered in the NLSY97 are also included. However, the main results are qualitatively the same when these samples are excluded.

including a ten-item inventory assessing the Big Five personality traits. It is worth noting, however, that the NLSY97 comprises younger cohorts who experienced the Great Recession during their early prime working years. To address this potential concern, robustness checks are conducted to ensure that the observed differences in average characteristics across groups are not primarily attributed to the effects of the Great Recession.

Figure 2.2 shows the decision tree considered in the model as well as the number of individuals who visit each state. Despite the numbers seeming small, the size of the sample (1,068) is comparable to previous studies using similar models such as Carneiro, Hansen and Heckman (2003) (1,161) and Prada and Urzúa (2017) (1,022). Moreover, the percentage of individuals choosing each option is comparable to summary statistics for close cohorts using external and representative sources of data. According to the National Center for Education Statistics (NCES), 23.1% and 36.8% of male recent high school graduates in 2000 enrolled in either a two- or four-year college, respectively. In my sample 24.25% of high school graduates or GEDs enrolled in these two-year colleges and did not switch to four year colleges. 42.60% of my sample enrolled directly into a four-year college. However, if we also consider individuals who switched from two-year to four-year colleges, the total percentage of four-year enrollees would rise to 51.96%. The six-year graduation rate for male first-time, full-time students in the 2000 entry cohort was 54.3%. In my sample, 72.25% of four-year enrollees attained a degree. Finally, 28.3% of males in the entry cohort in 2000 who were first-time, full-time students attained a two-year degree within 150 percent of the normal time required for completion of these programs. In my sample, 37.6% of two-year enrollees attained a degree.[19]. In general terms, the numbers in my sample are

[19]This calculation includes 41 four-year graduates that also attained a two-year degree but are classified in the decision tree as four-year graduates

close but larger, as I do not require individuals to graduate in any specific interval of time nor to enroll immediately after high school.

Tables 2.1 and 2.2 present summary statistics for all explanatory variables employed in this analysis. The final sample, consisting of 1,068 males, includes only observations with complete information for variables that remain constant over time, including the measurement system's test scores. The sample is further restricted to respondents with available schooling information and earnings data for a minimum of five years after high school graduation and at least two years for the final schooling choice. This selection process is executed after employing a three-year moving average to impute values for earnings, number of children, and region of residence. The imputation is particularly valuable given the transition of the NLSY97 to biannual data collection after 2011. In my analysis, I focus on males who completed high school before reaching the age of 21 and whose initial college enrollment occurred before age 26. The sample is restricted to individuals who took the ASVAB test before starting college, allowing the cognitive and mechanical measures to inform about abilities, uncontaminated by postsecondary choices. Table 2.4 outlines the criteria applied to establish the final sample.

Table 2.1 presents the mean and standard deviation in parentheses for variables that remain constant over time for the overall sample for individuals following each different schooling path. I use the terms "direct" to refer to four-year paths that began in a four-year institution and "2y" to refer to paths that started in a two-year institution. To ensure a comprehensive examination of the heterogeneous returns associated with various postsecondary choices, individuals from all racial backgrounds are included. The first group of variables consists of race and ethnicity dummies. The majority of the sample identifies as White, accounting for nearly 67% of respondents, while Black and Hispanic individuals make up 18% and 15% of the sample, respectively. A higher

proportion of Black individuals remained high school graduates or dropped out of any type of college, and we observe similar trends for Hispanics, except for dropping out of four-year college. The table also provides insights into individuals' residency in 1997, the first year of survey data collection. Around 32% of the sample resided in the South in 1997. High school graduates and four-year dropouts who started in a two-year college are more likely to have lived in the South in 1997, whereas four-year graduates, especially those who at some point enrolled in a two-year college, are much less likely to have lived in the South during their teenage years. Additionally, data on urban living in 1997 is included, with 71% of the sample reporting urban residence that year.[20] Interestingly, those who obtained either a two- or four- year degree and at one point attended a two-year institution are more likely to come from rural areas are more likely to come from rural areas (65-67%), while two-year dropouts are more likely to come from urban areas (87%).

I employ several questions from 1997 to define individuals' family backgrounds. During that year, respondents ranged in age from 12 to 17. Over 39% of individuals reported living in a single-parent home in 1997. This fraction is notably lower among those who earn a two-year degree (32%) and those who obtain a four-year degree but only through direct enrollment in a four-year institution (22%). The average family income in 1997 is $56,500, with significant variation across groups. Four-year graduates who directly enrolled in a four-year institution have the highest mean income ($76,800) and standard deviation ($54,200). In contrast, those who remain as high school graduates or decide to drop out of a two-year college have the lowest family income averages ($38,300 and $46,100, respectively).[21]

[20]The NLSY97 also collected similar information regarding residency at age 12, but due to a significant number of missing values, the data from 1997 was chosen for analysis.

[21]The family income variable is top-coded for the top 2% of the highest values.

The average number of people under age 18 at home in 1997 is 2.3, with a standard deviation of 1.13. This variable serves as a proxy for the number of siblings, a question directly asked in the 2011 survey. Using this variable instead of the 2011 question minimizes the generation of missing information. Among four-year graduates who enrolled directly in college, the average number of siblings is lowest (2.20), and the standard deviation is one of the lowest (0.83). On average, individuals in the sample had mothers who had completed more than 13 years of education by 1997, specifically 13.31 years of schooling. In general, those who follow four-year educational paths have more highly educated mothers, with four-year graduates who enrolled in a four-year institution having the most highly educated mothers on average (14.76). These two variables—mother's education and the number of people under age 18 at home—demonstrate the most significant differences compared to the NLSY79 data set. Both the increase in the average years of maternal education and the decrease in the number of siblings confirm demographic trends widely documented in other studies.

Dummies for birth year are included in all equations to differentiate cohorts. The summary statistics suggest that the cohorts are relatively balanced, with all proportions close to 20%. However, the first cohort (1980) is slightly under-represented, accounting for only 16% of the sample, while the 1983 cohort is slightly over-represented, with a participation rate of 23%.

I incorporate years of schooling as covariates when accounting for the timing of abilities measured by the ASVAB and the TIPI tests. The ASVAB test was administered from the summer of 1997 through the spring of 1998, a period during which most, but not all, individuals were in middle school or high school. To ensure that mechanical and cognitive abilities represent pre-college endowments, I restrict the sample to individuals with at most 12 years of schooling when the ASVAB was administered. On average, individuals had completed 8 and a half years

of schooling with little variation across groups. In contrast, the TIPI test was administered much later in round 12, to be published in 2008, when individuals were between the ages of 23 and 28. The average years of schooling stand at 14.21, varying as expected with the schooling category. While having measures of these tests prior to postsecondary schooling choices would be ideal, such data is unavailable in the NLSY97. To address potential concerns, recent research indicates that interpersonal abilities tend to remain relatively stable throughout a worker's lifetime (Lise and Postel-Vinay, 2020).

In Table 2.2, I present summary statistics for variables characterizing current region of residency, number of biological children living in the household, and marital status. Since these variables are time-variant, a formula, detailed in the following subsection, is employed to calculate a weighted average and aggregate information across years per schooling state. Table 2.2 also includes information for both the initial and final nodes.

The initial set of variables, observed in Panel A, pertains to the starting state: being a recent high school graduate (hsg). Every individual initiates their educational journey in this state, and at this stage, 72% of the individuals in the sample lived in urban areas. The same patterns observed for this variable in 1997 are evident here, even though the measurements were not taken simultaneously. Regarding current region of residence, we observe variation in postsecondary trajectory across the four regions considered. However, regional variation exists between those who pursue four-year college by directly enrolling in such institutions and those who initially enroll in a two-year college. For instance, the latter group is more likely to come from the South and the North Central Region. As expected, most of the individuals at this time have no children and are not married. However, we do observe that there is a slightly increased chance of having children for those staying as high school graduates, two-year graduates, and those who end up

getting a four-year degree through a two-year institution. Furthermore, the latter two groups exhibit a slightly elevated probability of being married.

In Panel B of Table 2.2, we present the same variables for the identical groups, but this time the measurements are taken at the culmination of their educational journey, reflecting their final status in the decision tree based on their chosen paths. Notably, the proportion of urban dwellers has increased to 81%, a shift that can be partially attributed to changes in measurement methods within the NLSY97 data set. Regarding regional residence, there is a noteworthy shift in the distribution. Overall, there is a higher prevalence of individuals residing in the Western region, while fewer individuals choose the North Central region, compared to the recent high school graduates observed in Panel A. This trend is consistent across most educational groups, except those who decide to stay with a high school diploma. Focusing on fertility choices, the average number of children stands at 0.29, with a slightly higher mean value of 0.34 observed for two-year dropouts and two-year graduates. Approximately 31% of the sample is now married, and those holding a college degree tend to have a higher likelihood of being married, with rates ranging from 0.36 to 0.40.

Table 2.3 shows which explanatory variables are considered in each equation.

2.3.1 Schooling choices and wages

Given the monthly granularity of the college schooling data and the limited range of pathways in our model, I must introduce certain assumptions to categorize individuals into the proposed schooling states. First, I define a dropout as an individual who transitions from enrollment to non-enrollment without completing their program in either the current year or the subsequent

year. Furthermore, if an individual simultaneously enrolls in both a two-year and four-year college during a specific year, we code that year as four-year enrollment. My model does not account for re-enrollment after dropping out, and, for such cases, I assume that the individual remains an active enrollee. Such occurrences are relatively rare in the sample. Another assumption is made regarding the distinction between a high school graduate and an individual who continues to be classified as a high school graduate. In this scenario, I assume that this choice is made in the year following high school graduation. Therefore, the first observation is assigned to the initial state, while subsequent years in which the individual is observed are classified under the second state (hsgc).

The model presented in Section 2.2 does not make any distinction in terms of years or time spent in each node. To address this, I follow the approach proposed by Eisenhauer, Heckman and Mosso (2015) to aggregate time-variant variables by state and normalize them for comparability among individuals with varying duration in each node. They propose the following weighted average:

$$\bar{Y}(s) = \frac{\sum_{t=1}^{D(s)} \left(\frac{1}{1+r}\right)^{t-1} Y(t,s)}{\sum_{t=1}^{D(s)} \left(\frac{1}{1+r}\right)^{t-1}}. \tag{2.12}$$

In this equation, $D(s)$ represents the number of years an individual spends in state s, $Y(t,s)$ denotes the annual earnings observed in year t within state s, and r represents the interest rate. All values are adjusted for real dollars in 2018 terms. This calculation results in an earnings average that assigns higher weights to earnings occurring earlier in the period due to the higher discounting factor. The same formula is applied to other variables $X(t,s)$ that vary across time.

Figure 2.3 presents the kernel densities of earnings after applying the previous formula for each state. All the kernel densities presented in this study are calculated using the optimal band-

width for normal distributions.[22] In Panel A, we find the approximate earnings distributions for the states of being a high school graduate and being an enrollee, differentiated by college type and path. The solid black line represents the initial state of being a high school graduate, which explains the high concentration of observations around zero, containing individuals without earnings. A similar pattern emerges for four-year graduates who complete their education directly at a four-year institution (blue dashed line). These individuals are notably less likely to work while studying compared to other types of enrollees. We observe a different pattern for those enrolling in a two-year college (yellow solid line) and four-year enrollees who started in a two-year college (gray solid line). In general, these students are more likely to work. While the difference between the yellow (two-year enrollees) and blue lines (four-year enrollees enrolling directly in a four-year institution) could be attributed to varying time investments required for different types of degrees, the disparities relative to the gray line (four-year enrollees who started in a two-year institution) suggest potential factors like credit constraints or a preference for working.

In Panel B of Figure 2.3, we can observe the kernel densities of the earnings for the final states of those who decided to enroll in college (2yd, 2yg, 4yd, and 4yg), pooling in the same group those who ended up being four-year dropouts or four-year graduates, regardless of the type of enrollment. As expected, four-year graduates exhibit the highest concentration of those earning very high wages. Dropouts have a higher concentration of low earnings relative to graduates. However, there are two interesting patterns. First, two-year dropouts earn similar wages regardless of the type of college they attended. Second, two-year graduates usually have similar earnings relative to four-year graduates. The main difference is the very high-income levels

[22] The bandwidth that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel was used.

observed for both four-year graduates and four-year dropouts. Although this pattern might be caused by the fact that I do not restrict the sample to individuals that complete schooling choices early in life, I see that age-duration in final state pairs are well represented across all college paths.[23]

Panel C in Figure 2.3 illustrates earnings distributions for four-year dropouts and graduates, differentiated by their type of enrollment. There are no significant differences in earnings between four-year graduates who directly enrolled in four-year college and those who did not. As expected, both types of dropouts earn lower earnings.

2.3.2 Test scores

As three latent factors are considered, I also consider three kinds of tests: those measuring cognitive abilities, those measuring mechanical abilities, and those measuring socioemotional behavior. For the first two groups, the NLSY97 offers exactly the same test used to measure these two dimensions in similar papers: the Armed Services Vocational Aptitude Battery (ASVAB). To measure cognitive abilities, I consider the following ASVAB components: i) arithmetic reasoning, ii) math knowledge, iii) word knowledge, iv) paragraph comprehension, v) coding speed, and vi) numerical operations. The mechanical measures comprise the following components of the ASVAB: i) mechanical comprehension, ii) auto information, iii) electronics information, and iv) shop information. All test scores are on continuous scales, and their selection was based on the same definition of cognitive and mechanical tests in Prada and Urzúa (2017).

To measure socioemotional abilities, studies using the NLSY79 have used the Rotter self-control scale or the Rosenberg self-esteem scale. However, the NLSY97 does not include these

[23] Results available upon request.

variables. Alternatively, the NLSY97 contains the Ten-Item Personality Inventory Scale (TIPI), where individuals are asked how well certain characteristics describe them. This is a short test that measures the Big-Five personality domains, containing only ten questions in comparison to previous and longer versions with at least 44 questions. Despite the length of the questionnaire, TIPI is still able to exhibit desirable statistical properties for tests measuring the Big-Five personality domains (Gosling, Rentfrow and Swann Jr, 2003). The possible answers to each question range from 1 to 7, where 1 means "disagree strongly" and 7 means "agree strongly." I follow the procedure recommended by the Measurement Instrument Database for Social Sciences to create the measure of each domain. In the first place, half of the questions are reversed-score items and hence, their answers need to be reversed to make all questions comparable. Then, the mean is calculated. This process creates measures that are discrete but ordered and can take between twelve and thirteen different values. Despite this limitation, previous studies have also considered the TIPI scale. For instance, Deming (2017) recently used the extroversion components of the NLSY97 to compare returns to social abilities in the NLSY97 and the NLSY79. The Big-Five personality domains are i) extroversion, ii) emotional stability, also known as neuroticism, iii) openness to experience, iv) agreeableness, and v) conscientiousness.

Figures 2.4-2.6 display the kernel densities for continuous measures and the fraction of individuals at each discrete level for the TIPI tests, categorized by their final schooling states. All continuous measures underwent standardization by subtracting the mean and dividing by the standard deviation to ensure comparable scales and facilitate the optimization procedure.

In Figure 2.4, which presents cognitive measures, it is unsurprising that four-year graduates exhibit the highest scores across all six measures. A consistent pattern emerges across these measures, with individuals scoring highest on cognitive abilities being four-year graduates, fol-

lowed by four-year dropouts, two-year graduates, and two-year dropouts. High school graduates tend to have the lowest scores. This pattern holds consistently across all measures, with four-year graduates outperforming the other groups. One of the most substantial gaps between four-year graduates and the other groups is evident in the measure for paragraph comprehension.

Figure 2.5 presents the distribution of individuals at each discrete level of socioemotional measures, categorized by their level of schooling. In contrast to cognitive measures, there is no clear hierarchical pattern among schooling levels. However, four-year graduates stand out with notably higher scores in emotional stability and conscientiousness.

A low score in emotional stability may indicate traits such as irritability, anxiety, and difficulty managing stress. In contrast, high scores in conscientiousness suggest qualities like self-discipline, organization, and impulse control. Therefore, the high scores achieved by four-year graduates align with the attributes we expect from individuals who have successfully completed their college studies and achieved success in the labor market.

Four-year graduates also appear to have a higher proportion of individuals at lower levels of extroversion compared to the other groups. This finding is intriguing, particularly in light of the observations made by Deming (2017), who concluded that jobs requiring social abilities experienced significant growth in the NLSY97 relative to the NLSY79, along with increased rewards for individuals with these abilities.

Figure 2.6 contains the mechanical kernel densities. For the mechanical comprehension and electronics information sections of the ASVAB test, we see a similar rank as the one observed in the cognitive tests, with a considerably heavy left tail for high school graduates. We also observe an accentuated gap between four-year graduates and the rest of the groups in the electronics information test. This ranking is not preserved for the shop and automotive information measures.

High school graduates exhibit the heaviest right tail for the auto information test, which asks questions about the mechanical functions and components of cars.

Panel A in Table 2.5 displays the correlations between ASVAB and TIPI test scores. As expected, the correlations between tests in the same category are relatively stronger and have a positive sign for the cognitive and mechanical factors. For the socioemotional measures, we observe that the correlation between them is never larger than 0.31 and in some cases, it is as low as 0.04 or 0.07. We also observe that socioemotional measures lack correlation with the ASVAB components, except for the case of emotional stability, which may have higher correlation coefficients between some ASVAB tests than with other tests in the socioemotional dimension. One possible explanation for this pattern is that a certain degree of emotional stability may be a prerequisite for performing well on tests in general.

2.3.3 Exploratory Factor Analysis

The decision to include three factors is conceptually motivated and supported by recent empirical findings, rather than motivated by the patterns exhibited in the data. However, an exploratory factor analysis also supports this choice. The principal factor analysis considering all tests simultaneously is presented in Table 2.6. The principal factor analysis shows that six factors have associated positive eigenvalues. This means that given the available data on tests and its variability, we can consider up to six factors. The first factor has an eigenvalue that corresponds to 86.1% of the sum of all eigenvalues. These values are 12.6% and 10.1% for the second and third factors respectively. Note that until this point the cumulative sum of these proportions becomes higher than one and the participation of the subsequent factors is relatively smaller (less

than 3%).

The second part of Table 2.6 shows the loadings associated with each test measure, which describes how much each measure contributes to each principal factor. Diekhoff (1992) proposes the rule where loadings with a magnitude higher than 0.3 in absolute terms point out relevant relationships between the factors and the observed tests. Although Prada and Urzúa (2017) suggest that the first factor affects all tests, for the NLSY97 there is no evidence of this factor affecting socioemotional tests. Therefore, I allow the cognitive factor to affect the mechanical factor but not the socioemotional factor, with only the cognitive and mechanical factors allowed to be correlated. Figure 2.7 shows a graphical representation of the analysis. I obtained very similar qualitative results than those produced by Prada and Urzúa (2017) after conducting the same exercise, except for the fact that the loadings for the mechanical knowledge and electronics tests are slightly less than 0.3 in the NLSY97. The explanatory factor analysis using only the TIPI tests suggests that all tests are relevant following the same rule. [24]

2.3.4 High School Transcripts

The NLSY97 contains rich information documenting the high school experience of participants, including high school transcripts. Therefore, this section explores the inclusion of this information in the measurement system given the importance of grades in determining different schooling outcomes and their potential correlation with abilities.[25] Nonetheless, I present evidence below that the inclusion of GPA does not contribute significantly to my analysis.

The exact measure that incorporates information from high school transcripts in this study

[24] Results not presented but available upon request.

[25] For instance, according to Heckman and Kautz (2012) at citing Bowen, Chingos and McPherson (2018), high school grades are more predictive of first-year college performance than SAT scores.

is the most recent available GPA by academic year weighted by Carnegie credits. This measure is already adjusted to be in a comparable scale across schools by the National Longitudinal Surveys (NLS). In the original sample of 1,068 observations, 13% of individuals never granted permission to collect high school information.

Other factors, like noncompliance on the part of schools to provide access to transcripts, further increases the number of missing observations. Thus, in an attempt to maximize the number of individuals in the sample, transcript data is selected according to last year available—as opposed to the final year of high school or a specific grade level—yielding a sample size of 834 observations.

Panel B in Table 2.5 shows the correlation of high school GPA with the measures discussed in the previous subsection. We can observe that GPA never exhibits a strong correlation with any of the test scores. The highest coefficients are exhibited with the cognitive test of the ASVAB, where values range from 0.35 to 0.22. This pattern contrasts with the results in Panel A, where the lowest correlation experienced between the cognitive ASVAB tests is 0.48. The correlations of high school GPA with the mechanical and socioemotional tests are even weaker.

The weak relation of GPA with the other measures is confirmed with an exploratory factor analysis, considering also GPA. These results are shown in Table 2.7. This table shows how high school GPA barely passes the threshold of 0.3 to be classified as a relevant measure for the cognitive factor, with an associated loading of only 0.328. Moreover, high school GPA does not pass this threshold for the other two factors and including high school GPA does not drastically change the way the other measures relate with the factors. On top of these results, the estimated distribution of abilities does not change substantially with the addition of high school transcripts to the measurement system. Considering this evidence alongside the potential effects of a 20%

reduction in sample size, I choose to exclude high school GPA from this analysis.

2.4 Estimation

The model will be solved using backward induction, while the estimation will be conducted using Conditional Maximum Likelihood Estimation (CMLE). Although CMLE is well known for allowing the simplification of full information maximum likelihood estimations, the main motivation for its implementation is theoretical. Given that the ultimate goal of the introduction of a measurement system is providing a meaningful and clear identification of the abilities, allowing a two-step procedure permits the factor variables to be mainly identified as theoretically proposed, instead of the distribution of the factors also being contaminated with post-secondary choices.

Denote $\mathbf{M}$ the set that contains all the observed measures that are used as dependent variables in the measurement system, hence $\mathbf{M} = \{c_1, ..., c_6, s_1, ..., s_5, m_1, ...m_4\}$. Additionally, define Γ as the set that contains all states that are visited by the agent and $G(s)$ as an indicator function that takes the value of one if the agent visited state s. Hence, the likelihood function of each individual is given by:

$$\int_{S_\theta} \left\{ \prod_{m \in \mathbf{M}} f(m|D, \theta; \delta) \prod_{s \in S} [f(Y(s)|D, \theta; \delta) \text{Pr}(G(s) = 1|D, \theta; \delta)]^{\mathbb{1}[s \in \Gamma]} \right\} dF(\theta) \tag{2.13}$$

where S_θ is the support of θ, D represents the set of explanatory variables, and δ the vector of all parameters. $f(m|D, \theta; \delta)$ and $f(Y(s)|D, \theta; \delta)$ are density functions calculated from the assumptions on functional forms of the error terms stated in Section 2.2. $\text{Pr}(G(s) = 1|D, \theta; \delta)$ are the choice probabilities derived from solving the model by backward induction.

The distribution of the factors is not imposed to follow a normal distribution, but allowed

to follow a flexible distribution using mixture of normal distributions. According to Carneiro, Hansen and Heckman (2003) using mixtures instead of assuming normal distributions is important to reach a good fit of the model. Therefore, the factors are assumed to distribute as follows:

$$\theta_i \sim \sum_{j=1}^{h_i} p_j^i N(\mu_j^i, \sigma_j^{i2}) \qquad \text{for } i = c, s, u \tag{2.14}$$

where μ_j^i and σ_j^{i2} denote the means and variances for each component j of each factor θ_i. θ_u is the uncorrelated component of the mechanical system, as $\theta_m = \alpha\theta_c + \theta_u$. In order to identify α, I assume one of the mechanical measures to be exclusively informative for the mechanical factor (Prada and Urzúa, 2017). The number of mixture components h_i is selected for each ability θ_i using Likelihood Ratio Tests. The cognitive and mechanical factors have two components and the socioemotional factor has one component.[26] The mean of each factor variable is restricted to be zero ($\sum_{j=1}^{h_i} p_j^i \mu_j^i = 0$), which allows the identification of the intercepts. The integrals over the factors are solved using Monte Carlo integration and employing 100 draws.

Now, consider a partition of δ into δ_M and δ_D, where δ_M contains all the parameters related to the measurement system, specifically those in equations 2.6 and 2.14, which means δ_M also includes the parameters of the mixtures of the factors. δ_D contains the parameters related to the dynamic part of the model, specifically to the earnings and costs. This partition allows a better description of the steps that are considered in the CMLE. The individual likelihood function of the first stage is given by:

$$\int_{S_\theta} \left\{ \prod_{m \in \mathbf{M}} f(m|D, \theta; \delta_M) \right\} dF(\theta) \tag{2.15}$$

which derives an estimate $\hat{\delta}_M$. While the individual likelihood function of the second stage is

[26] The Likelihood Ratio tests for using more components does not reject the null hypothesis.

given by:

$$\int_{S_\theta} \left\{ \prod_{s \in S} \left[f(Y(s)|D, \theta; \hat{\delta}_M, \delta_D) \Pr(G(s) = 1|D, \theta; \hat{\delta}_M, \delta_D) \right]^{\mathbb{1}[s \in \Gamma]} \right\} dF(\theta) \tag{2.16}$$

whose minimization leads to obtain an estimate $\hat{\delta}_D$. Here, $\hat{\delta}_M$ is fixed throughout the estimation of the second stage. In order to obtain the correct variance-covariance matrix, one single iteration of the joint likelihood function is considered, using as initial parameters $\hat{\delta}_M$ and $\hat{\delta}_D$.

2.5 Results

2.5.1 Goodness of fit

Before covering the main results in this article, I present some statistics and graphs informing about the goodness of fit of the model. Table 2.8 shows the two-sample Kolmogorov-Smirnov test for the ASVAB tests to compare the observed data with the data generated by the model. The simulated data is obtained following the assumptions imposed in section 2.2 and replicating 100 times the database, which leads to a total of 106,800 observations.

The p-values indicate that five measures fail to achieve the desired goodness of fit: word knowledge, paragraph comprehension, coding speed, mechanical comprehension, and electronics information at a conventional significance level of 95%. For these variables, there is statistical evidence to reject that the simulated and observed data come from the same distribution. Despite these results, I also present Figure 2.8 which depicts the simulated and observed CDFs for the same variables, adding the discrete measures for the TIPI test. These figures allow us to analyze qualitatively the goodness of fit. Although several variables fail to obtain a satisfactory result

using the Kolmogorov-Smirnov test, these graphs show that for most of the variables, the model is able to replicate similar distributions, especially for the socioemotional measures.

To assess the goodness of fit for choice probabilities, I compare the percentage of individuals visiting each state for both the observed and simulated data. Table 2.9 demonstrates that the simulated percentages closely match those observed in the data. This table also provides insights into the fit of earnings by schooling level, comparing the means and variances for the simulated and observed data. Remarkably, the means and variances are highly similar.

Figure 2.9 presents a comparison between simulated and observed kernel densities for wages, categorized by schooling choices. The goodness of fit varies across different schooling levels, with notably poor fits for high school graduates (initial node) and four-year enrollees, where zero wages are more common. Conversely, goodness of fit is especially good for two-year dropouts and two-year graduates. Despite the discrepancies in the distributions in some nodes, Table 2.9 illustrates that the model excels in replicating the means and variances of earnings in each state.

2.5.2 Ability Sorting

Figure 2.10 shows the distribution of three dimensions of ability considered in the study. These distributions do not come from raw test scores but rather are the estimated distributions of abilities under the assumptions discussed in 2.2. This graph depicts the three factors together regardless of education level. This figure also offers information about the variances of the factors. The cognitive factor presents a uni-modal distribution with a thick left tail and variance of 0.47. This variance lies in a similar range as those estimated by Carneiro, Hansen and Heckman

(2003) (0.30 and 0.57). The socioemotional ability follows a normal distribution (by assumption) and has a variance of 0.05, smaller than the variance of the cognitive factor. Finally, the mechanical factor has a variance of 0.16 and a thicker right tail. The estimated correlation between the mechanical and cognitive factors is 0.39.

Figure 2.11 shows the density (on the left) and empirical cumulative distribution functions (CDFs, on the right) of each ability by schooling choice, pooling four-year graduates and four-year dropouts, regardless of the type of enrollment in their paths. In Panel A, we can observe the estimated distributions for the cognitive ability. There is a clear established ordering across the different schooling levels, where those who continue as high school graduates along with two-year dropouts present the lowest levels of cognitive abilities, followed by two-year graduates, four-year dropouts, and four-year graduates. A large gap is also observed between four-year graduates and the rest of the groups. These findings are consistent with the patterns observed in the descriptive statistics for the cognitive tests. This ordering is supported by the CDFs displayed on the right, where visually, we can deduct first-order stochastic dominance among these groups.

Panel B shows the inferred distributions for the socioemotional factor. We can see that graduates have the lowest relative endowments, while high school graduates have the highest. However, sorting in terms of socioemotional ability is relatively weak, as all schooling paths exhibit very similar distributions.

In Panel C, we observe the densities and CDFs for the mechanical factor. All groups exhibit a heavy right tail, with particularly thick tails for individuals who continued as high school graduates. Here, there is a clear ordering across schooling levels, but this ordering differs significantly from the one observed for the cognitive factor. High school graduates stand out as having the highest mechanical abilities, followed by two-year graduates and the others.

Figure 2.12 replicates the analysis of the ability distribution, focusing solely on individuals following four-year college paths, with differentiation by type of enrollment and final choice. In the graphs, purple lines represent individuals who initiated their college trajectories in a two-year institution, solid lines represent four-year graduates, and dashed lines represent four-year dropouts.

These graphs reveal differences in socioemotional abilities between those who follow a two-year path and those who enroll directly in four-year colleges. The former group exhibits notably higher relative endowments of socioemotional abilities. This observation stands in contrast to the absence of sorting seen when various types of four-year college students were combined into the same groups in Figure 2.11. Furthermore, four-year graduates and dropouts who initially enrolled in two-year institutions before transitioning to four-year colleges display no difference in cognitive endowments compared to their counterparts who enrolled directly in four-year colleges. These findings contribute to the existing literature, as to the best of my knowledge, this chapter is the first to characterize ability sorting while considering these postsecondary paths and addressing selection bias.

I also contribute to the existing literature by concluding that two-year college graduates do not exhibit high endowments of any ability relative to individuals following other paths. This finding contrasts with the specialization observed for four-year graduates in terms of cognitive ability and for those remaining as high school graduates in terms of mechanical ability. These latter two patterns align previous literature findings (see Prada and Urzúa, 2017 and Heckman, Humphries and Veramendi, 2018).

To conclude the analysis of latent abilities, I follow Prada and Urzúa (2017) and I conduct a variance decomposition of the measurement system. This decomposition allows us to understand

the relative importance of the factors, or unobserved abilities, at explaining the ASVAB and TIPI tests. For the socioemotional tests, I decompose the associated

Several common characteristics emerged in comparison to the variance decomposition of the NLSY79, as illustrated in Figure 2 in Prada and Urzúa (2017). There is a generally low fraction of variance explained by observed variables, with a significant portion attributed to measurement error. This pattern is particularly pronounced in most socioemotional tests, which is consistent with findings using data from the NLSY79. The high fraction explained by other components rather than the factors or abilities underscore the importance of employing a measurement system to address the contamination of raw measures by measurement error.

This analysis also reveals that, apart from the math and word knowledge tests, most tests are better explained by abilities than by observed variables. However, there is a subtle difference relative to the NLSY79. In the NLSY97, observed variables play a more significant role in explaining the variance of the test measures, with participation rates exceeding 20% for several tests.

Tables 2.12, 2.13, and 2.14 show the estimated results for the measurement system; tables 2.10 and 2.11 display the results for the costs and the earnings equations. As the main interest in this article is the analysis of counterfactual distributions, I will omit the interpretation of these coefficients.

2.5.3 Sensitivity to Uncertainty

Under rationality, a central assumption of the model, uncertainty plays a pivotal role in the analysis conducted in this study. It explains why, irrespective of the path agents choose, always

aimed at generating the maximum expected value, those choices may appear "sub-optimal" in hindsight when alternatives are compared. The sequential nature of decision-making intertwines with this uncertainty. Recent college graduates begin their decision-making process based on continuation values that encapsulate the value of retaining the option to make subsequent decisions. Therefore, agents in this model do not make commitments with a given schooling trajectory at period zero. Policy functions allow these actors to make the optimal choice given the information set at each point of the decision-making process. In other words, the path that individuals follow will be contingent on the revelation of information at different periods.

In this section, I will explore how uncertainty influences schooling choices, quantify potential welfare improvements measured in terms of the net value attained from chosen educational paths if individuals possessed perfect foresight, and identify those most sensitive to uncertainty across different educational path comparisons. I then differentiate between uncertainty stemming from costs and that arising from earnings.

The nature of uncertainty faced by agents with varying characteristics is inherently different. In this model, individuals from different family income quartiles, assessed during their teenage years, are allowed to encounter idiosyncratic shocks originating from distinct distributions. This is possible given the heteroskedastic nature of earnings shocks. I refrain from imposing assumptions regarding the structure of this heteroskedasticity. Instead, I allow the variations in earnings across groups to dictate the distribution from which each income group draws its shocks. Consequently, we will discover that even individuals from the top income quartile group do not necessarily experience lower variance in their earnings. Unlike Arcidiacono et al. (2023), I do not model the precise source or mechanism that generates this uncertainty. Thus, I must remain agnostic about the mechanisms responsible for the uncertainty influencing educa-

tional choices and earnings. This uncertainty can encompass a range of interpretations, including shocks related to liquidity constraints, information, available opportunities, access to networks, preferences for work or studying, and more.

Consider Figure 2.14 as a first set of results. The figure shows which option generates the highest ex-post net value for individuals choosing each schooling path. In Panel A, we find individuals who decided to enroll directly in a four-year college and obtain a four-year degree. We can observe that 83% would find that the best ex-post option is indeed obtaining a four-year degree, but only 71.94% would do so by enrolling directly in a four-year college. 11.14% would still prefer to enroll in a two-year college to get a four-year degree, had they perfect foresight. 8.60% would prefer to get a two-year degree, which is much higher than the percentage that would instead drop out of four-year college (4.24%). In Panel B, we can see the same analysis for four-year graduates who enroll first in two-year colleges when facing uncertainty. 81.19% would conclude that getting a four-degree is indeed the best ex-post option. However, 78.32% would do so precisely within their chosen path, i.e., enrolling in a two-year college. This figure contrasts with the 71.94% observed for those deciding to enroll directly in a four-year college that we analyzed in Panel A. After getting a four-year degree, the most frequent path leading to achieving the highest ex-post outcome is dropping out of a two-year college (8.14%), followed by obtaining a two-year degree (6.15%). This pattern also contrasts with the case where individuals decide to enroll directly in a four-year college.

Panel C presents the results for two-year graduates. 76% of two-year graduates would achieve the highest net value in their choice. This number is higher than for four-year graduates enrolling in a four-year college directly but lower than for four-year graduates who started their college journey in a two-year college. The second most frequent option is getting a four-year de-

gree: 16.66% of two-year graduates would get the best ex-post outcome as a four-year graduate; almost 70% of this latter group would do so through a path starting in a two-year college (purple bar). 6.11% would find the best ex-post outcome as a two-year dropout.

Lastly, for Panel D, we can observe that 69.61% of those who decide to stay as high school graduates find that staying with only a high school diploma is the highest net value path. Note that this is the lowest percentage of finding the actual choice coincides with the path generating the highest net value. Moreover, 12.47% of high school graduates would find the best ex-post outcome in a four-year degree and (6.74% through direct enrollment) and 10.81% in a two-year degree.

From this analysis, I want to highlight that the percentage of individuals finding the path they chose under uncertainty coincides with the best option in ex-post terms varies depending on the choice made by the individual. Although this will be analyzed later, it is essential to acknowledge that the people belonging to each of these bars do not necessarily have the same characteristics; people with different characteristics will have different probabilities of belonging to a particular bar in Figure 2.14, and hence to concluding that their choice is the ex-post highest net value path.

2.5.4 Costs-Earnings Decomposition

In this section, I break down the previous analysis to uncover whether differences in costs, earnings, or both are the main factors driving the deviation from selecting the path with the highest net value. To facilitate the clarity and presentation of the procedure, consider the following

simplified version of the net value formula:

$$NV(\overrightarrow{s}(s_1,\dot{s})) = \sum_{\tilde{s}\in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s},\tilde{s}^{-1}))\right],$$

where $PV(\cdot)$ denotes the present value formula.

Then, we can divide this formula according to the contributions of earnings and the contributions of costs as follows:

$$NV(\overrightarrow{s}(s_1,\dot{s}))^y = \sum_{\tilde{s}\in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s}))\right], \tag{2.17}$$

the earnings component of ex-post net value, and:

$$NV(\overrightarrow{s}(s_1,\dot{s}))^c = \sum_{\tilde{s}\in \overrightarrow{s}(s_1,\dot{s})} \left[PV(C(\tilde{s},\tilde{s}^{-1}))\right], \tag{2.18}$$

the costs component of ex-post net value. Note that $NV(\overrightarrow{s}(s_1,\dot{s}) = NV(\overrightarrow{s}(s_1,\dot{s})^y - NV(\overrightarrow{s}(s_1,\dot{s})^c$. Recall equation 2.9, which will identify if the path chosen is the highest net value choice:

$$\mathbb{1}[NV(\overrightarrow{s}(s_1,\dot{s})^{\#}) - NV(\overrightarrow{s}(s_1,\dot{s})^{*}) < 0],$$

where $\overrightarrow{s}(s_1,\dot{s})^{\#}$ represents the path chosen under uncertainty, and $\overrightarrow{s}(s_1,\dot{s})^{*}$ corresponds to the path that would generate the highest net value. Considering the equations 2.17 and 2.18 presented earlier, equation 2.9 is fulfilled when any of the following three mutually exclusive cases occur:

1. $NV(\overrightarrow{s}(s_1,\dot{s})^{\#}) < NV(\overrightarrow{s}(s_1,\dot{s})^{*})$ and

   $NV^y(\overrightarrow{s}(s_1,\dot{s})^{\#}) < NV^y(\overrightarrow{s}(s_1,\dot{s})^{*})$ and

$NV^c(\overrightarrow{s}(s_1, \dot{s})^{\#}) \leqslant NV^c(\overrightarrow{s}(s_1, \dot{s})^{*})$

2. $NV(\overrightarrow{s}(s_1, \dot{s})^{\#}) < NV(\overrightarrow{s}(s_1, \dot{s})^{*})$ and

   $NV^y(\overrightarrow{s}(s_1, \dot{s})^{\#}) \geqslant NV^y(\overrightarrow{s}(s_1, \dot{s})^{*})$ and

   $NV^c(\overrightarrow{s}(s_1, \dot{s})^{\#}) > NV^c(\overrightarrow{s}(s_1, \dot{s})^{*})$

3. $NV(\overrightarrow{s}(s_1, \dot{s})^{\#}) < NV(\overrightarrow{s}(s_1, \dot{s})^{*})$ and

   $NV^y(\overrightarrow{s}(s_1, \dot{s})^{\#}) < NV^y(\overrightarrow{s}(s_1, \dot{s})^{*})$ and

   $NV^c(\overrightarrow{s}(s_1, \dot{s})^{\#}) > NV^c(\overrightarrow{s}(s_1, \dot{s})^{*})$.

In each of these cases, the chosen path's total net value falls below that of the highest net value path, $\overrightarrow{s}(s_1, \dot{s})^{*}$. In the first case, the chosen path has lower earnings but remains less costly. Hence, the primary explanation for not achieving the highest net value in this scenario is lower earnings. In the second case, although the chosen path has higher earnings, it also incurs higher costs, making costs the primary explanation. In the third case, the path followed under uncertainty exhibits both lower earnings and higher costs compared to the alternative with the highest net value. Therefore, both factors contribute to the deviation from achieving the highest net value.

Panels A-D in Figure 2.15 and Figure 2.16 show the decomposition for the two types of four-year graduates, two-year graduates, and high school graduates. On the left side of each panel, there are graphs showing the percentage of individuals who choose the same path under uncertainty but for whom a different path actually yields the best ex-post outcome. For example, in Panel A, we see the highest net value path for four-year graduates who enrolled directly in a four-year college when it is not obtaining a four-year degree throug this specific path of direct

enrollment. The colors in the graph represent the main factors that determine the main driver behind being more vulnerable to uncertainty and hence not reaching the best ex-post outcome, which might be due to earnings (dark blue), costs (gray), or both (light blue). The numbers displayed in the graphs represent the percentage of individuals who choose to be four-year graduates with direct enrollment under uncertainty.

From the figure, we can see that less than 2% of four-year graduates would have found the highest net value by being a two-year dropout. Additionally, about 7.5% of four-year graduates would have concluded that obtaining a two-year degree yields the highest net value. The third bar shows that 4.52% of four-year graduates would have found the highest net value by dropping out of four-year college, while only around 2.5% would have found the highest net value by remaining as high school graduates. The figure on the right side presents the main results, specifically showing the total contribution of earnings and costs in explaining the percentages observed in each bar on the respective graph on the left. Panels B-D follow the same structure for four-year graduates enrolling in a two-year college, two-year and high school graduates, respectively.

Overall, the figure demonstrates that costs are a significant factor in explaining why four-year graduates may find their choice is sub-optimal ex-post relative to obtaining a two-year degree or staying as a high school graduate. The same applies to two-year graduates finding higher net value as four-year or high school graduates. On the other hand, earnings have a greater impact when dropping out represents the highest net value alternative or when high school graduates could achieve greater net value through different choices. These results highlight the sensitivity of the net value of specific trajectories to variations in costs and earnings. The findings provide insights into which choice margins are more responsive to policies targeting cost reductions, as well as those that are less sensitive and primarily driven by labor market conditions.

2.5.5 Perfect information

In this subsection, I conduct a counterfactual exercise that assumes perfect information for all individuals. In this scenario, every individual would select the alternative with the highest ex-post net value. First, I find that under this policy, aggregate net value would increase by 10.79% compared to the status quo. However, 68% of individuals would still make the same choices, resulting in unchanged net value. Focusing on those individuals who would have made different choices with perfect foresight, their aggregate net value would rise by 47%. Net value serves as a proxy for welfare derived from these schooling choices. Consequently, this analysis highlights the gains that individuals forgo as they confront uncertainty within a sequential decision-making process.

Figure 2.17 compares schooling choices under the status quo, where individuals face uncertainty (light blue), with the policy exercise where we provide complete information to all agents (dark blue). Several intriguing patterns merit attention. First, the number of individuals with a two-year degree would increase by 6.9 percentage points (77.15%), while the number of individuals with a four-year degree would only marginally increase by 2.08 percentage points (5.59%). The number of individuals transitioning from a two-year college to a four-year institution would notably increase by 5.78 percentage points (61.79%). Even without the uncertainty of future earnings and costs, a non-trivial fraction of individuals would still decide to drop out of college, especially from a two-year institution. Approximately 9.4% of individuals would choose to be four-year dropouts, and 16.4% would decide to be two-year dropouts. This finding aligns with previous literature that has examined the returns on collecting some college credits without completing a degree.

Arcidiacono et al. (2023) quantify the role of uncertainty in terms of its impact on four-year graduation rates, revealing an increase of 4.4-6.4 percentage points. In this chapter, a scenario of perfect information would lead to an increase in the four-year college graduation rate, estimated at 8.8 percentage points. This heightened effect aligns with the scope of my study, where I investigate the broader spectrum of uncertainty affecting earnings and costs, whereas Arcidiacono et al. (2023) focus on the specific information frictions.

2.5.6 Characterization of Individuals More Sensitive to Uncertainty

Tables 2.15-2.17 present the results that reveal differences in characteristics among individuals who, when faced with uncertainty, choose to pursue the same educational path. I compare those who achieve the highest ex-post net value with this choice to those who do not. This analysis allows us to identify the characteristics that increase the likelihood to make sub-optimal choices due to uncertainty. An alternative interpretation is that this analysis enables us to determine the characteristics that assist students in specific paths in mitigating the impact of uncertainty and increasing their likelihood of achieving the highest net value with their choice

All tables in this study follow a consistent structure. First, all results come from the simulation exercise I explained in Section 2.2. Second, all simulated individuals considered in a given table follow the same path under uncertainty. Third, the initial column consistently presents the mean characteristics of the different variables analyzed for the reference group. This reference group consists of those who achieve the highest ex-post net value with the path analyzed in the table. Fourth, in the next group of columns, I analyze groups that could achieve a higher ex-post net value under alternative schooling paths rather than the one chosen (the one that everyone

considered in the table also chose). In particular, I present the average of the characteristic, the standardized mean difference (SMD) relative to the reference group, and stars indicating standard significance levels for a mean difference t-test between the reference group and the group being analyzed.[27] The standardized mean difference serves as a measure to assess the magnitude of differences while considering that variables may be measured in different units. Moreover, abilities are standardized in order to easy interpretation of the results.

Table 2.15 presents the analysis for simulated individuals who opt for a four-year degree by directly enrolling in a four-year institution. In this table, I compare those who achieve the highest net value with this choice to those who find higher net value as four-year graduates following different educational paths, obtaining a four-year degree through two-year college enrollment, being four-year dropouts, two-year graduates, and high school graduates.

First, consider the first variable: mother's education, measured as the number of years the mother had completed in 1997. Across all comparisons, the standardized mean difference (SMD) is negative and the mean differences are statistically significant. This suggests that individuals who, in hindsight, would have achieved higher ex-post net value by accumulating fewer credits tend to have mothers with fewer years of education (SMD: -0.43 to -0.14). Similarly, they tend to come from families with lower income in 1997 (SMD: -0.40 to -0.07) and are more likely to come from families where both parents are not present, except when we examine the value of a two-year degree (SMD: 0.04 to 0.13). Additionally, they tend to exhibit lower average levels of cognitive ability (SMD: -0.34 to -0.05), except when compared to those who find higher value in a four-year degree through a different enrollment path. All these patterns indicate that individuals deciding

[27]The standard deviation of the reference group is considered to calculate the standardized mean difference, instead of using the pooled standard deviation. This decision aims to make standardized mean difference comparable across columns.

to enroll in a four-year college and obtain a four-year degree are more sensitive to uncertainty if they are long- and short-credit constrained. Long-term credit constrained refers to the constraints that stem from a sustained level of low resources and, consequently, low investments in abilities, which also influence expectations and readiness to attend college Carneiro and Heckman, 2002.

Furthermore, individuals who, in comparison to those opting for four-year degree paths, find higher value as two-year graduates or high school graduates, are more likely to originate from and reside in rural areas (SMD: -0.20 to -0.12). Regarding race and ethnicity, those who find higher value in a two-year degree are less likely to be Black or Hispanic (SMD: -0.15 to -0.05). In contrast, individuals who are more likely to find higher net value as four-year dropouts are more likely to be Black or Hispanic. Additional variations manifest in terms of abilities. However, it's important to emphasize that abilities do not consistently exhibit the most significant differences in all comparisons. Notably, their influence is less pronounced when comparing the value of a two-year degree or a four-year degree obtained through a pathway starting in a two-year college.

In terms of socioemotional ability, we find higher socioemotional ability levels among those who yield a higher net value from being a four-year graduate enrolling through a two-year college or from remaining a high school graduate (SMD: 0.11 - 0.16). Higher levels of mechanical ability are present for four-year graduates finding higher value as two-year or high school graduates (SMD: 0.15 -0.18).

Table 2.16 is dedicated to analyzing individuals who choose to remain as high school graduates when confronted with uncertainty. The groups under comparison consist of high school graduates who believe they would achieve higher ex-post net value by following any path leading to a two-year degree. Long- and short-term credit constraints are again critical factors. However, now the direction of these influences changes as we compare paths where individuals accumu-

late more years or credits of education. High school graduates who are relatively less credit-constrained are more likely to find higher ex-post net value in a path where they would pursue a college degree. Race reveals significant disparities. Individuals more inclined to find higher net value in a college degree are less likely to be Black and, to a lesser extent, less likely to be Hispanic. Another noteworthy variable is urban residency. Once again, those who determine that a two-year degree holds greater value than their current choice are more likely to originate from and reside in rural areas.

Table 2.17 is dedicated to analyzing individuals who choose a two-year degree in the face of uncertainty. Consistent with the structure of previous tables, I compare those who achieve the highest ex-post net value within the available two-year degree paths to those who find higher value in various paths leading to a four-year degree, as two-year dropouts, or as high school graduates. When examining individuals who would achieve the highest ex-post net value with a four-year degree, there is some evidence that these individuals are less likely to be credit-constrained, as observed in the previous table. However, the standardized mean differences are smaller, especially when considering the four-year college path that also includes two-year college enrollment. Evaluating differences in scenarios where fewer credits would be accumulated, it becomes apparent that while variables representing credit constraints still play a role in assessing the value of remaining a high school graduate, they have less influence in situations where dropping out would have resulted in higher ex-post net value. Race and ethnicity play almost no role. There is only a lower probability of being Hispanic when a obtaining a four-year degree through directly enrollment generates higher net value.

Regarding the type of residence, some noteworthy patterns emerge. Two-year graduates who find higher value in staying as high school graduates are more likely to come from rural

areas but do not exhibit differences in the type of residence after making their choices. In contrast, those who find higher value as two-year dropouts or as four-year graduates starting with two-year college enrollment are more likely to come from and reside in urban areas (SMD: 0.05 - 0.10). In fact, these variables show the most pronounced differences when comparing the value of being a two-year dropout (along with coming from a single-parent home, SMD: 0.10). Combining the findings from other tables and this one, the type of residence indeed has a substantial impact on the likelihood of achieving the highest net value as in a two-year degree. Rural residence increases the likelihood of finding a two-year degree more valuable than one's initial choice. In contrast, if an individual decides to become a two-year graduate, urban residency enhances the likelihood of considering being a two-year dropout or a four-year graduate with two-year enrollment as better alternatives.

Additional patterns emerge concerning abilities. Two-year graduates who find higher value in alternative paths are more likely to possess higher socioemotional endowments (SMD: 0.12 - 0.26), except when compared to the value of becoming a four-year graduate who would enroll through a two-year college, as these individuals typically exhibit stronger socioemotional abilities. Moreover, they tend to have lower endowments in mechanical ability, although this pattern is less pronounced.

Table 2.18 presents the results for individuals who choose to become four-year graduates but begin their college journey in a two-year institution. First, it is intriguing to analyze the first column, which depicts the characteristics of those who actually achieve the highest net value under this path. They differ from those who obtain the same degree and achieve the highest net value without enrolling in a two-year college.

These individuals have lower cognitive ability endowments (0.14 S.D.) and an average

family income during their teenage years that is approximately $20,000 lower. They also have a higher likelihood of being Black and Hispanic. Consequently, those who find higher net value in a four-year degree with direct enrollment have significantly higher cognitive ability endowments (SMD: 0.54) and appear to be less constrained by credit limitations compared to those who actually achieve the highest net value by taking the path through a two-year college. Additionally, they are less likely to be Black or Hispanic (SMD: 0.16 - 0.18) and more likely to come from rural areas. However, they do not exhibit differences in terms of type of residence after completing their educational choices (in the final state).

In general, individuals pursuing a four-year college degree after beginning their educational journey in a two-year college and finding higher net value in alternative paths are more likely to have lower average endowments of mechanical ability (SMD: -0.26 to -0.04), except for those finding higher value in staying as high school graduates. They are also less likely to be Black or Hispanic (SMD: -0.23 to 0.12), with the exception of those finding higher value as dropouts. In general, those who find higher value as four-year dropouts do not exhibit many differences in terms of observed characteristics, but they do show distinctions in terms of abilities. They have lower cognitive (SDM: -0.28) and mechanical (SMD: -0.12) ability levels.

Finally, when analyzing individuals who find higher net value in a two-year degree, we observe patterns that align with what we have seen in previous tables in several variables: i) a higher probability of coming from and living in a rural area (SMD: -0.09 to -0.08), ii) a lower probability of being Black or Hispanic (SMD: -0.23 to -0.12), and a reduced likelihood of coming from a single-parent home (SMD: -0.25). Highlighting these findings is important to recognize the connections between these patterns and the characteristics of individuals more likely to respond to the two-year college subsidy study later. In addition to these general patterns, it's interesting to

note that four-year graduates who enroll in a two-year college and find higher value in a two-year degree appear to be less likely to be credit-constrained. This contrasts with the patterns observed in previous analyses when evaluating the value of paths requiring fewer years of education.

2.5.6.1 The Role of Heteroskedasticity

The introduction of heteroskedasticity in the context of the role of uncertainty in determining post-secondary schooling choices and ex-post value is new. Therefore, in this subsection I discuss the impact of these assumptions in my analysis, especially focusing on the analysis that determines the characteristics that make individuals more sensitive or vulnerable to uncertainty. Although the consideration of heteroskedasticity is theoretical, a likelihood ratio test favors a model with varying variances across family income groups over one assuming homoskedasticity.

Table 2.19 presents the estimates for the standard deviations across family income quartile groups and schooling levels. Notably, these estimates reveal significant differences across income quartiles, and these patterns diverge when we consider different schooling levels. For instance, among four-year graduates, we observe an increase in the standard deviation with rising family income. In contrast, two-year graduates exhibit an intriguing inverse U-shaped relationship between the standard deviation and family income. These patterns are not imposed but rather derived from the inherent variation in earnings across different family income groups within the data set. Recognizing these patterns in the coefficients underscores how the findings related to differences in variables representing short- and long-term credit constraints in the previous analysis should not an artifact of allowing for heteroskedasticity. This would be a concern if we consistently observed that higher income groups always had lower variability, particularly within

paths involving college degrees.

Tables 2.20-2.23 compare the standardized mean differences and statistically significant levels obtained when assuming heteroskedasticity with the results obtained in Tables 2.15-2.18. In general, shutting down heteroskedasticity does not systematically affect the results associated with family income or correlated variables in any specific direction, aligning with the patterns observed in Table 2.19.

Nonetheless, there are some noteworthy differences to discuss. For four-year graduates enrolling directly in a four-year institution and high school graduates, the key conclusions remain qualitatively unchanged, and in most cases, the magnitudes of the standardized mean differences also remain very similar. Among the former group, the most notable difference pertains to family income for those finding higher value as dropouts. The standard deviation shifts from -0.07 in the model with heteroskedasticity to -0.15 in the model with homoskedasticity. However, these differences do not alter the patterns discussed previously.

Table 2.22 compares the standardized mean differences under both error structures for two-year graduates, while Table 2.23 focuses on this comparison for individuals who opt for a four-year degree but begin their journey in a two-year institution. These tables reveal more differences, although, in most cases, these differences are not substantial enough to change the direction of the effects, although significance levels might vary.

In general terms, the patterns discussed previously would be more pronounced under homoskedasticity.

2.5.6.2 Robustness Check for the Great Recession

In order to consider how robust the results presented in the previous subsection are when exposure to the Great Recession is factored in, I replicate tables 2.15 through 2.18 but consider an alternative model. In this model, I include a variable measuring the proportion of years that earnings are observed since 2008 as a control variable in the earnings equation for each schooling state. I refer to this variable as exposure to the crisis. Importantly, 76% of the individuals in the sample had already completed their schooling choices by the time the Great Recession arrived. This analysis allows me to assess the impact of exposure to the crisis on the results and the robustness of the findings in light of this significant external factor.[28]

The results of this analysis can be found in Tables 2.24 through 2.27. These findings maintain the same qualitative patterns observed in the previous analysis. However, there may be variations in the magnitude of differences and significance levels, particularly in variables related to race, ethnicity, and type of residency. Notably, the analysis for high school graduates and four-year graduates who directly enroll in four-year colleges remains relatively stable. On the other hand, we observe that the analysis for two-year graduates and four-year graduates beginning their educational journey in two-year institutions is more susceptible to changes when considering exposure to the Great Recession. It is crucial to emphasize that changes in the direction of the effects are not common under this robustness check. Generally, if differences arise, they tend to increase the magnitude of the standardized mean difference.

Now, we will focus on analyzing the effect of the exposure to the Great Recession on

[28] I also consider an alternative model where this variable affects earnings but it is ignored when calculating choice probabilities. This allows to model the fact that individuals can not anticipate the Great Recession. The results are nosier as the fit for two-year graduates and four-year dropouts is poorer. For populated enough simulated paths the analysis discussed in this section is preserved.

increasing the sensitivity to uncertainty. In Table 2.24, four-year graduates who enroll directly in a four-year college and find higher ex-post value in alternative paths are more likely to have had less exposure to the Great Recession in the last period. This is especially true for those who find higher value in staying with a high school diploma (SMD: -0.19). Conversely, for those who choose to stay as high school graduates (Table 2.25), we observe the opposite trend. Those who find that pursuing a college degree instead of staying as high school graduates would have been a better choice are more likely to have been more exposed to the Great Recession than high school graduates achieving the highest net value (SMD: 0.06 - 0.13). This suggests that they graduated from high school closer to the Great Recession. The last notable difference is observed in the table analyzing those who decide to pursue a four-year degree but start as two-year enrollees (Table 2.27). Individuals who find that going to a four-year college directly and obtaining a four-year degree would have generated higher net value are more likely to have graduated closer to the Great Recession. They have accumulated more years after completing their college choices, in the final states, than those achieving the highest net value (SMD: 0.15).

Combining these patterns suggests that a path where individuals obtain a four-year degree through direct enrollment in a four-year institution was more likely to be optimal ex-post after the Great Recession. The Great Recession likely increased sensitivity to uncertainty for those following alternative paths, especially for those who decided to stay with a high school diploma and those who chose to pursue a four-year degree but through two-year college enrollment.

2.5.6.3 Risk Preferences

This subsection aims to investigate the potential correlation between risk aversion and sensitivity to uncertainty. Understanding this relationship is relevant, as investing in higher education carries a certain degree of risk. Existing literature has suggested that risk aversion can act as a deterrent, influencing individuals' decisions regarding higher education (Belzil and Leonardi, 2013, Heckman and Montalto, 2018). For instance, Belzil and Leonardi (2013) find that individual risk aversion is nearly as significant as parental education in explaining higher education enrollment, particularly for individuals who complete their education up to at least senior year of high school. To achieve this objective, I propose an approach that incorporates a risk aversion measure into the cost equations. The goal is to determine whether more risk-averse individuals are more or less likely to choose the alternative with the highest net value.[29].

The NLSY97 contains lottery questions that can be used to derive risk preference parameters. However, these questions have some disadvantages that merit discussion. Firstly, all available questions were measured later in life, starting in 2010, when most individuals had already made their schooling choices and after the Great Recession. Previous research has shown that risk preferences are time-varying (Sahm, 2012, Frey et al., 2017, and Schildberg-Hörisch, 2018), as they can be influenced by factors such as age and macroeconomic conditions. However, Sahm (2012) concludes that while risk preferences change over time, persistent differences across individuals are a more important source of variation, explaining over 70% of the systematic variation in risk preferences. Secondly, these measures can be endogenous, as post-secondary schooling paths may affect risk aversion. Moreover, the questions are observed only once per individual,

[29]This could be considered as a reduced-form approach to actually considering utility functions that allow for risk aversion

which precludes the use of factor variables to recover a continuous risk measure that is free of measurement error, as has been done in previous studies. Instead, I will use the lottery questions available in the NLSY97 to determine the upper and lower bounds of the relative risk tolerance coefficient ρ_i for each person (see Barsky et al., 1997, Light and Ahn, 2010, and Heckman and Montalto, 2018). Where ρ_i is the inverse of the relative risk aversion parameter.[30]

Figure 2.18 explains how the lottery questions are used to classify each individual according to her relative risk tolerance (RRT). The lottery questions consider hypothetical scenarios of the following fashion: "Suppose you are the only income earner in the family, but that your current job is ending. You have to choose between two new jobs. The first job would guarantee your current family income for life. The second job is also guaranteed for life and possibly better paying, but the income is less certain. There is a 50-50 chance that the second job will double your current family income for life and a 50-50 chance that it will cut your current family income by x for life." where x can be a third, a fourth, or a half.

Figure 2.19 displays the distribution of individuals across relative risk tolerance groups by observed schooling choices. Belonging to a lower category of RRT, indicates lower risk tolerance, meaning they are more risk averse. This graph shows several interesting patterns. In general, four-year college paths are associated with less risk aversion, except for the case of four-year graduates who enroll directly in four-year college. Along with those staying with a high school diploma, these individuals seem to be the most risk averse in the sample. Two-year dropouts are also relatively more risk averse than other individuals in the sample, including relative to two-year graduates. Finally, those who decide to follow four-year paths but start their educational

[30] $U(\mathcal{K}) = \frac{\mathcal{K}^{1-\frac{1}{\rho_i}}}{1-\frac{1}{\rho_i}}$.

journey in a two-year college have the highest fractions of more risk tolerant individuals. This is an important difference relative to those who enroll directly in four-year college.

Tables 2.28, 2.29, 2.30, and 2.31 present the analysis of sensitivity to uncertainty, incorporating indicator variables for individuals' relative risk tolerance. While differences in risk preferences between individuals achieving the highest net value and those who do not are not consistently observed, there are several noteworthy findings that merit attention. Four-year graduates who directly enroll in a four-year college exhibit relatively higher levels of risk aversion, as illustrated in Figure 2.19. However, they are more likely to be even more risk averse if they subsequently discover that another path might have been more advantageous ex-post. This is explained by the fact that individuals finding higher value in alternative paths have higher concentrations in the first categories of risk tolerance who indicate higher risk aversion, and lower in the upper categories who identified individuals less risk averse (Table 2.28). On the contrary, four-year graduates who start in a two-year institution are less risk averse, and if they find higher value in other alternatives paths, they are usually more likely to be even less risk averse (Table 2.31). For two-year graduates, although there are some differences in terms of risk preferences, there are no clear patterns to highlight(Table 2.30).

However, it is not always the case that risk preferences become more pronounced when individuals are more susceptible to uncertainty. For example, high school graduates exhibit more risk aversion relative to individuals pursuing alternative paths within the sample (Table 2.29). Nevertheless, if they place a higher value on obtaining a college degree, they are more likely to be less risk averse. Furthermore, these patterns may not necessarily be associated with the variability of net values under different paths, as there is no clear link between the aforementioned patterns and the standard deviation of the net value across different paths, as indicated in the last row of

the tables.

In terms of how previous results remain robust to the inclusion of variables indicating risk preferences, most of the results usually remain qualitatively unchanged. While there may be changes in the magnitudes of effects and significance levels, alterations in the direction of the effects are relatively uncommon. However, in this analysis, we observe that conclusions regarding socioemotional and mechanical abilities might change, though these differences were not as pronounced and strong as those observed for cognitive abilities in the main analysis.

Lastly, It is crucial to acknowledge that the inclusion of risk preference variables leads to a reduction in the sample size. Specifically, the sample size decreases by nearly 5% (1,017 individuals). To comprehensively assess the impact of these changes, further investigations are necessary to disentangle the extent to which our results are influenced by the alteration in sample size and how much is attributable to the incorporation of risk preference variables.

2.5.7 Ex-ante Probabilities

While the previous exercises primarily centered on comparing ex-post simulated net values, this section introduces an analysis of ex-ante probabilities. These ex-ante probabilities represent the exact values calculated through backward induction that are are utilized in estimating the model (to compute the likelihood function). Idiosyncratic shocks do not affect these probabilities as they are integrated out. It is important to note that these probabilities are functions of individuals' abilities and, consequently, will vary among different simulated individuals who possess varying abilities.

The main goal of this analysis is to explore individuals with high ex-ante probabilities of

pursuing one of three primary paths: remaining as a high school graduate, attaining a two-year degree, or achieving a four-year degree. Similar to previous sections, I distinguish between paths leading to a four-year degree directly from high school and those that start in a two-year institution. In this context, I concentrate on the likelihood of individuals choosing a specific path, given their high ex-ante probability of doing so. More precisely, I examine how various characteristics can either enhance or diminish the likelihood of opting for a path for which individuals already exhibit a predisposition.

While this analysis differs from the one proposed to identify the characteristics of individuals more sensitive to uncertainty, they are closely related. The analysis in this subsection primarily centers on how various characteristics impact an individual's sensitivity to uncertainty, particularly during the decision-making process. This analysis does not take into account the final realization of shocks that become known only in the final state. It is worth highlighting that, although shocks do not impact ex-ante probabilities, they do play a partial role in individuals' choices who are still used in the analysis. An important distinction here is that the reference point is the information available to individuals before they initiate any decision-making, specifically at the point of their high school graduation, instead of the ex-post value that they would receive under alternative paths.

Figure 2.20 displays histograms that depict the ex-ante probabilities of each educational path analyzed. In the graphs, the blue bars represent those who ultimately decide to pursue the respective path when faced with uncertainty, while the orange bars represent those who opt for any other available path. Panel A illustrates the probabilities of remaining a high school graduate, Panel B depicts the probability of attaining a two-year degree, while Panels C and D show the probabilities of embarking on four-year paths leading to a four-year degree. In Panel C, we

consider the path that involves direct enrollment in a four-year college, while in Panel D, we explore the path that commences with enrollment in a two-year institution. The dashed black line indicates the 80th percentile for the entire simulated sample, while the red dashed line represents the 80th percentile exclusively for individuals who ultimately select the corresponding path. This black dashed line serves as the threshold used in the analysis to identify individuals with high probabilities. Consequently, every simulated individual to the right of the dashed line is included in the subsequent analysis.

Figure 2.20 presents histograms illustrating the ex-ante probabilities of each educational path: Panel A. shows the probabilities of achieving a four-year degree, panel b) displays the probabilities of obtaining a two-year degree, and panel c) represents the probabilities of sticking with just a high school diploma. In each graph, the blue bars represent individuals who ultimately select the indicated path, while the orange bars represent those who opt for any other available path in the decision tree. The dashed black line indicates the 80th percentile for the entire simulated sample, while the red dashed line represents the 80th percentile exclusively for those individuals who ultimately choose the corresponding path. This dashed black line serves as the threshold used in the analysis to define individuals with high probabilities. Therefore, every simulated individual to the right of the dashed line is considered in the subsequent analysis.

Figure 2.21 showcases the principal findings of this subsection. This graph illustrates the likelihood of individuals pursuing a path for which they had a high ex-ante probability, conditioned on quartiles of various characteristics. These characteristics include family income, mother's education, cognitive abilities, socioemotional abilities, and mechanical abilities. The black dashed line represents the probability of selecting a path with a high ex-ante probability, independent of any specific characteristic conditioning.

In Panel A, I depict the probability of individuals remaining high school graduates when they have a high ex-ante probability to do so. The conditional probability of staying a high school graduate, given a high ex-ante probability, is approximately 61%. Both family income and mother's education display a similar downward trend and have comparable effects: transitioning from the lowest to the highest quartile results in a reduction in the probability of about 5 percentage points. Individuals in the lowest cognitive quartile or the highest mechanical quartile exhibit the most significant increase in the likelihood of staying with a high school diploma. However, there is a noticeable cognitive gradient that reduces the likelihood of remaining a high school graduate across all levels of cognitive ability, while the effect associated with mechanical ability remains relatively stable and small, except for the last quartile group.

This graph reveals several intriguing patterns. First, both cognitive ability and family income exhibit an inverse U-shaped relationship with the probability of achieving a two-year degree. Second, the probability of obtaining a two-year degree peaks when individuals belong to the second quartile of either of these two characteristics or to the lowest quartile of socioemotional ability. Third, the lowest likelihood of becoming a two-year graduate is observed among individuals in the top cognitive quartile. Lastly, both mother's education and socioemotional ability diminish the likelihood of attaining a two-year degree, although to a lesser extent than the impact of family income.

Panel C depicts the probability of attaining a four-year degree through direct enrollment in a four-year institution for individuals with a high ex-ante probability of doing so. It reveals that approximately 72% of those with a high ex-ante probability of obtaining a four-year degree through this path ultimately achieve it. Notably, mother's education exhibits the most pronounced slope among the analyzed variables, surpassing both cognitive ability and family income. The

transition from the lowest quartile to the highest results in an increase of more than 12 percentage points in the likelihood of becoming a four-year graduate. Cognitive ability and family income also exhibit a positive slope, although the effects from transitioning from the lowest to the highest quartiles are smaller, amounting to 10 and 8 percentage points, respectively. Moreover, other abilities appear to have a limited influence on this probability.

Finally, Panel D presents the probability for the path leading to a four-year degree but through enrollment in a two-year institution. The unconditional probability in this case is just slightly under 14%. Interestingly, the patterns observed here differ significantly from those noted for the probability of obtaining the same degree but through direct enrollment in a four-year college (Panel C). Notably, mother's education again exhibits the most pronounced slope, but this time it is negative. Cognitive and socioemotional ability show a positive slope, but cognitive ability primarily acts to reduce the probability for individuals in the lowest quartiles. Interestingly, family income does not appear to play a significant role in determining this probability. In general, it is intriguing to observe that four-year graduates are influenced by distinct factors when pursuing different paths leading to such a degree.

This analysis underscores the importance of considering multiple college paths and the potential transition from two- to four-year college when examining post-secondary educational decisions. It is evident how these five factors play distinct roles in influencing the likelihood of pursuing various educational pathways, even when there is significant overlap in the paths followed, as seen in panels C and D.

2.5.8 Policy Simulation - Two-year college subsidy

The United States has been engaged in a significant debate regarding the feasibility of providing free two-year college education, a topic of national importance. This discussion gained prominence when President Biden included this policy as a key element of his 2020 campaign agenda and proposed a substantial $90 billion plan in the 2024 fiscal budget. This chapter aims to contribute to this ongoing discourse by conducting a policy simulation that evaluates the potential impact of an annual subsidy for two-year college education. This policy exercise further helps us understand the role of credit constraints or financial incentives on schooling choices. According to Ma and Pender (2022), the average annual cost for public two-year college attendance, covering tuition, room and board, and additional expenses, is approximately $16,500.[31] Therefore, I conduct a policy exercise on which each of the transitioning costs associated to two-year college are reduced by this amount (two arrows in the decision tree).

Figure 2.22 provides a comparative analysis of choices under two scenarios: the status quo, which represents the absence of the policy, and the scenario following the introduction of the subsidy. The introduction of the subsidy results in a significant shift in educational attainment. Specifically, the proportion of individuals obtaining a two-year degree increases from 8.97% to 13.39%, marking a substantial rise of 4.5 percentage points (equivalent to a 50.39% increase). Additionally, the fraction of individuals with only a high school diploma experiences a reduction of 3.2 percentage points (representing an 13.78% decrease), along with a 0.8 percentage point decline (5.78% decrease) in the fraction of four-year dropouts. This shift comes at the cost of an increase in the number of two-year dropouts by 2.13 percentage points (13.62%) and a decrease in

[31] This number is adjusted to real prices of 2018, so that it has the same metric of costs. Interestingly, this amount is similar to what subsidizing one year of schooling in K-12 education costs.

the number of four-year graduates by 2.3 percentage points (6.2%). These findings underscore the complex trade-offs associated with the introduction of the subsidy and its impact on educational choices.

A natural question that may arise is whether the introduction of the policy increases the percentage of individuals who reach the highest net value under their chosen path. Table 2.32 and Figure 2.23 aim to address this question. Table 2.32 shows the change in the percentage of individuals reaching the highest net value for different groups, with a focus on those making two-year college choices. Always-takers in this context are individuals who follow a two-year path regardless of the presence of the subsidy. This group is further divided into those who would obtain a two-year degree and those who would become two-year dropouts, regardless of the introduction of the subsidy. On the other hand, compliers are those who were choosing something else in the status quo and now, given the introduction of the subsidy, would choose to be either two-year graduates or two-year dropouts.[32] In all cases, we observe that the fraction of always-takers and compliers achieving the highest net value option in two-year college choices increases, indicating that the policy is helping individuals along these margins to increase their ex-post highest net value. However, compliers are generally less likely to achieve the highest net value. This is explained by the fact that individuals on the margin are much more sensitive to uncertainty, as even small shocks can make them rank alternatives differently ex-post than when making choices, since the expected value of different alternatives were already too close.

This table also shows that, in the aggregate, this policy is not able to meaningfully change the percentage of individuals reaching the highest net value. The reason behind this finding

[32]Note that there might also be compliers who end up as four-year graduates or dropouts in response to the subsidy, as they get an incentive to follow these paths starting in a two-year college. However, to simplify the analysis, I focus on those whose terminal decisions are two-year college choices.

is better illustrated in Figure 2.23. The figure demonstrates how different sizes of subsidies, specifically in the two-year college sector, affect the percentage of individuals who find their choice to be the best ex-post outcome. The blue line represents the fraction of two-year graduates reaching the highest net value for various subsidy sizes. The yellow lines represent the fraction of four-year graduates reaching the highest net value for different subsidy sizes, differentiating between direct (solid line) and two-year (dashed) enrollment types. It becomes evident that there is a trade-off between those achieving the highest net value in one sector versus the other. As the value of becoming a two-year graduate increases due to the subsidy, some individuals who were not in the zone where uncertainty was likely to affect them begin to do so. This is explained by the narrowing of the gap in expected terms between different alternatives.

Finally, Table 2.33 characterizes the compliers who, due to the policy, decide to pursue a two-year degree. We use individuals who were making the same choice as these compliers in the status quo but continued to choose the same path under the counterfactual policy (never-takers) as the reference group. The table follows a similar structure to the ones used to characterize sensitivity to uncertainty.

From this table, we observe that individuals more likely to respond to this policy by obtaining a two-year degree are more likely to be white, hail from and reside in rural areas, and come from two-parent households. The role of variables that proxy for credit constraints differs depending on the comparison margin we analyze. Those transitioning from four-year college choices are more likely to face credit constraints and exhibit lower levels of cognitive ability than their never-taker counterparts. However, those who would have chosen to be two-year dropouts or high school graduates in the absence of the policy are not credit constrained. This aligns with the idea that, for these individuals, the expected value of becoming a two-year graduate was al-

ready close to the value of their actual choice. Therefore, this policy would ease credit constraints primarily for four-year college graduates and dropouts, who are also more likely to find that their choice is not the highest net value alternative.

In general, this table complements the results shown in Tables 2.15-2.17, as we find qualitatively similar patterns, although with varying magnitudes in the columns where individuals making different choices under uncertainty would find higher net value as a two-year graduate.

In general, these results emphasize the complexities associated with introducing a subsidy in higher education for just one sector. Despite the subsidy affecting only the costs of one type of college, it alters decisions and ex-post preference rankings for individuals across all dimensions.

2.6 Conclusions & Discussion

This chapter aims to explore the role of uncertainty in the decision-making process for postsecondary schooling choices and to identify the individuals most susceptible to its effects. To address this question, I design a model allowing for uncertainty to differ among individuals from different backgrounds, by including earnings shocks heteroskedastic by family income groups.

Through a simulation exercise where all individuals receive perfect information, I find that the uncertainty affecting college investment decisions imposes significant costs. In the absence of uncertainty, aggregate net value, which proxies for individuals' welfare, would increase by 11%. Moreover, it becomes apparent that not everyone is equally affected by uncertainty. To identify those more sensitive to its impacts, I compare individuals who achieve sub-optimal ex-post outcomes to those following the same path and who would not change their choice even if they could have had perfect foresight.

The observation that another alternative, rather than the one chosen under uncertainty, could generate a higher ex-post net value is not unexpected but instead a natural consequence of dealing with unpredictable factors. This study contributes to the existing literature by shedding light on how this phenomenon varies between two- and four-year college paths and how individuals with distinct characteristics specific to their chosen educational trajectory can exhibit varying degrees of sensitivity to uncertainty. The research reveals noteworthy disparities in the attributes of individuals who attain the highest net value from their chosen path compared to those who do not, despite following the same educational route. Family income, family structure, race, cognitive abilities, and urban or rural background can render individuals more susceptible to unfavorable shock realizations, affecting their likelihood of achieving the highest ex-post net value. This analysis provides a deeper understanding of the impact of uncertainty on individuals' decision-making processes. I conduct a decomposition analysis that dissects the extent to which variations in costs, earnings, or a combination of both factors contribute to explaining sensitivity to uncertainty. This analysis underscores the finding that cost uncertainty is usually more likely to have a negative impact on individuals who decide to get a college degree.

Finally, I conduct a policy simulation to assess the implications of an annual two-year college subsidy. This policy analysis enables us to examine which individuals are more likely to adjust their decisions when financial constraints are mitigated. Introducing the subsidy triggers a shift in educational choices, resulting in more individuals obtaining two-year degrees. However, it also incentivizes an increase in the number of two-year dropouts and, in general, exerts an influence across all decision margins. In addition, I find that individuals who pursue a two-year degree due to the subsidy are more susceptible to adverse shocks, in contrast to those who were already inclined toward that type of degree in the absence of the subsidy. Taken together,

these findings underscore the complexities of designing effective policies for higher education, especially when targeting only one sector. The two-year college subsidy elicits compliance across all decision margins, and these individuals, positioned at the margins of indifference and thus more likely to respond, simultaneously exhibit a heightened sensitivity to uncertainty.

2.7 Figures and Tables

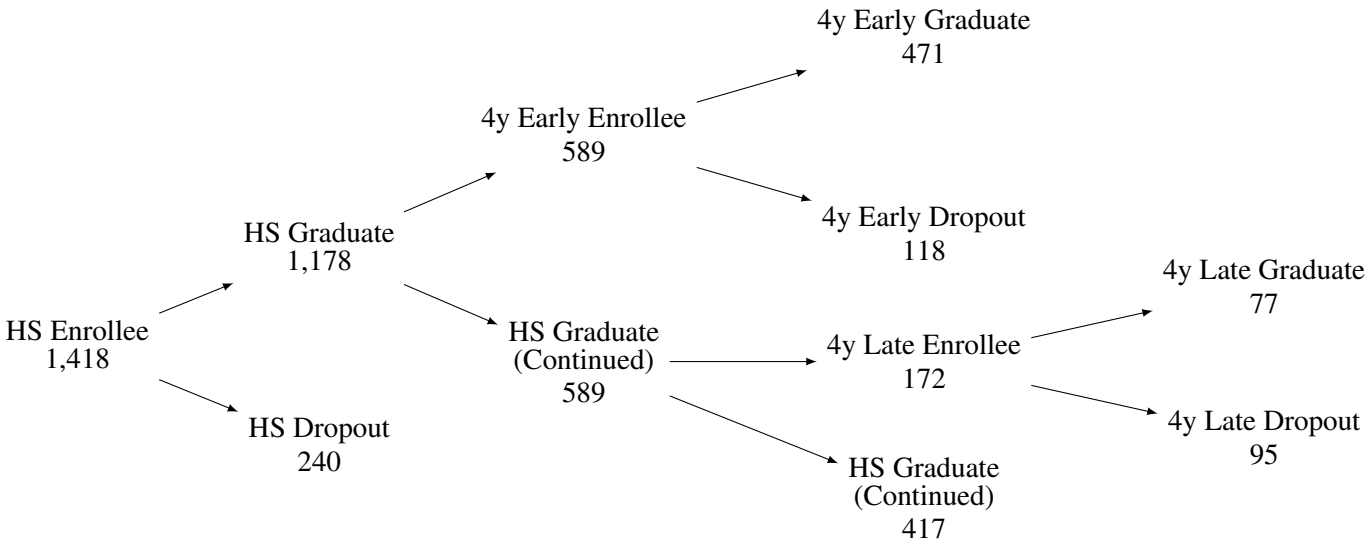


Figure 2.1: Decision Tree in Eisenhauer, Heckman and Mosso (2015)

Note: The number of observed individuals visiting each state is shown below the name of each choice. HS is an abbreviation for High School and 4y for four-year college.

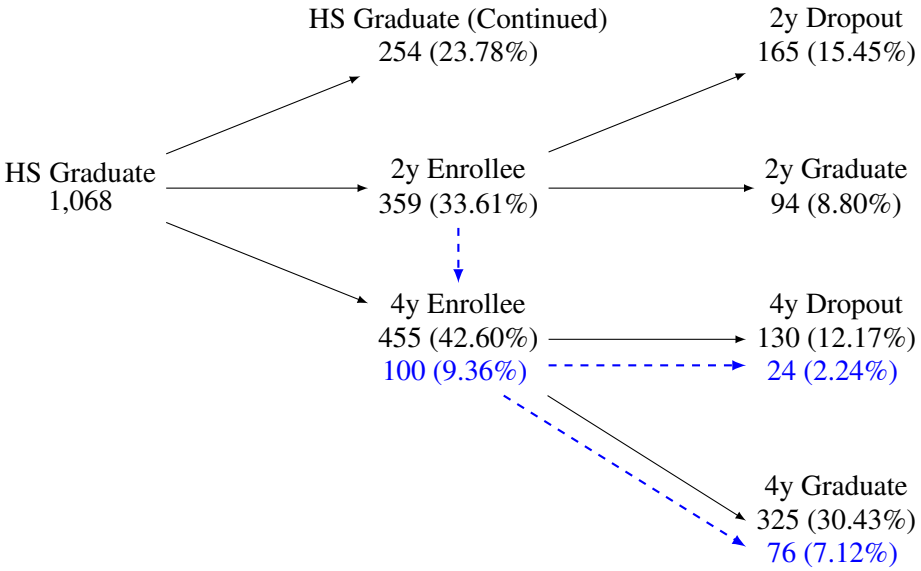


Figure 2.2: Decision Tree in This Study

Note: The number of observed individuals and the percentage of individuals visiting each state are shown below the name of each choice. HS is an abbreviation for High School, 2y for two-year college, and 4y for four-year college.

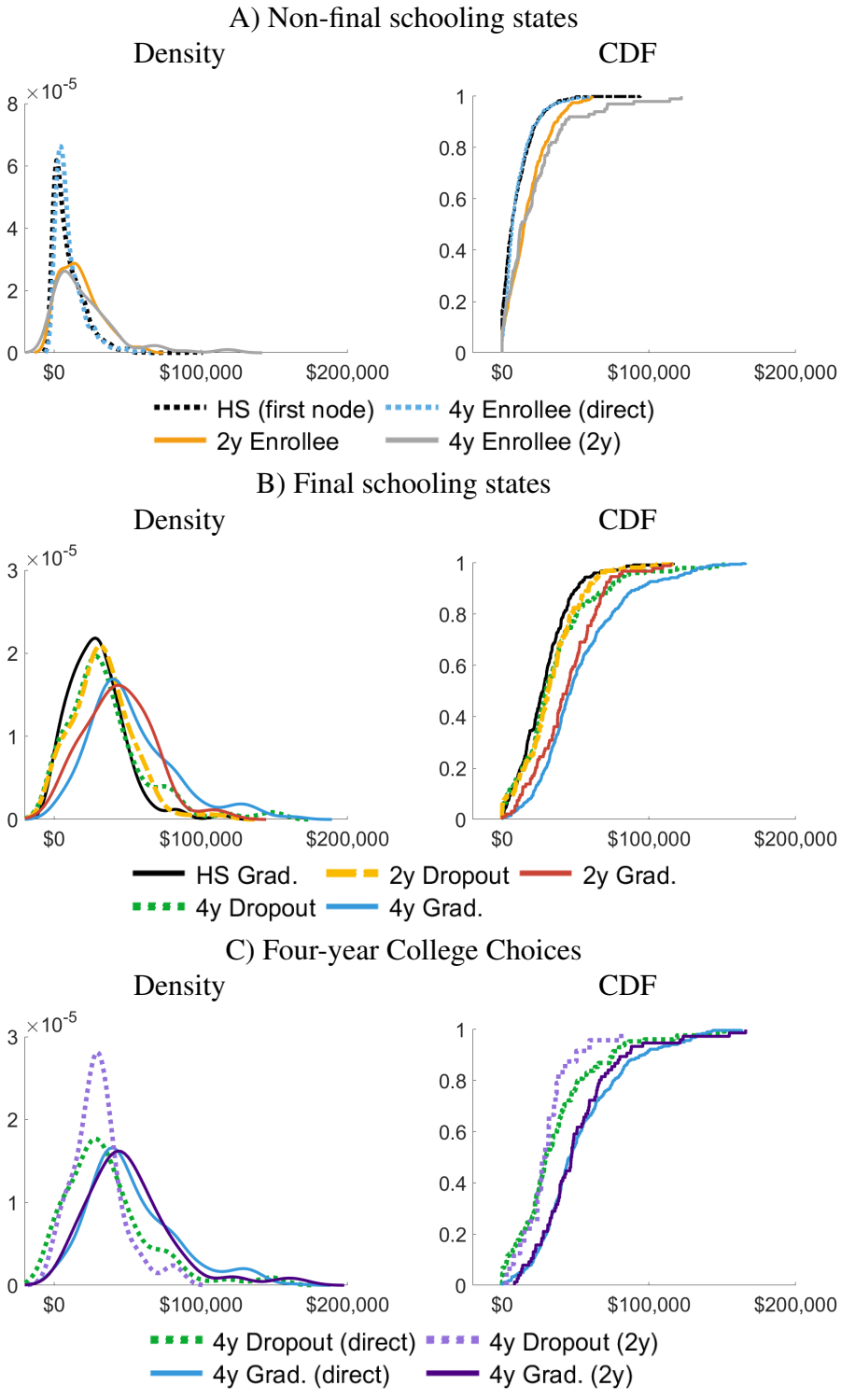


Figure 2.3: Kernel Densities (on the left) and the Empirical Cumulative Density Function (on the right) of Weighted Average Earnings by Schooling Level (Adjusted to 2018 Real Prices).

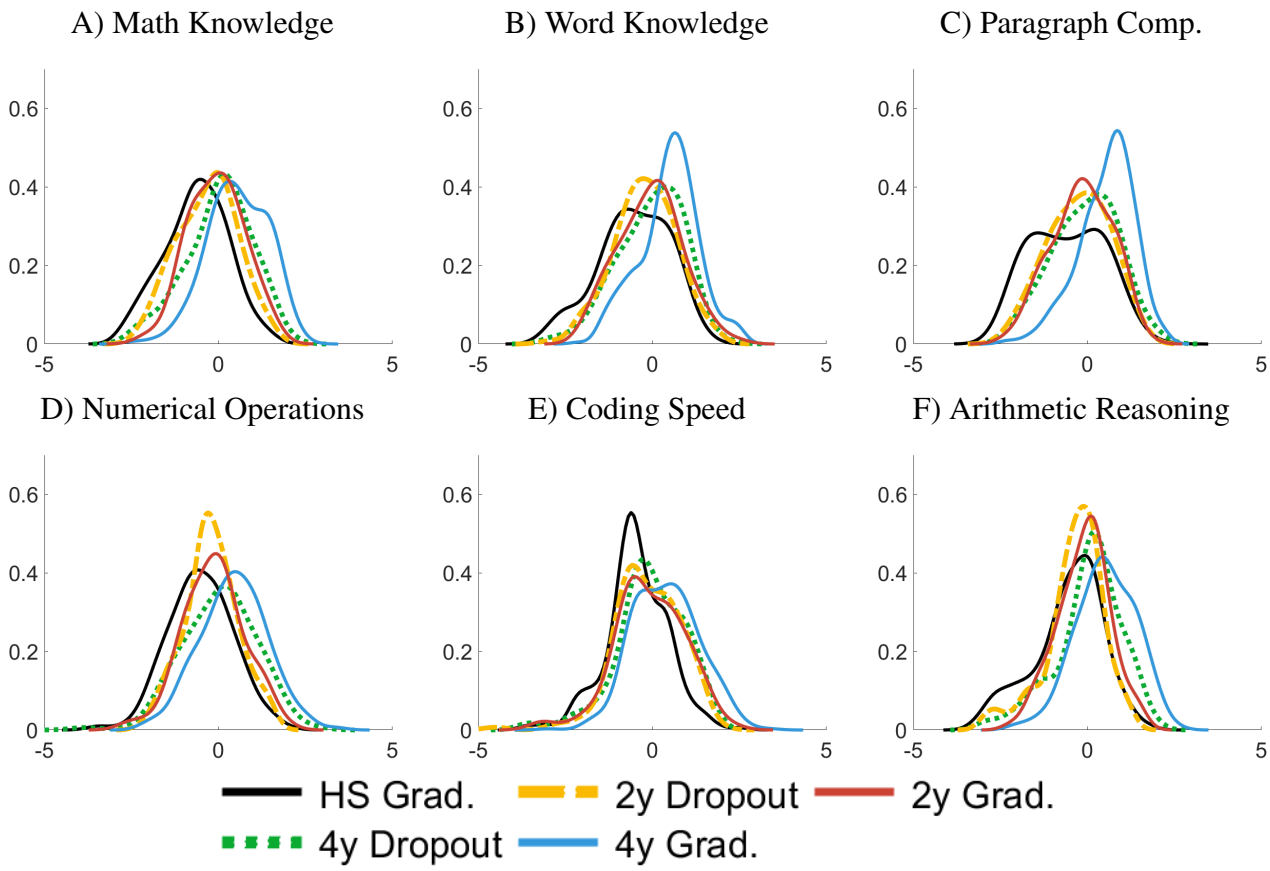


Figure 2.4: Kernel Densities of Standardized ASVAB Test Scores in the Cognitive System by Schooling Level.

Note: Paragraph Comp. stands for paragraph comprehension. Individuals who ultimately select the same four-year college choice are grouped together, irrespective of their prior enrollment in a two-year college.

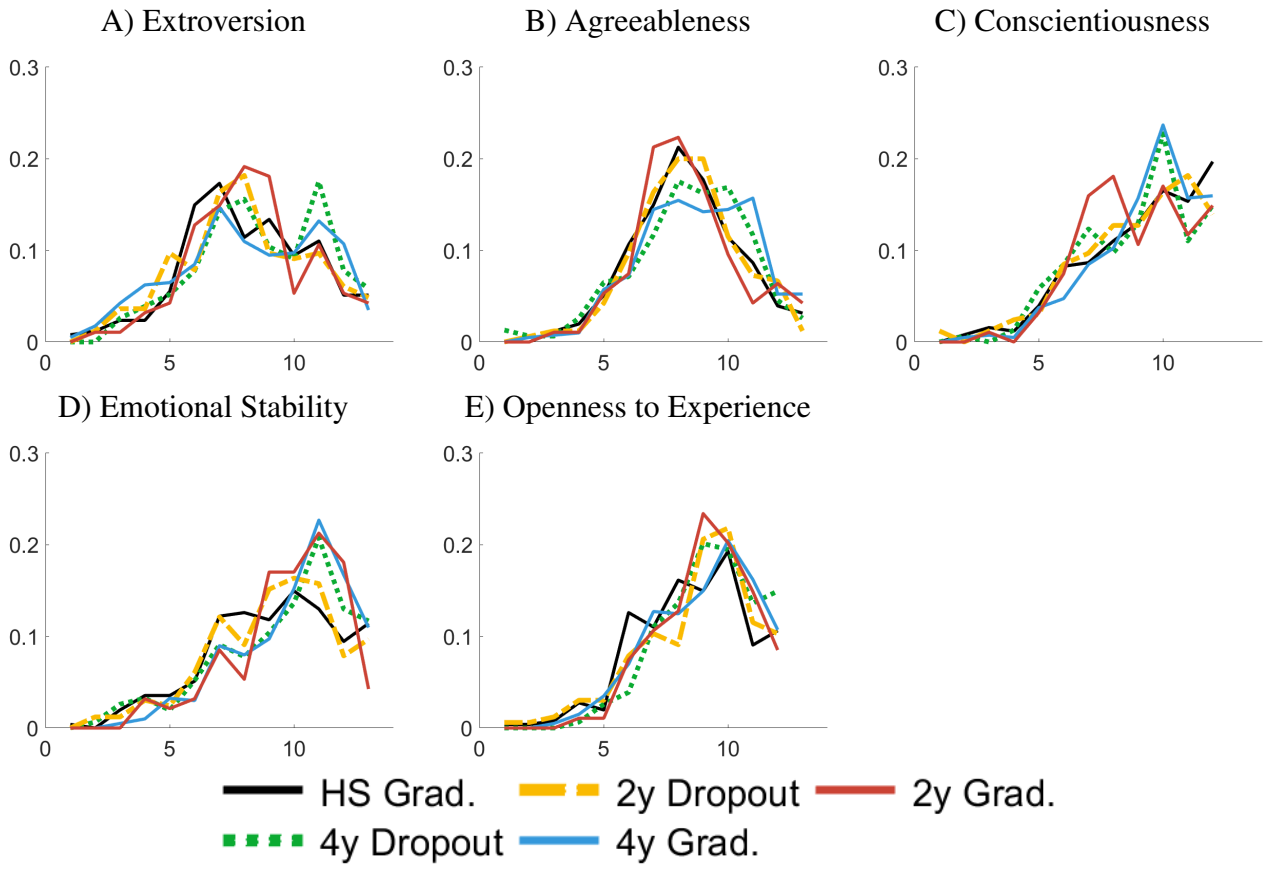


Figure 2.5: Fraction of Individuals per Answer of the TIPI Measures in the socioemotional System by Schooling Level.

Note: Individuals who ultimately select the same four-year college choice are grouped together, irrespective of their prior enrollment in a two-year college.

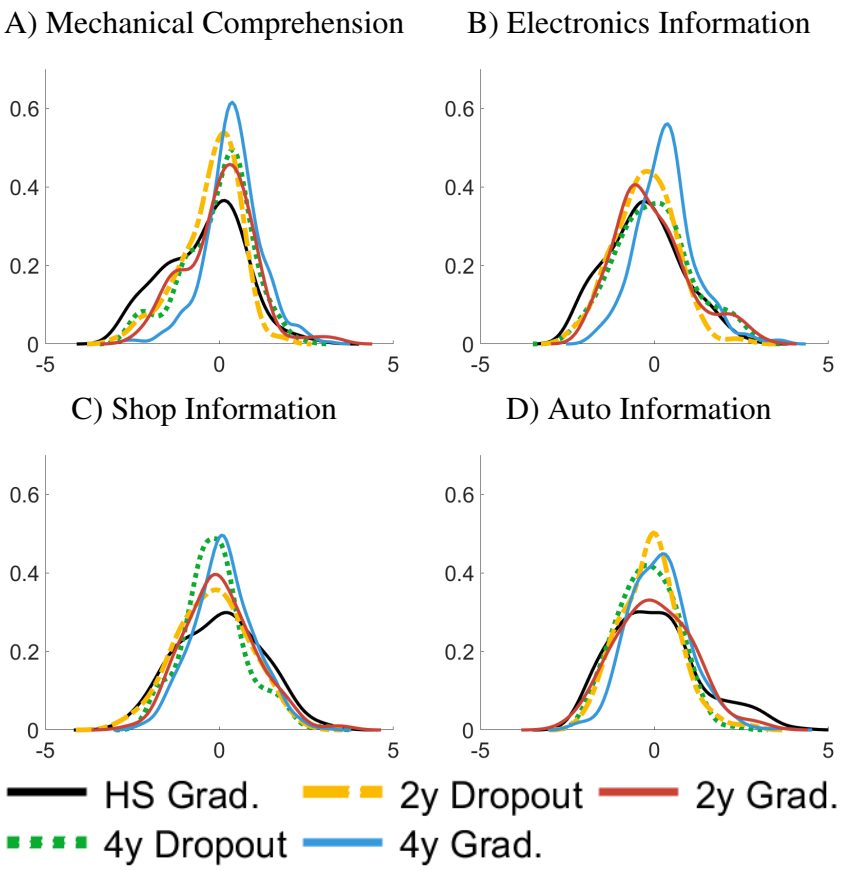


Figure 2.6: Kernel Densities of Standardized ASVAB Test Scores in the Mechanical System by Schooling Level.

Note: Individuals who ultimately select the same four-year college choice are grouped together, irrespective of their prior enrollment in a two-year college.

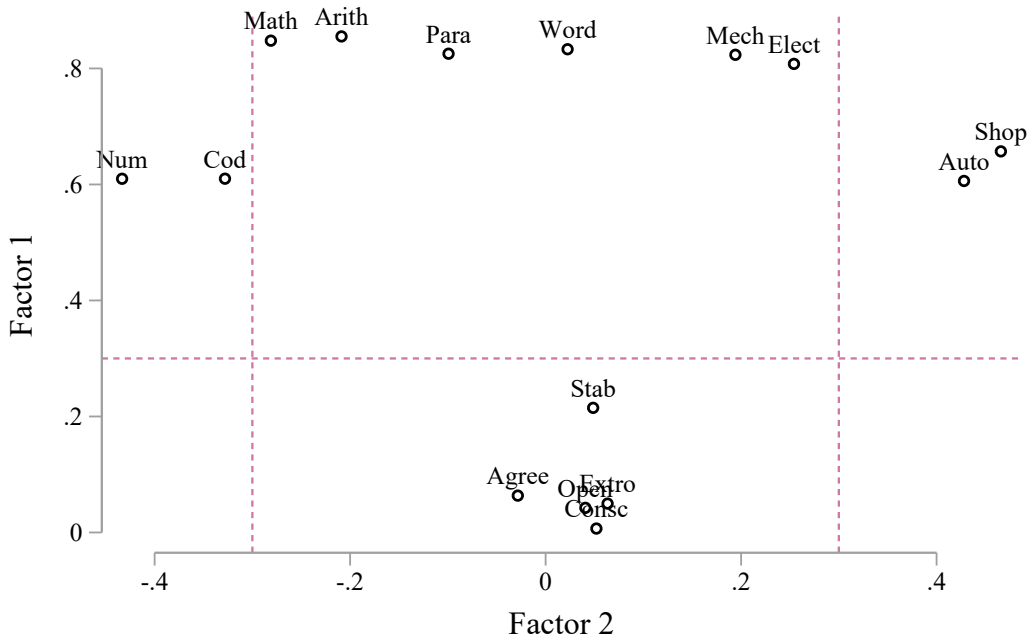


Figure 2.7: Loadings from the Exploratory Factor Analysis for ASVAB Tests. Using the Results Only for the First Two Factors.

Note: Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations, Mech = mechanical comprehension, Auto = auto information, Shop = shop information, Elect = electronics information, Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = Conscientiousness.

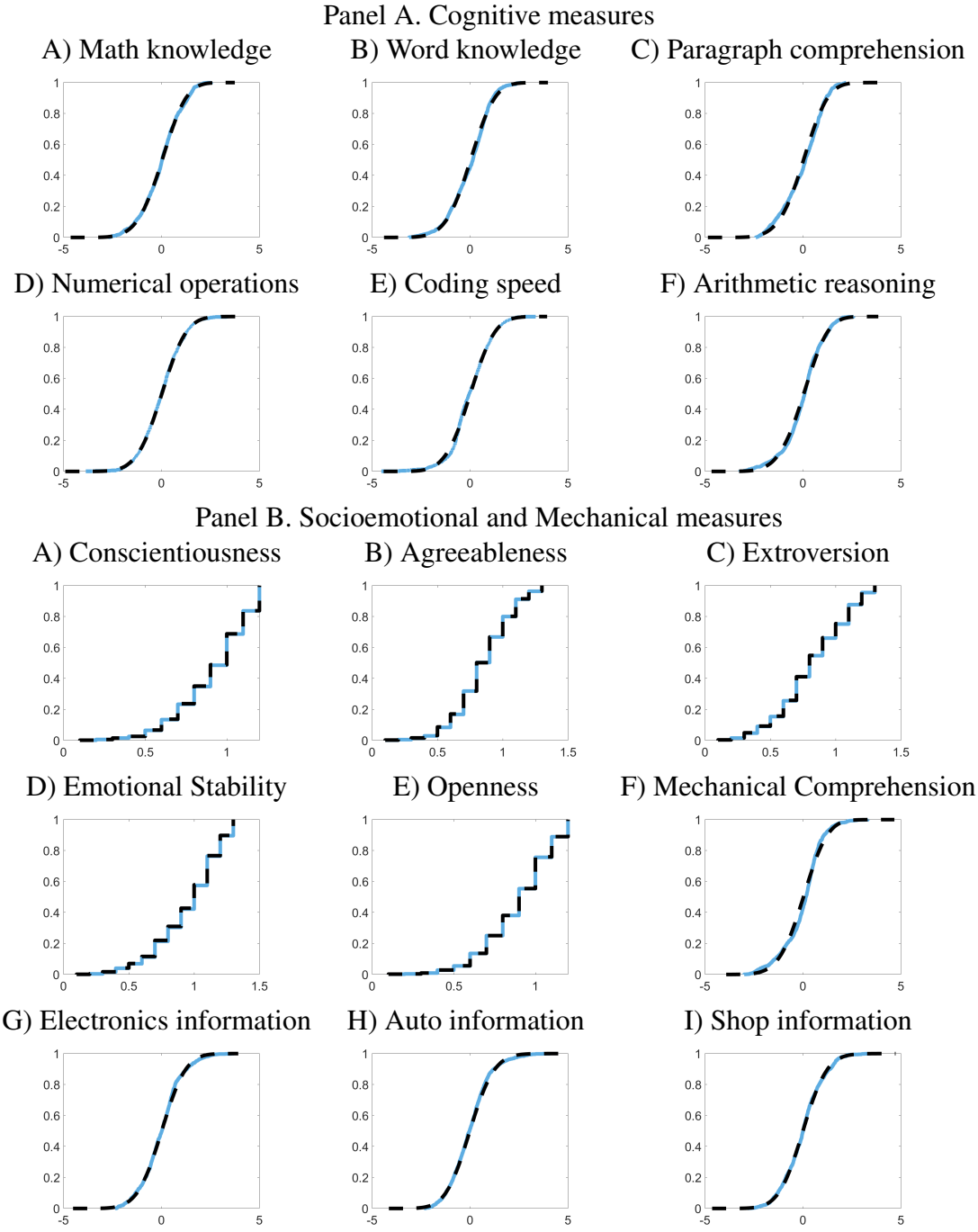


Figure 2.8: Goodness of Fit of Measures.

Note: Comparison between the CDF of the observed data (blue, solid line), the CDFs of the simulated data (black, dashed line). The simulated data contains 100 replications of the data (106,800 observations in total).

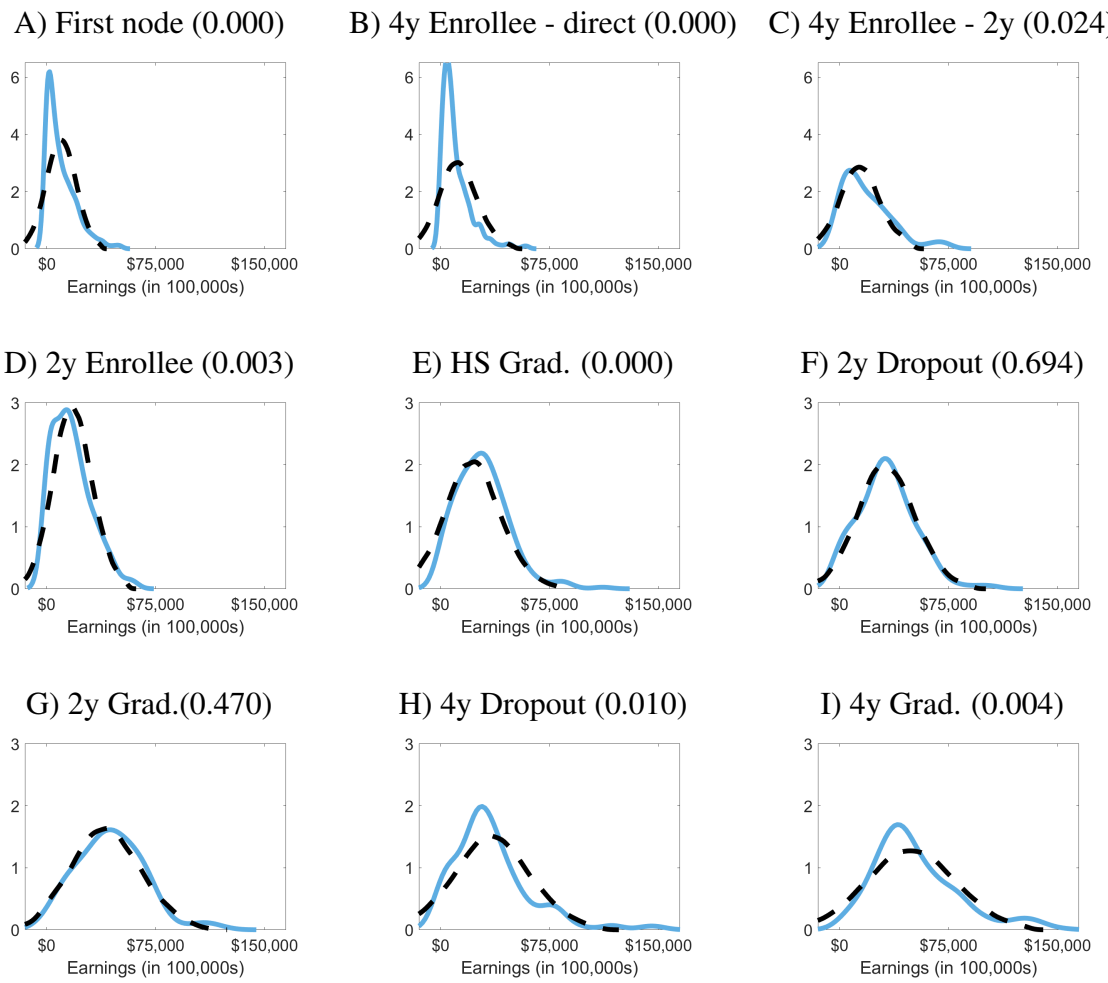


Figure 2.9: Goodness of Fit of Earnings.

Note: Comparison between the CDF of the observed data (blue, solid line) and the CDF of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. The simulated data contains 100 replications of the data (106,800 observations in total).

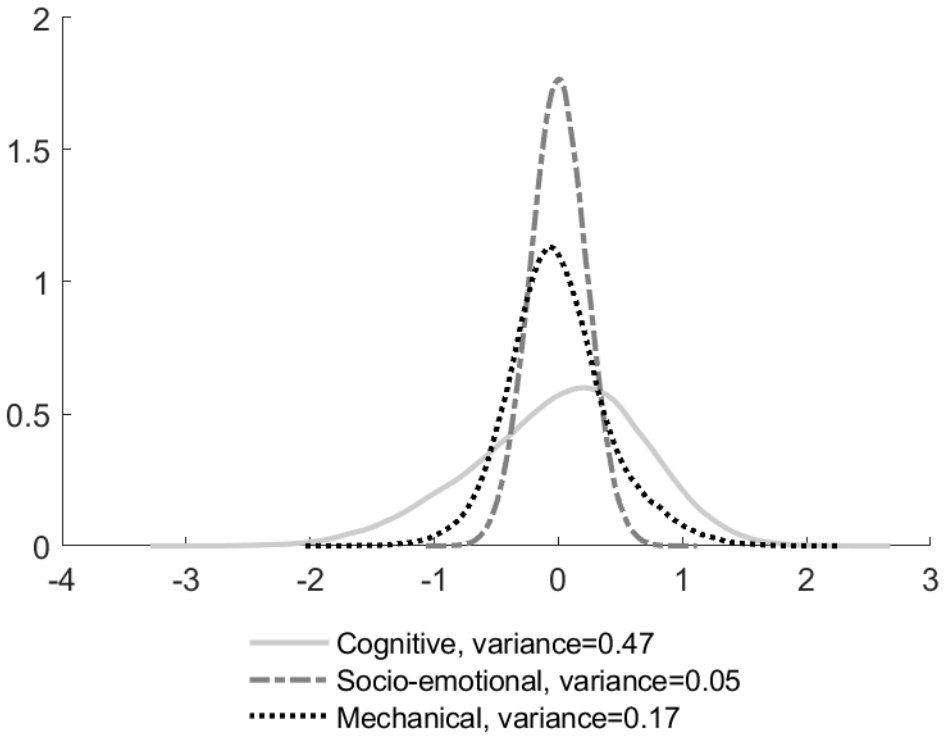


Figure 2.10: Densities of Simulated Abilities, Regardless of the Schooling Choice.

Note: The simulated data contains 100 replications of the data (106,800 observations in total).

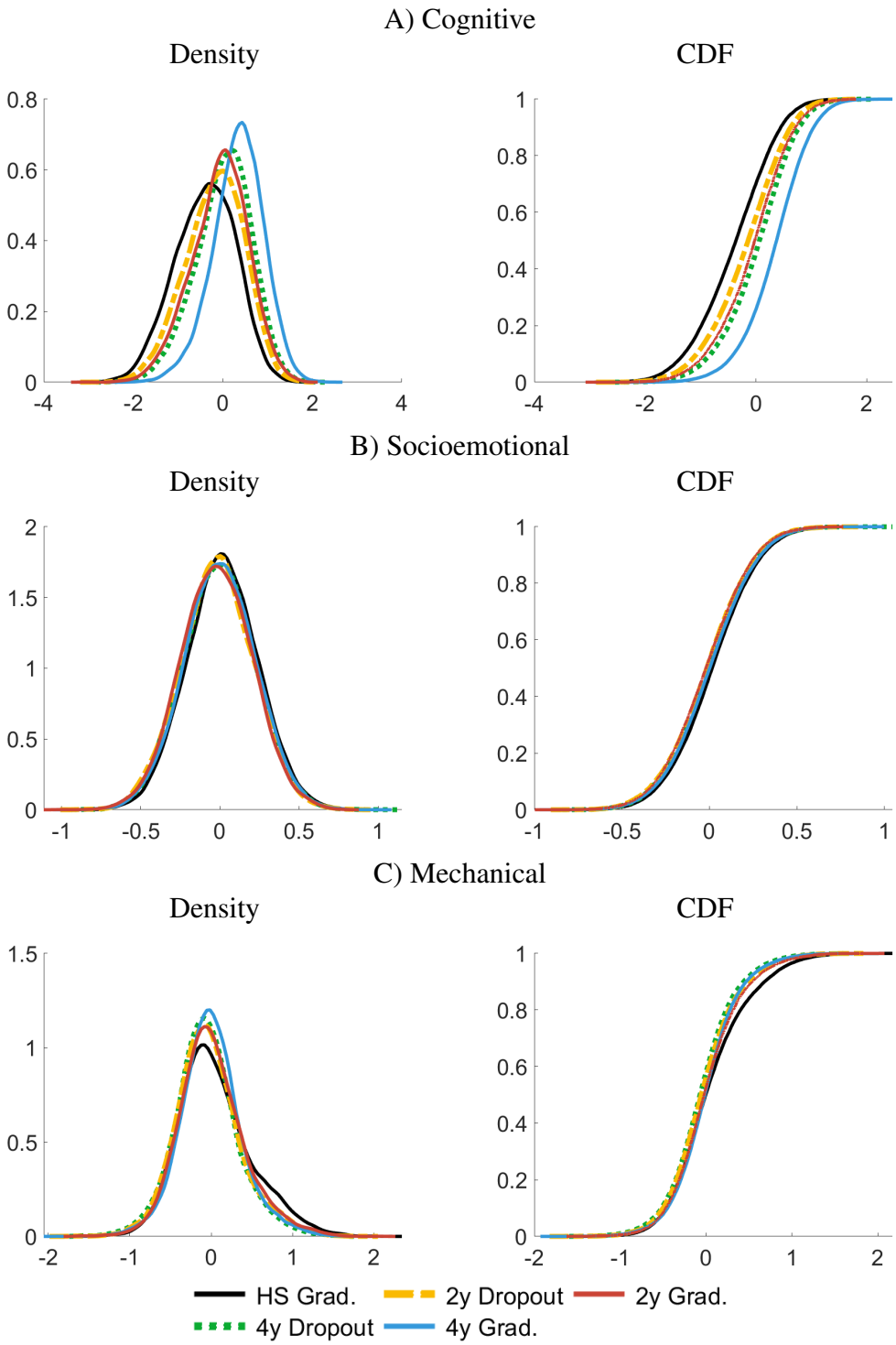


Figure 2.11: Density and CDF of Each Simulated Ability, Differentiating by Schooling Level.

Note: The simulated data contains 100 replications of the data (106,800 observations in total). Kernel densities (on the left) and empirical cumulative distribution functions (on the right) for the simulated abilities by schooling trajectory. Individuals who ultimately select the same four-year college choice are grouped together, irrespective of their prior enrollment in a two-year college.

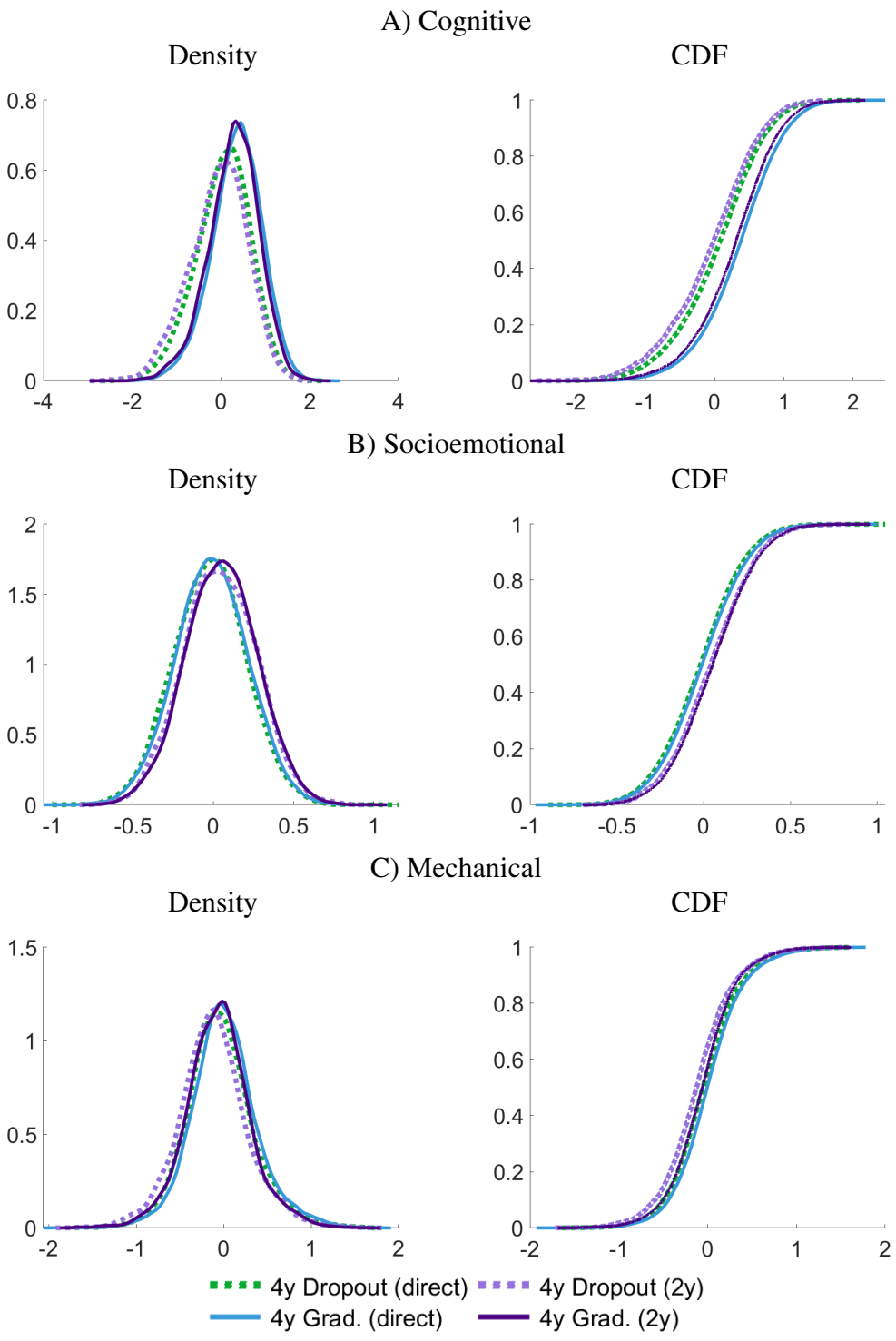


Figure 2.12: Distribution of Abilities for Four-year Graduates and Dropouts

Note: The simulated data contains 100 replications of the data (106,800 observations in total). Kernel densities (on the left) and empirical cumulative distribution functions (on the right) for the simulated abilities by schooling trajectory.

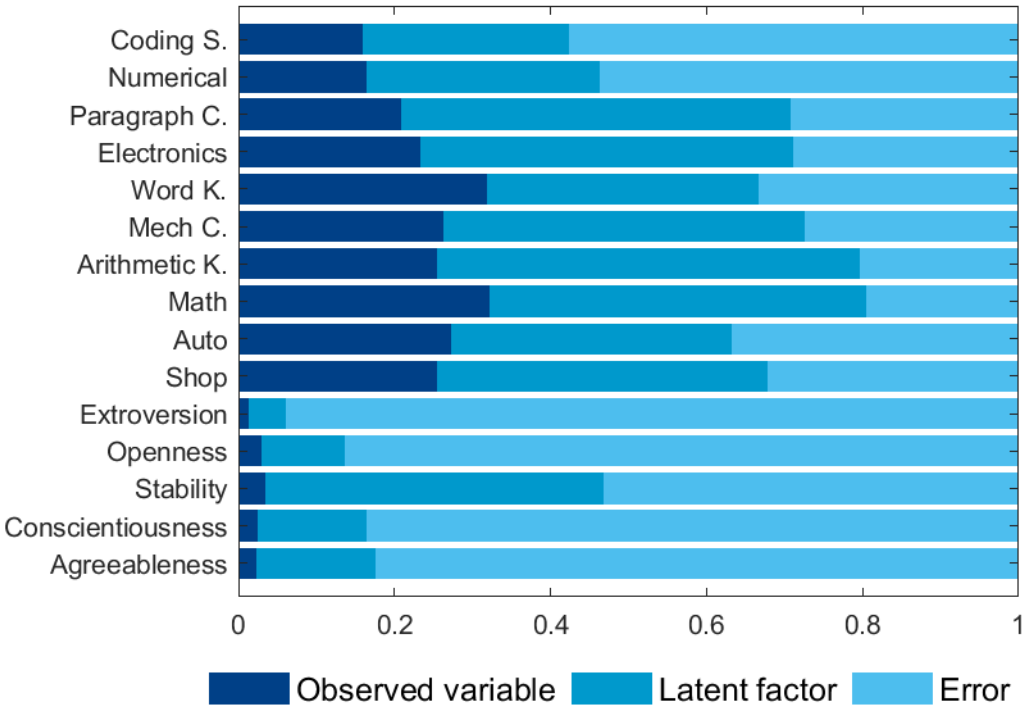


Figure 2.13: Variance Decomposition of the Measurement System.

Note: The simulated data contains 100 replications of the data (106,800 observations in total). Arithmetic K. = arithmetic reasoning, Math = math knowledge, Word K. = word knowledge, Paragraph C. = paragraph comprehension, Coding S. = coding speed, Numerical = numerical operations, Mech C. = mechanical comprehension, Auto = auto information, Electronics = electronics information, Shop = shop information, Stability = emotional stability.

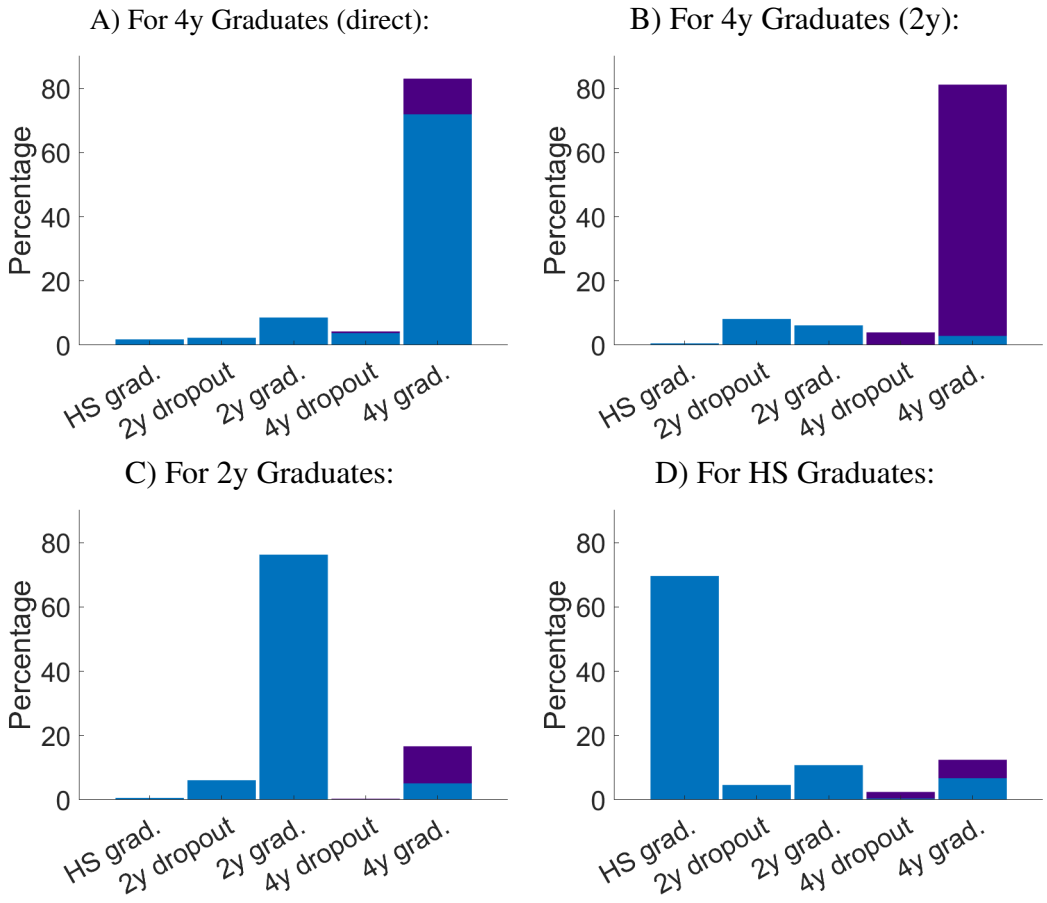


Figure 2.14: Percentage of Individuals Achieving the Highest Net Value Option Under Different Schooling Paths

Note: the title indicates the path that is followed under uncertainty. The category of the bar indicates the option generating the highest net value in ex-post terms, which might coincide or not with the chosen schooling path. Purple differentiates four-year paths that started college enrollment in a two-year institution. Those making these choices are differentiated in the title with the term "2y," while those enrolling directly in four-year college are differentiated by the term "direct."

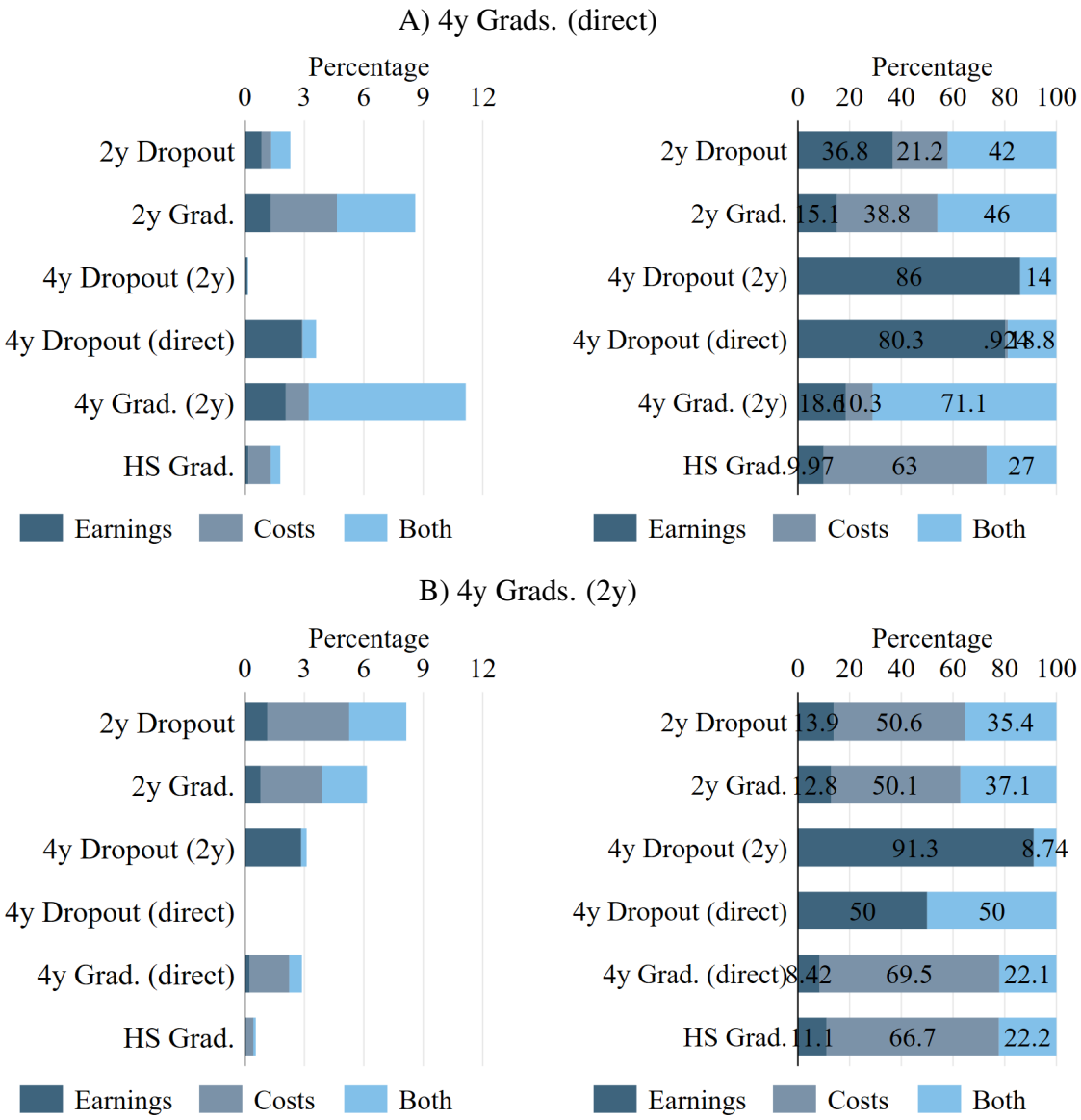


Figure 2.15: Role of Earnings and Costs in Determining that the Path Selected Under Uncertainty is not the Highest Net Value Path

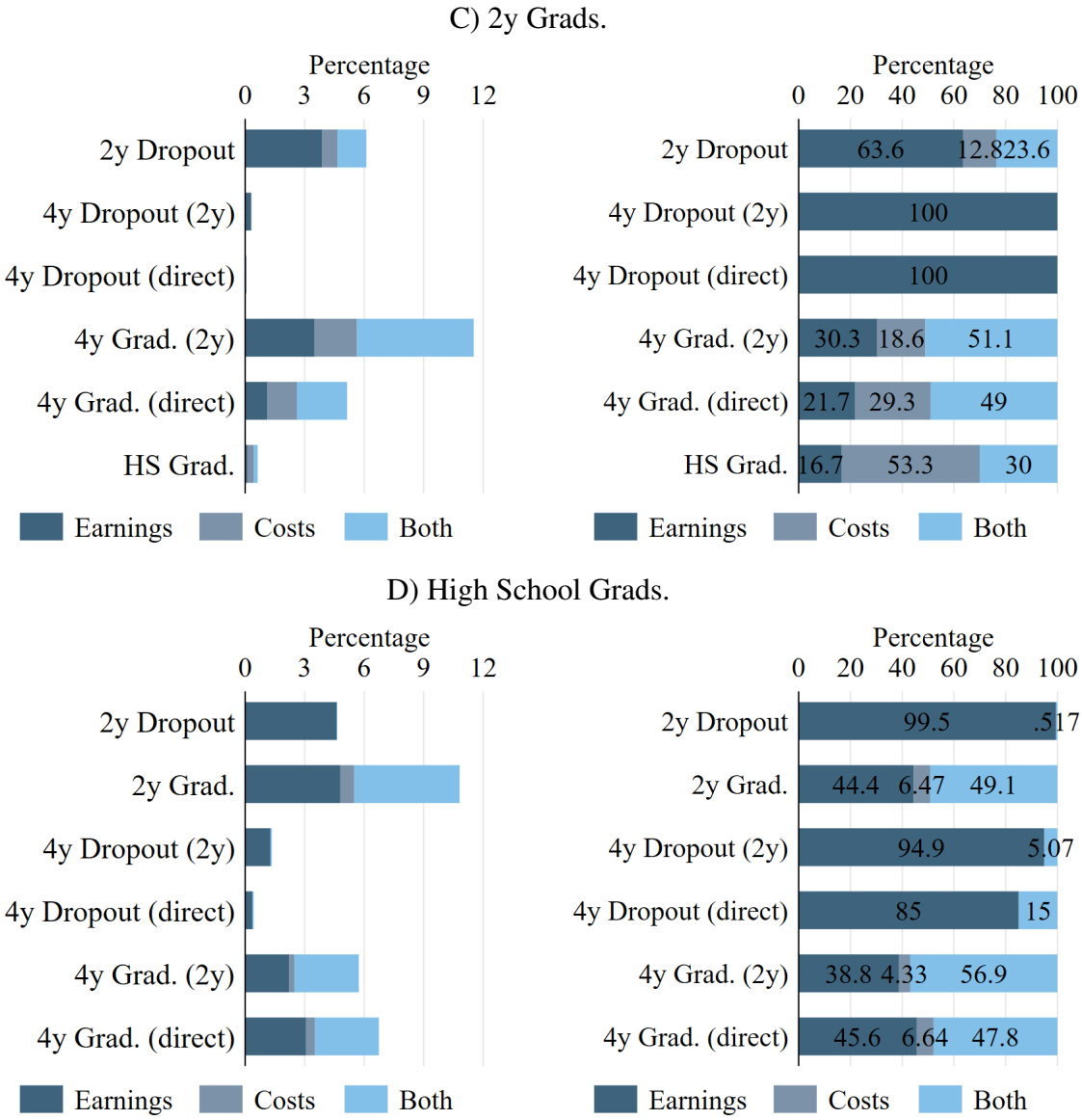


Figure 2.16: Role of Earnings and Costs in Determining that the Path Selected Under Uncertainty is not the Highest Net Value Path

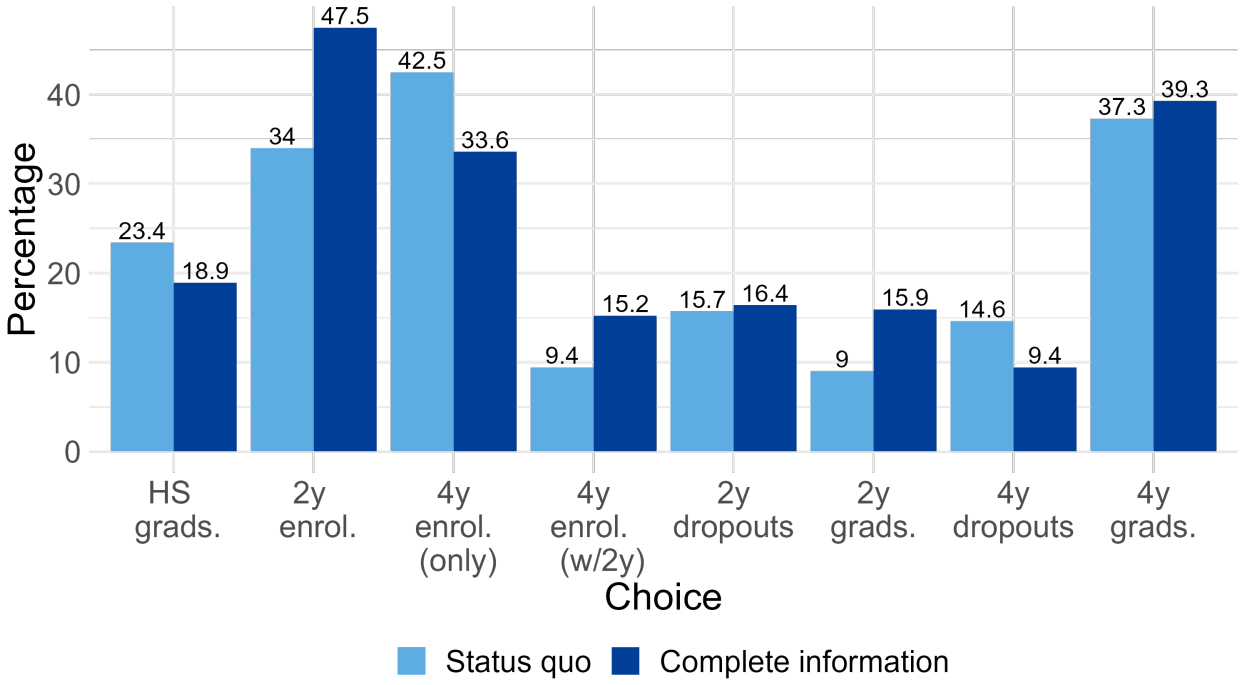


Figure 2.17: Comparison of Choices under the Status Quo and Complete Information.

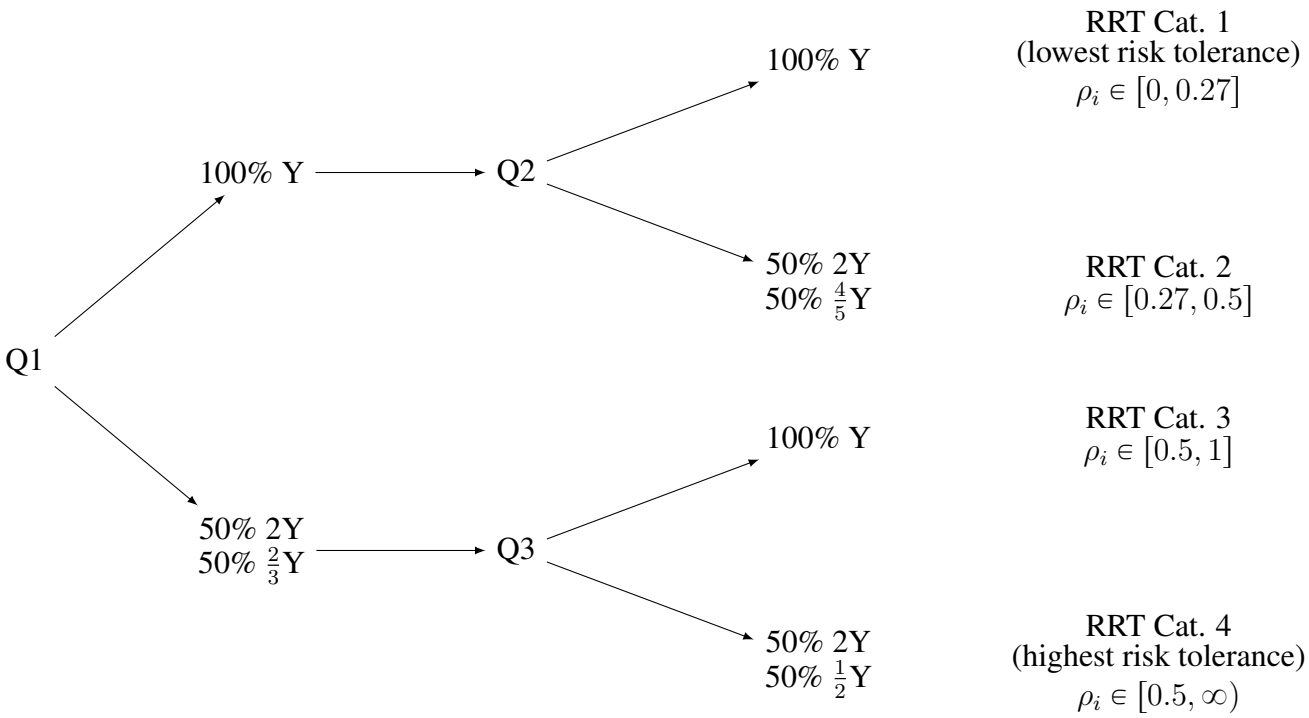


Figure 2.18: Measuring Risk Preferences in the NLSY97

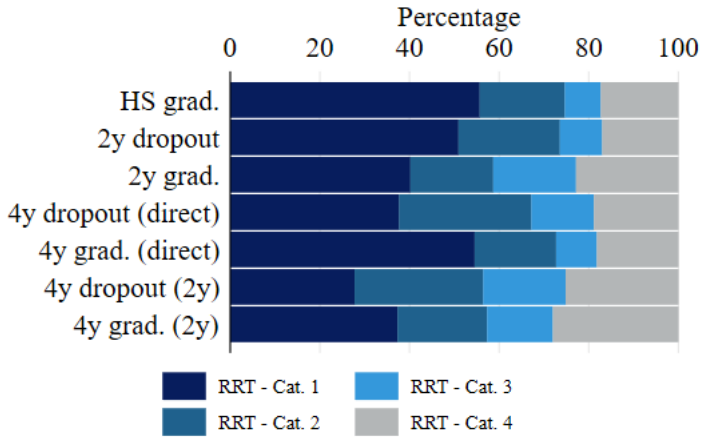


Figure 2.19: Relative Risk Tolerance (RRT) for Individuals Choosing Different Schooling Paths

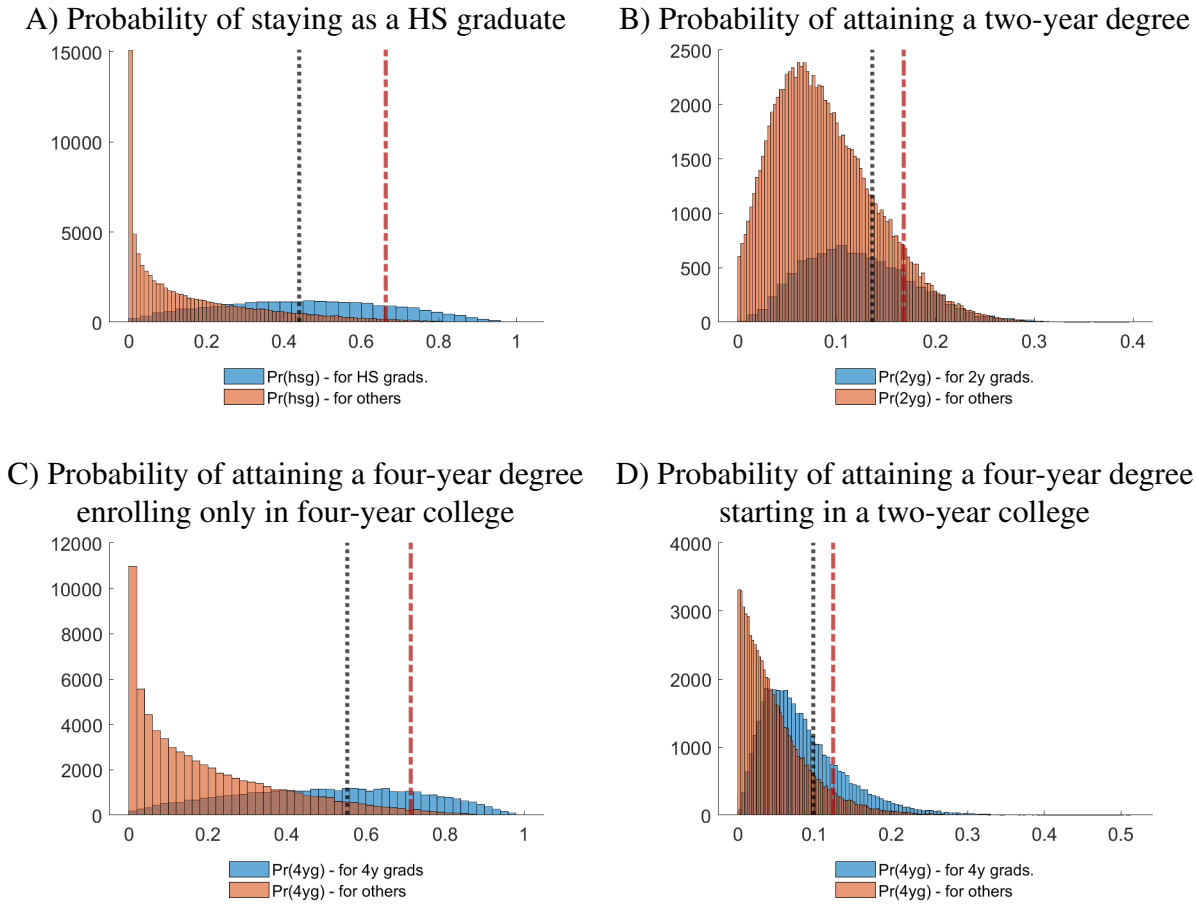


Figure 2.20: Histograms of Simulated Ex-Ante Probabilities.

Note: The dashed black line represents the 80th percentile for all simulated individuals. While the dashed red line marks the 80th percentile of individuals actually choosing to pursue the path analyzed in each graph (blue bars).

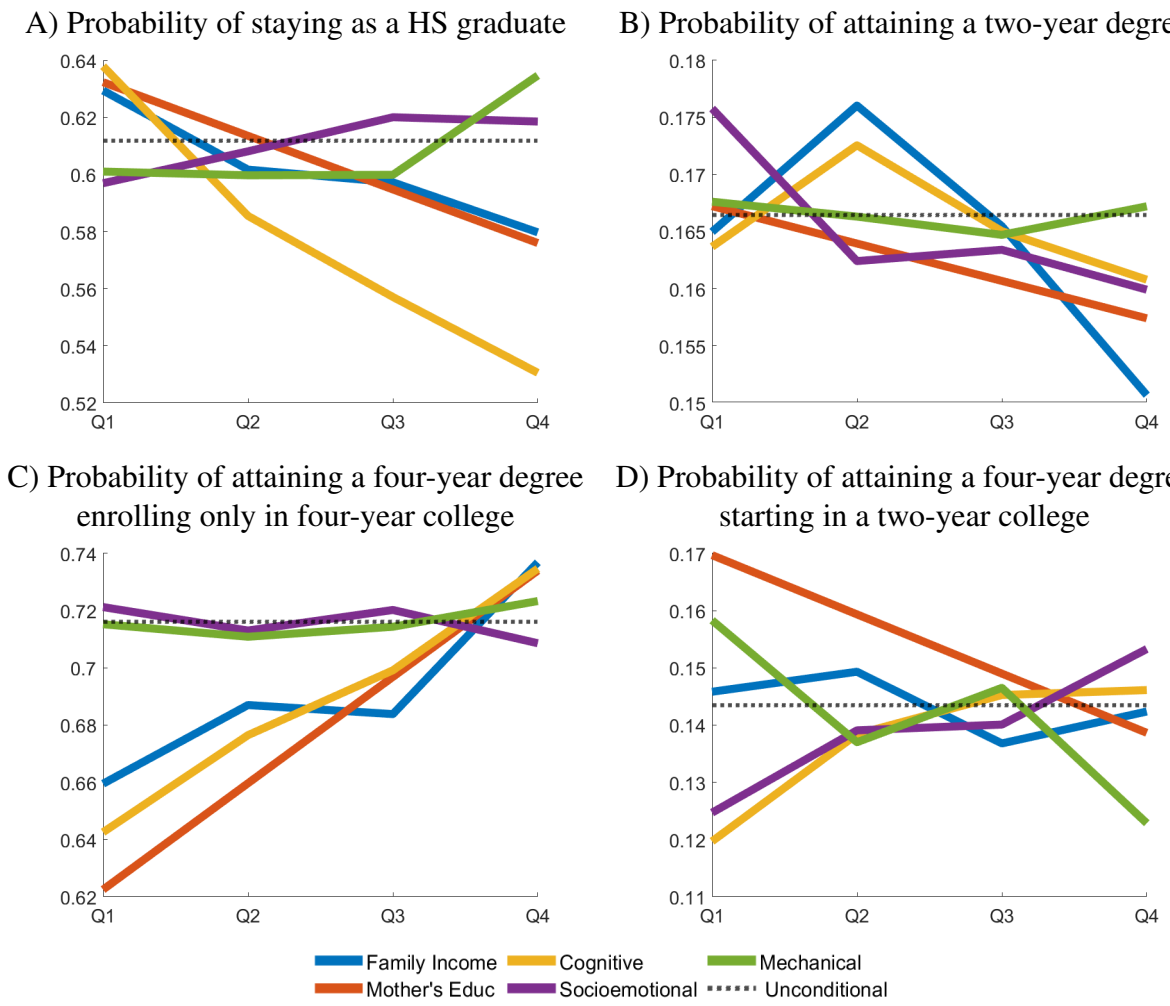


Figure 2.21: Simulated Probability of Choosing a Path Having Ex-ante High Probability, Conditional on Quartiles of Different Characteristics.

Note: The dashed black line represents the unconditional probability of choosing a path having ex-ante high probability. High probability is defined in this case as having a probability above the 80th percentile (dashed black line in Figure 2.20).

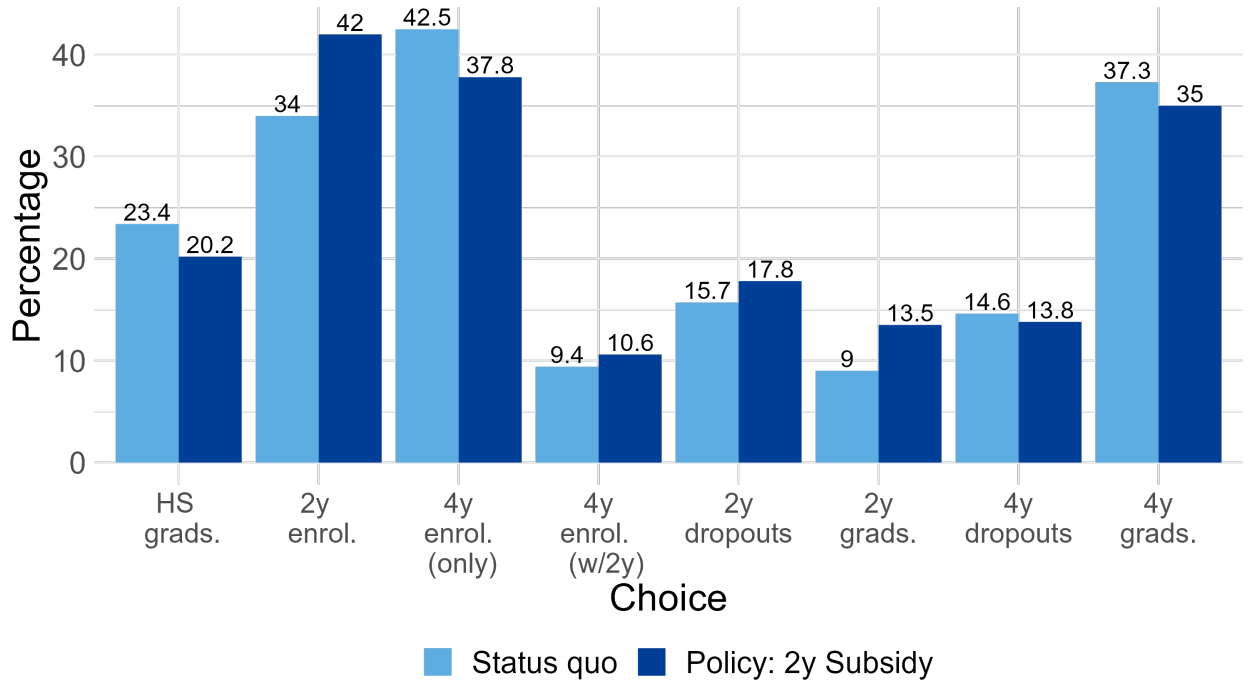


Figure 2.22: Two-year College Subsidy - Percentage of Individuals Choosing Each Path

Note: The lighter blue represents the fractions for the status quo, i.e., in the absence of the policy. The darker blue shows the choices considering the subsidy in the costs of a two-year college.

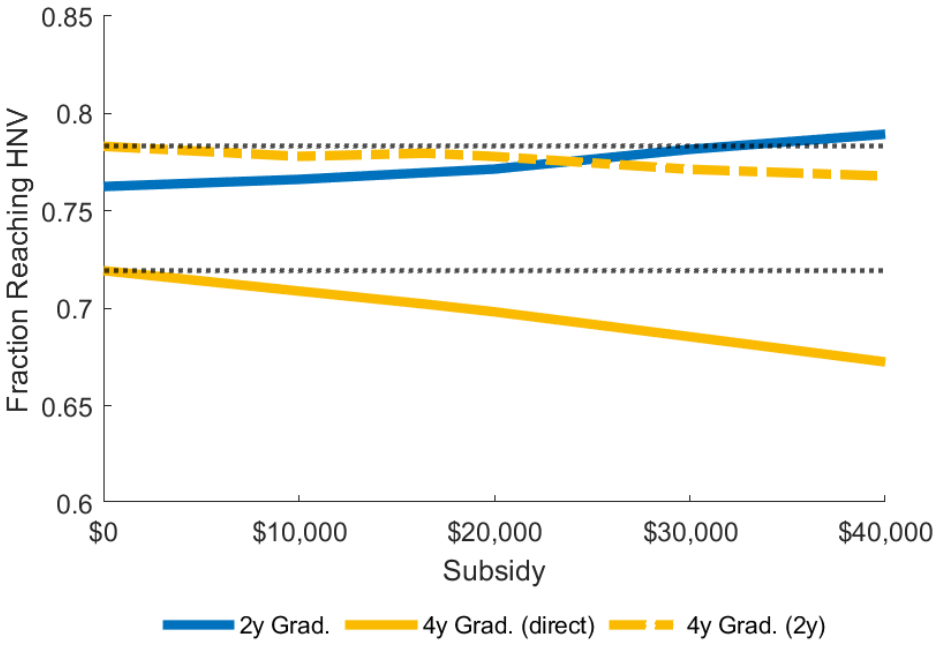


Figure 2.23: Policy Simulation - Increasing the Size of the Subsidy .

Note: This graph shows the fraction of simulated two-year graduates (blue, solid line) reaching the highest net value (HNV) with a two-year degree, for different subsidy sizes. Same information is presented for four-year graduates enrolling directly (yellow, solid line) and those enrolling through two-year college (yellow, dashed line) achieving the highest ex-post net value with their choice. The dotted black lines indicate the fraction of four-year graduates reaching the highest net value with their choice in the status quo.

Table 2.1: Summary Statistics I.

	All	By Schooling Trajectory						
		HS	2y	2y	4y dropouts		4y grads.	
		grads.	dropouts	grads.	(direct)	(2y)	(direct)	(2y)
Black	0.18	0.23	0.22	0.12	0.23	0.25	0.11	0.16
	(0.38)	(0.42)	(0.42)	(0.32)	(0.42)	(0.44)	(0.31)	(0.37)
Hispanic	0.14	0.17	0.24	0.14	0.15	0.00	0.08	0.17
	(0.35)	(0.37)	(0.43)	(0.35)	(0.35)	(0.00)	(0.27)	(0.38)
Living in the South in 1997	0.32	0.37	0.28	0.30	0.33	0.38	0.30	0.25
	(0.46)	(0.48)	(0.45)	(0.46)	(0.47)	(0.49)	(0.46)	(0.44)
Living in an urban area in 1997	0.71	0.65	0.83	0.65	0.71	0.67	0.73	0.71
	(0.45)	(0.48)	(0.38)	(0.48)	(0.46)	(0.48)	(0.45)	(0.46)
Single parent home in 1997	0.39	0.52	0.52	0.32	0.42	0.42	0.22	0.39
	(0.49)	(0.50)	(0.50)	(0.47)	(0.50)	(0.50)	(0.42)	(0.49)
Family income in 1997 ($10,000s)	5.65	3.83	4.61	5.01	5.99	5.68	7.68	5.58
	(4.59)	(2.99)	(3.66)	(3.05)	(5.07)	(4.84)	(5.42)	(4.25)
Household size under 18 in 1997	2.37	2.48	2.50	2.33	2.40	2.21	2.20	2.47
	(1.13)	(1.29)	(1.17)	(1.10)	(1.15)	(0.83)	(0.92)	(1.25)
Mother's years of schooling in 1997	13.31	12.00	12.70	12.97	13.49	12.83	14.76	13.11
	(2.66)	(2.13)	(2.55)	(2.50)	(2.74)	(1.66)	(2.43)	(2.86)
Cohort of 1981	0.21	0.20	0.26	0.18	0.15	0.17	0.23	0.20
	(0.41)	(0.40)	(0.44)	(0.39)	(0.36)	(0.38)	(0.42)	(0.40)
Cohort of 1982	0.19	0.23	0.16	0.16	0.18	0.17	0.20	0.14
	(0.39)	(0.42)	(0.37)	(0.37)	(0.38)	(0.38)	(0.40)	(0.35)
Cohort of 1983	0.23	0.19	0.21	0.26	0.32	0.33	0.25	0.17
	(0.42)	(0.39)	(0.41)	(0.44)	(0.47)	(0.48)	(0.43)	(0.38)
Cohort of 1984	0.21	0.21	0.21	0.27	0.19	0.17	0.19	0.26
	(0.41)	(0.41)	(0.41)	(0.44)	(0.40)	(0.38)	(0.39)	(0.44)
Years of schooling when the ASVAB was taken	8.58	8.49	8.61	8.43	8.58	8.71	8.63	8.72
	(1.55)	(1.61)	(1.49)	(1.48)	(1.40)	(1.37)	(1.58)	(1.69)
Years of schooling when the TIPI was taken	14.21	11.86	12.73	14.29	13.90	13.50	16.57	15.83
	(2.39)	(1.03)	(1.05)	(1.05)	(1.74)	(1.25)	(1.89)	(1.43)
Observations	1,068	254	265	94	130	24	325	76

Table 2.2: Summary Statistics II.

	All	By Schooling Trajectory						
		HS	2y	2y	4y dropouts		4y grads.	
		grads.	dropouts	grads.	(direct)	(2y)	(direct)	(2y)
Panel A: First node								
Urban area (currently)	0.72	0.67	0.82	0.67	0.71	0.76	0.72	0.74
	(0.44)	(0.47)	(0.36)	(0.47)	(0.45)	(0.41)	(0.45)	(0.43)
Current residency: Northeast	0.18	0.20	0.16	0.13	0.15	0.08	0.21	0.14
	(0.38)	(0.40)	(0.37)	(0.34)	(0.36)	(0.28)	(0.40)	(0.35)
Current residency: South	0.32	0.37	0.31	0.29	0.33	0.42	0.30	0.26
	(0.47)	(0.48)	(0.46)	(0.45)	(0.47)	(0.50)	(0.46)	(0.43)
Current residency: North central	0.29	0.23	0.22	0.36	0.36	0.33	0.31	0.27
	(0.45)	(0.42)	(0.41)	(0.48)	(0.48)	(0.47)	(0.46)	(0.45)
Current residency: West	0.21	0.19	0.31	0.21	0.15	0.17	0.18	0.33
	(0.41)	(0.40)	(0.46)	(0.40)	(0.36)	(0.38)	(0.38)	(0.47)
Number of children	0.02	0.05	0.02	0.07	0.02	0.09	0.00	0.00
	(0.17)	(0.26)	(0.11)	(0.28)	(0.15)	(0.37)	(0.00)	(0.00)
Married	0.01	0.01	0.01	0.02	0.01	0.03	0.00	0.00
	(0.08)	(0.11)	(0.09)	(0.11)	(0.09)	(0.13)	(0.01)	(0.04)
Panel B: Final node								
Urban area (currently)	0.81	0.69	0.87	0.80	0.82	0.78	0.87	0.85
	(0.31)	(0.37)	(0.26)	(0.34)	(0.30)	(0.39)	(0.26)	(0.27)
Current residency: Northeast	0.16	0.20	0.13	0.12	0.14	0.13	0.17	0.10
	(0.35)	(0.39)	(0.32)	(0.32)	(0.33)	(0.34)	(0.35)	(0.27)
Current residency: South	0.34	0.37	0.33	0.31	0.35	0.44	0.32	0.30
	(0.45)	(0.47)	(0.45)	(0.44)	(0.45)	(0.49)	(0.43)	(0.44)
Current residency: North central	0.26	0.24	0.20	0.33	0.30	0.20	0.28	0.23
	(0.42)	(0.42)	(0.39)	(0.45)	(0.44)	(0.41)	(0.42)	(0.41)
Current residency: West	0.24	0.18	0.34	0.24	0.20	0.23	0.22	0.34
	(0.41)	(0.37)	(0.46)	(0.40)	(0.38)	(0.42)	(0.39)	(0.46)
Number of children	0.29	0.31	0.34	0.34	0.30	0.23	0.23	0.27
	(0.45)	(0.42)	(0.50)	(0.53)	(0.49)	(0.43)	(0.40)	(0.50)
Married	0.31	0.21	0.25	0.38	0.29	0.36	0.38	0.40
	(0.36)	(0.29)	(0.34)	(0.38)	(0.37)	(0.42)	(0.38)	(0.40)
Observations	1,068	254	265	94	130	24	325	76

Table 2.3: Empirical Specification.

	Costs	Earnings	TIPI tests	ASVAB tests
Cohort dummies	✓	✓	✓	✓
Race dummy (being Black)	✓	✓	✓	✓
Ethnicity dummy (being Hispanic)	✓	✓	✓	✓
Living in the South in 1997	✓		✓	✓
Living in an urban area in 1997	✓		✓	✓
Single Parent home in 1997	✓		✓	✓
Family income in 1997	✓		✓	✓
No. people under age 18 at home in 1997	✓		✓	✓
Mother's years of schooling in 1997	✓		✓	✓
Regional average public tuition at age 17	✓			
Years of schooling when TIPI was taken			✓	
Years of schooling when ASVAB was taken				✓
Living in an urban area (currently)		✓		
Region of current residency (dummies)		✓		
Number of biological children in the household		✓		
Dummy variable for being married		✓		
Regional unemployment rate by age group		✓		
Regional hourly wage by age group		✓		

Note: I consider two age groups for the last two variables: people 30 or younger, and people older than 30.

Table 2.4: Sample Restrictions.

Selection criterion	Number of persons
Full NLSY97 sample	8,984
Drop individuals who participated in the survey less than five rounds	8,796
Drop females	4,499
Drop if missing ASVAB scores	3,489
Drop if missing TIPI tests	2,821
Drop if missing Mother's education	2,678
Drop if missing family income in 1997	2,067
Drop if missing type of residency in 1997	1,977
Drop if missing years of schooling when the ASVAB or TIPI were taken	1,928
Drop if HS graduation was after age 20 or if never graduated	1,641
Drop observations before HS graduation	1,641
Drop if first college enrollment is after age 25	1,574
Drop if missing information of income*	1,393
Drop if still enrolled in college in last observed year	1,230
Drop if not observed at least two periods in the final schooling state	1,157
Drop if less than five observations are available	1,089
Drop if missing number of children	1,086
Drop if schooling pattern is incoherent	1,079
Drop if TIPI scores are perfect	1,075
Drop if ASVAB was taken after starting college education	1,068

Note: *After imputing values

Table 2.5: Correlations Between Test Measures.

Variables	Arith	Math	Word	Para	Cod	Num	Mech	Auto	Shop	Elect	Extro	Stab	Open	Agree	Consc	GPA
Panel A (1,068 observations):																
Cognitive - ASVAB test:																
Arith	1.00															
Math	0.81	1.00														
Word	0.70	0.70	1.00													
Para	0.74	0.73	0.74	1.00												
Cod	0.56	0.60	0.48	0.52	1.00											
Num	0.62	0.65	0.48	0.51	0.59	1.00										
Mechanical - ASVAB test:																
Mech	0.68	0.65	0.67	0.66	0.46	0.40	1.00									
Auto	0.43	0.40	0.49	0.43	0.22	0.21	0.59	1.00								
Shop	0.46	0.41	0.56	0.47	0.28	0.20	0.66	0.65	1.00							
Elect	0.63	0.62	0.71	0.67	0.41	0.37	0.72	0.61	0.66	1.00						
Socioemotional - TIPI test:																
Extro	0.04	0.03	0.03	-0.02	0.01	0.06	0.04	0.06	0.08	0.02	1.00					
Stab	0.21	0.18	0.17	0.16	0.10	0.10	0.17	0.14	0.15	0.14	0.13	1.00				
Open	0.02	0.02	0.08	0.03	0.02	-0.02	0.03	0.00	0.01	0.04	0.19	0.18	1.00			
Agree	0.04	0.07	0.08	0.07	0.02	0.04	0.02	0.02	-0.01	0.01	-0.01	0.30	0.17	1.00		
Consc	-0.01	-0.01	-0.06	-0.02	0.01	0.03	-0.01	0.05	0.02	-0.01	0.12	0.27	0.13	0.09	1.00	
Panel B (834 observations):																
High School Transcripts:																
GPA	0.32	0.35	0.24	0.32	0.26	0.22	0.25	0.08	0.11	0.20	0.02	0.14	-0.01	0.06	0.05	1.00

Note: All measures have been standardized. Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations, Mech = mechanical comprehension, Auto = auto information, Elect = electronics information, Shop = Shop information, Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = Conscientiousness.

Table 2.6: Exploratory Factor Analysis using All Tests.

Principal factor analysis			Loadings			
Factor	Eigenvalue	Proportion	Variable	Factor 1	Factor 2	Factor 3
Factor1	5.753	0.832	Arith	0.855	-0.209	0.008
Factor2	0.942	0.136	Math	0.848	-0.281	0.012
Factor3	0.767	0.111	Word	0.833	0.023	-0.018
Factor4	0.225	0.033	Para	0.825	-0.099	-0.029
Factor5	0.118	0.017	Cod	0.610	-0.328	-0.008
Factor6	0.033	0.005	Num	0.610	-0.433	0.014
Factor7	-0.007	-0.001	Mech	0.824	0.194	-0.050
Factor8	-0.019	-0.003	Auto	0.606	0.428	-0.023
Factor9	-0.053	-0.008	Elect	0.808	0.254	-0.080
Factor10	-0.078	-0.011	Shop	0.657	0.466	-0.041
Factor11	-0.092	-0.013	Extro	0.050	0.063	0.255
Factor12	-0.113	-0.016	Stab	0.215	0.049	0.514
Factor13	-0.130	-0.019	Open	0.042	0.041	0.369
Factor14	-0.179	-0.026	Consc	0.007	0.052	0.382
Factor15	-0.249	-0.036	Agree	0.064	-0.028	0.379

Note: Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations, Mech = mechanical comprehension, Auto = auto information, Elect = electronics information, Shop = Shop information, Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = Conscientiousness.

Table 2.7: Exploratory Factor Analysis including GPA.

Principal factor analysis			Loadings			
Factor	Eigenvalue	Proportion	Variable	Factor 1	Factor 2	Factor 3
Factor1	5.770	0.822	Arith	0.855	-0.203	0.005
Factor2	1.007	0.143	Math	0.845	-0.276	0.016
Factor3	0.750	0.107	Word	0.827	0.032	-0.034
Factor4	0.226	0.032	Para	0.819	-0.092	-0.075
Factor5	0.140	0.020	Cod	0.607	-0.329	0.003
Factor6	0.081	0.012	Num	0.605	-0.427	0.048
Factor7	0.030	0.004	Mech	0.813	0.205	-0.046
Factor8	-0.012	-0.002	Auto	0.587	0.446	-0.023
Factor9	-0.045	-0.006	Elect	0.653	0.462	-0.038
Factor10	-0.056	-0.008	Shop	0.799	0.277	-0.086
Factor11	-0.093	-0.013	Extro	0.068	0.099	0.274
Factor12	-0.097	-0.014	Stab	0.214	0.071	0.493
Factor13	-0.113	-0.016	Open	0.049	0.071	0.347
Factor14	-0.118	-0.017	Consc	-0.015	0.063	0.408
Factor15	-0.181	-0.026	Agree	0.050	-0.032	0.337
Factor16	-0.268	-0.038	GPA	0.328	-0.185	0.103

Note: Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations, Mech = mechanical comprehension, Auto = auto information, Shop = shop information, Elect = electronics information, Extro = extroversion, Stab = emotional stabilifty, Open = openness to experience, Agree = agreeableness, Consc = Conscientiousness.

Table 2.8: Kolmogorov-Smirnov Test to Check Fit of the Measurement System.

	P-value	Kolmogorov-Smirnov Statistic
Math	0.475	0.026
Word	0.012	0.049
Para	0.006	0.052
Num	0.935	0.016
Cod	0.018	0.047
Arith	0.068	0.040
Mech	0.000	0.075
Elect	0.043	0.042
Shop	0.455	0.026
Auto	0.311	0.030

Note: The replicated data contains 100 replications of the data (106,800 observations in total). Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations, Mech = mechanical comprehension, Auto = auto information, Shop = shop information, Elect = electronics information.

Table 2.9: Fit of Schooling Choices and Earnings

	Schooling Choices		Earnings (in 100,000s)			
	Percentage of individuals		Mean		Variance	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
HS graduate (initial)	100%	100%	0.099	0.100	0.106	0.106
Enrollees:						
2y enrollee	33.61%	34.04%	0.174	0.181	0.138	0.139
4y enrollee (all)	51.96%	51.90%	0.123	0.127	0.140	0.139
4y enrollee (2y)	9.36%	9.37%	-	-	-	-
Final nodes:						
HS graduate	23.78%	23.43%	0.289	0.223	0.189	0.204
2y dropout	15.45%	15.70%	0.329	0.326	0.207	0.207
2y graduate	8.80%	8.97%	0.440	0.414	0.229	0.249
4y dropout	14.42%	14.64%	0.357	0.357	0.283	0.276
4y graduate	37.55%	37.26%	0.530	0.495	0.305	0.313

Note: The simulated data contains 100 replications of the data (106,800 observations in total).

Table 2.10: Estimates for the Cost Equations.

	hsg-2ye	hsg-4ye	2ye-2yg	4ye-4yg	2ye-4ye
Constant	-0.826**	0.680	0.683**	-0.644**	1.069***
	(0.372)	(0.418)	(0.329)	(0.291)	(0.083)
Black	-0.006	-0.088	0.515**	0.272	-
	(0.170)	(0.200)	(0.252)	(0.192)	
Hispanic	-0.123	-0.112	0.352	0.289	-
	(0.187)	(0.218)	(0.233)	(0.197)	
Living in the South in 1997	0.405**	-0.014	-0.290	0.110	-
	(0.165)	(0.166)	(0.192)	(0.136)	
Living in an urban area in 1997	-0.366***	-0.306*	0.222	0.015	-
	(0.140)	(0.156)	(0.178)	(0.134)	
Single-parent home in 1997	-0.017	0.207	0.457***	0.422***	-
	(0.129)	(0.150)	(0.164)	(0.132)	
Family income 1997	-0.244***	-0.372***	0.157	-0.050	-
	(0.090)	(0.098)	(0.106)	(0.059)	
No. people under age 18 at home in 1997	-0.032	0.012	0.068	0.024	-
	(0.054)	(0.065)	(0.068)	(0.060)	
Mother's years of schooling in 1997	-0.223***	-0.476***	-0.055	-0.253***	-
	(0.070)	(0.082)	(0.087)	(0.067)	
Cohort 1981	0.050	-0.054	-0.213	-0.198	-
	(0.200)	(0.238)	(0.282)	(0.206)	
Cohort 1982	0.439**	0.062	-0.371	0.043	-
	(0.201)	(0.241)	(0.259)	(0.205)	
Cohort 1983	0.111	-0.410*	-0.451**	0.218	-
	(0.200)	(0.234)	(0.229)	(0.193)	
Cohort 1984	0.187	0.087	-0.531**	-0.051	-
	(0.198)	(0.237)	(0.229)	(0.197)	
Avg. Regional Public Tuition	2.595***	-0.119	-1.409*	0.132	-
	(0.932)	(0.364)	(0.823)	(0.271)	
Cognitive factor	-0.417***	-0.825***	-0.221*	-0.472***	-0.254**
	(0.095)	(0.114)	(0.118)	(0.106)	(0.111)
Socioemotional factor	0.064	0.066	-0.018	0.026	-0.167
	(0.090)	(0.113)	(0.076)	(0.081)	(0.118)
Mechanical factor	0.294***	0.531***	-0.004	0.098	0.268**
	(0.085)	(0.108)	(0.056)	(0.098)	(0.109)

Note: Standard errors are in parenthesis. Family income in 1997, number of people under age 18 at home, mother's years of schooling are standardized, and abilities are standardized.

Table 2.11: Estimates for the Earning Equations.

	hsg	hsgc	2ye	4ye	2yd	2yg	4yd	4yg
Constant	0.220**	1.118*	0.400*	0.582	-0.284	-0.204	0.270***	0.274
	(0.088)	(0.635)	(0.208)	(0.386)	(0.484)	(0.346)	(0.052)	(0.321)
Black	-0.033***	-0.156***	-0.049***	0.016	-0.072**	-0.029	-0.021	-0.080*
	(0.009)	(0.025)	(0.018)	(0.015)	(0.035)	(0.070)	(0.044)	(0.048)
Hispanic	-0.007	-0.051*	-0.015	-0.015	-0.027	0.052	0.010	-0.075
	(0.010)	(0.029)	(0.018)	(0.018)	(0.036)	(0.063)	(0.060)	(0.050)
Living in an urban area (currently)	-0.011	-0.024	-0.002	0.000	-0.021	-0.064	0.017	0.143***
	(0.007)	(0.027)	(0.017)	(0.014)	(0.050)	(0.061)	(0.059)	(0.055)
Region of residency: South	-0.024**	-0.079*	-0.010	-0.046***	-0.008	0.011	-0.001	-0.048
	(0.010)	(0.046)	(0.025)	(0.011)	(0.046)	(0.076)	(0.065)	(0.051)
Region of residency: North Central	0.002	0.088	0.029	0.044	-0.148***	0.063	0.084	-0.011
	(0.012)	(0.056)	(0.027)	(0.041)	(0.047)	(0.072)	(0.057)	(0.054)
Region of residency: West	-0.006	0.120*	0.045	0.060***	-0.104**	-0.053	0.030	-0.020
	(0.015)	(0.063)	(0.029)	(0.007)	(0.044)	(0.083)	(0.062)	(0.056)
Cohort 1981	-0.003	-0.109***	-0.019	-0.002	0.012	-0.028	0.084	-0.017
	(0.010)	(0.033)	(0.021)	(0.017)	(0.040)	(0.074)	(0.064)	(0.048)
Cohort 1982	-0.018*	-0.106***	-0.037	-0.017	-0.040	-0.109	0.015	-0.058
	(0.011)	(0.032)	(0.023)	(0.018)	(0.044)	(0.078)	(0.060)	(0.050)
Cohort 1983	-0.040***	-0.156***	-0.043*	-0.058***	-0.024	-0.150**	-0.006	-0.090*
	(0.011)	(0.038)	(0.022)	(0.018)	(0.041)	(0.068)	(0.052)	(0.049)
Cohort 1984	-0.047***	-0.142***	-0.048**	-0.065***	0.020	-0.138**	-0.014	-0.072
	(0.013)	(0.038)	(0.023)	(0.019)	(0.041)	(0.065)	(0.059)	(0.050)
Children in the Household	0.082***	0.061**	0.045*	0.012	0.065*	0.008	-0.016	0.008
	(0.019)	(0.027)	(0.024)	(0.025)	(0.034)	(0.053)	(0.049)	(0.041)
Married	0.063*	0.128***	0.190***	0.204***	0.145***	0.211***	0.250***	0.182***
	(0.038)	(0.042)	(0.032)	(0.030)	(0.051)	(0.066)	(0.058)	(0.047)
Regional Unemployemnt	1.478*	10.257***	-1.242	2.419***	-0.397	3.403	4.914	8.558***
	(0.820)	(3.928)	(1.270)	(0.091)	(5.082)	(7.831)	(3.132)	(2.709)
Regional Wage Rate ($10s)	-0.182*	-1.732**	-0.232	-0.77	1.007*	0.745	-0.411	-0.465
	(0.107)	(0.787)	(0.260)	(0.488)	(0.596)	(0.486)	(1.041)	(0.383)
Cognitive factor	-0.030***	0.013	-0.016	-0.032***	-0.010	-0.086**	-0.023	0.056**
	(0.004)	(0.013)	(0.010)	(0.009)	(0.021)	(0.033)	(0.030)	(0.024)
Socioemotional factor	0.003	0.018	-0.012	-0.003	-0.002	-0.028	-0.028	0.012
	(0.007)	(0.013)	(0.016)	(0.010)	(0.020)	(0.043)	(0.025)	(0.023)
Mechanical factor	0.022***	0.019*	0.038***	0.037***	0.053**	0.050*	0.065**	0.031
	(0.005)	(0.012)	(0.011)	(0.009)	(0.022)	(0.028)	(0.031)	(0.024)

Note: Standard errors are presented in parenthesis. Coefficients associated with factor variables are standardized. The coefficients associated with the constant term in columns 4 and 5, the north central region in column 4, regional unemployment in columns 5 and 6, and regional wage rate in columns 4, 5 and 7 are derived using the scores' outer method.

Table 2.12: Estimates for the Measurement System: Cognitive Measures.

	Math	Word	Para	Num	Cod	Arith
Constant	0.188**	0.332***	0.336***	-0.034	-0.009	0.168*
	(0.092)	(0.094)	(0.100)	(0.107)	(0.108)	(0.096)
Black	-0.551***	-0.678***	-0.512***	-0.304***	-0.390***	-0.738***
	(0.068)	(0.070)	(0.074)	(0.079)	(0.080)	(0.071)
Hispanic	-0.230***	-0.449***	-0.207**	-0.259***	-0.162*	-0.362***
	(0.088)	(0.085)	(0.094)	(0.093)	(0.092)	(0.092)
Living in the South in 1997	-0.077	-0.165***	-0.125**	0.020	0.043	-0.099*
	(0.054)	(0.055)	(0.059)	(0.062)	(0.062)	(0.057)
Living in an urban area in 1997	0.110**	0.119**	0.016	0.131**	0.112*	0.096*
	(0.053)	(0.054)	(0.058)	(0.061)	(0.062)	(0.056)
Single-parent home in 1997	-0.114**	-0.067	-0.123**	-0.021	-0.120*	-0.124**
	(0.058)	(0.058)	(0.063)	(0.064)	(0.064)	(0.061)
Family income 1997	0.075***	0.066**	0.055*	0.056*	0.022	0.053*
	(0.026)	(0.027)	(0.029)	(0.031)	(0.031)	(0.027)
No. people under age 18 at home in 1997	-0.022	-0.049*	-0.034	-0.057**	-0.070**	0.000
	(0.025)	(0.025)	(0.027)	(0.028)	(0.028)	(0.026)
Mother's years of schooling in 1997	0.180***	0.205***	0.184***	0.116***	0.132***	0.182***
	(0.027)	(0.028)	(0.030)	(0.031)	(0.031)	(0.029)
Cohort 1981	0.195**	0.036	0.145	0.152	0.172*	0.192**
	(0.085)	(0.086)	(0.092)	(0.097)	(0.097)	(0.089)
Cohort 1982	0.017	-0.077	-0.135	0.110	0.022	0.106
	(0.094)	(0.097)	(0.103)	(0.111)	(0.112)	(0.098)
Cohort 1983	-0.078	-0.212*	-0.205*	0.087	0.111	0.020
	(0.108)	(0.112)	(0.118)	(0.128)	(0.129)	(0.113)
Cohort 1984	-0.448***	-0.472***	-0.464***	-0.192	-0.058	-0.194
	(0.130)	(0.134)	(0.142)	(0.153)	(0.155)	(0.136)
Years of schooling when the ASVAB was taken	0.251***	0.176***	0.095**	0.247***	0.261***	0.179***
	(0.042)	(0.043)	(0.046)	(0.050)	(0.051)	(0.044)
Cognitive factor	1	0.849***	1.020***	0.791***	0.744***	1.060***
	-	(0.034)	(0.035)	(0.039)	(0.040)	(0.032)

Note: Standard errors are presented in parenthesis. Family income in 1997, number of people under age 18 at home, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations.

Table 2.13: Estimates for the Measurement System: socioemotional Measures.

	Extro	Agree	Consc	Stab	Open
Black	-0.015	-0.049	0.220**	-0.167	0.128
	(0.095)	(0.101)	(0.102)	(0.124)	(0.099)
Hispanic	-0.039	0.020	-0.017	-0.019	0.042
	(0.099)	(0.105)	(0.105)	(0.130)	(0.103)
Living in the south in 1997	-0.022	0.086	0.123	0.004	0.129*
	(0.071)	(0.075)	(0.076)	(0.093)	(0.074)
Living in an urban area in 1997	-0.088	-0.206***	-0.116	-0.207**	0.035
	(0.072)	(0.076)	(0.077)	(0.094)	(0.075)
Single-parent home in 1997	0.085	-0.105	-0.036	-0.052	0.151**
	(0.072)	(0.076)	(0.077)	(0.094)	(0.075)
Family income 1997	0.113***	0.009	0.027	0.055	0.040
	(0.037)	(0.039)	(0.039)	(0.049)	(0.038)
No. people under age 18 at home in 1997	-0.013	0.026	0.023	0.016	-0.095***
	(0.032)	(0.034)	(0.035)	(0.042)	(0.034)
Mother's years of schooling in 1997	-0.013	-0.006	-0.070*	-0.036	0.023
	(0.037)	(0.041)	(0.040)	(0.052)	(0.039)
Cohort 1981	-0.013	-0.168	-0.079	-0.080	-0.115
	(0.106)	(0.112)	(0.113)	(0.138)	(0.110)
Cohort 1982	0.060	-0.200*	-0.056	-0.113	-0.097
	(0.108)	(0.114)	(0.114)	(0.139)	(0.112)
Cohort 1983	0.066	-0.212*	-0.269**	-0.016	-0.104
	(0.104)	(0.110)	(0.111)	(0.134)	(0.108)
Cohort 1984	0.014	-0.177	-0.135	-0.145	0.088
	(0.106)	(0.113)	(0.114)	(0.139)	(0.111)
Age when the TIPI was taken	-0.023	0.089**	0.082**	0.189***	0.081**
	(0.036)	(0.040)	(0.040)	(0.059)	(0.038)
Socioemotional factor	1	1.897***	1.810***	3.997***	1.551***
	-	(0.579)	(0.426)	(1.083)	(0.416)

Note: Standard errors are presented in parenthesis. Family income in 1997, number of people under age 18 at home, mother's years of schooling, and the years of schooling when the TIPI test was taken are standardized. Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = Conscientiousness.

Table 2.14: Estimates for the Measurement System: Mechanical Measures.

	Mech	Elect	Auto	Shop
Constant	0.412***	0.554***	0.609***	0.669***
	(0.101)	(0.104)	(0.105)	(0.104)
Black	-0.853***	-0.569***	-0.874***	-0.658***
	(0.074)	(0.076)	(0.076)	(0.076)
Hispanic	-0.446***	-0.482***	-0.565***	-0.448***
	(0.089)	(0.090)	(0.084)	(0.082)
Living in the South in 1997	-0.108*	-0.185***	-0.188***	-0.110*
	(0.057)	(0.059)	(0.058)	(0.057)
Living in an urban area in 1997	-0.104*	-0.044	-0.197***	-0.300***
	(0.055)	(0.056)	(0.056)	(0.056)
Single-parent home in 1997	-0.138**	-0.160***	-0.051	-0.098*
	(0.059)	(0.060)	(0.057)	(0.056)
Family income 1997	0.021	-0.011	-0.038	-0.099***
	(0.026)	(0.027)	(0.027)	(0.027)
No. people under age 18 at home in 1997	-0.011	-0.005	0.012	-0.008
	(0.026)	(0.026)	(0.026)	(0.026)
Mother's years of schooling in 1997	0.137***	0.117***	0.039	0.061**
	(0.028)	(0.028)	(0.028)	(0.028)
Cohort 1981	0.193**	0.046	0.110	0.075
	(0.088)	(0.090)	(0.089)	(0.088)
Cohort 1982	-0.026	-0.198*	-0.023	-0.177*
	(0.103)	(0.106)	(0.106)	(0.105)
Cohort 1983	-0.079	-0.373***	-0.299**	-0.364***
	(0.119)	(0.123)	(0.125)	(0.124)
Cohort 1984	-0.249*	-0.562***	-0.488***	-0.470***
	(0.141)	(0.146)	(0.147)	(0.146)
Years of schooling when the ASVAB was taken	0.131***	0.111**	0.077	0.203***
	(0.046)	(0.047)	(0.048)	(0.048)
Mechanical factor	1	1.150***	1.538***	1.447***
	-	(0.081)	(0.101)	(0.100)
Cognitive factor	0.567***	0.503***	0.055	0
	(0.039)	(0.042)	(0.049)	-

Note: Standard errors are presented in parenthesis. Family income in 1997, number of people under age 18 at home, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Mech = mechanical comprehension, Auto = auto information, Elect = electronics information.

Table 2.15: Sensitive to Uncertainty: Four-year graduates - Direct Enrollment.

	Obtains the Highest Value as a 4y grad. (direct)	Higher Value as a 4y grad. (2y)		Higher Value as a 4y dropout (direct)		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	14.67	14.32***	-0.14	14.18***	-0.20	14.25***	-0.17	13.60***	-0.43
Single-parent home in 1997	0.24	0.26***	0.04	0.29***	0.13	0.19***	-0.11	0.28***	0.09
Family income in 1997	76.48	69.93***	-0.11	72.41***	-0.07	64.24***	-0.21	53.28***	-0.40
Proxy for siblings in 1997	2.24	2.30***	0.06	2.30***	0.06	2.24	0.00	2.28	0.04
Urban area in 1997	0.72	0.75***	0.06	0.74	0.03	0.66***	-0.14	0.63***	-0.20
Urban area (final state)	0.82	0.83	0.02	0.83	0.00	0.79***	-0.12	0.78***	-0.15
Black	0.12	0.11*	-0.03	0.16***	0.11	0.07***	-0.15	0.13	0.02
Hispanic	0.08	0.10***	0.08	0.11***	0.10	0.07***	-0.05	0.09	0.02
Cognitive factor	0.53	0.60***	0.09	0.24***	-0.34	0.49***	-0.05	0.31***	-0.26
Socioemotional factor	-0.05	0.11***	0.16	-0.07	-0.03	-0.07	-0.02	0.06***	0.11
Mechanical factor	0.02	-0.02***	-0.04	-0.06***	-0.09	0.16***	0.15	0.19***	0.18
Percentage	71.9%	14.4%		6.6%		11.7%		3.4%	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a four-year college, under uncertainty are considered. They are classified according to whether the net value of being a four-year graduate, starting in a four-year college, is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1,\dot{s})) = \sum_{\tilde{s}\in\overrightarrow{s}(s_1,\dot{s})}\left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1},\tilde{s}))\right]$, where $\overrightarrow{s}(s_1,\dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.16: Sensitive to Uncertainty: High School graduates.

	Obtains the Highest Value as a HS grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	11.94	12.77***	0.33	12.35***	0.16	12.23***	0.11
Single-parent home in 1997	0.53	0.41***	-0.24	0.47***	-0.12	0.39***	-0.28
Family income in 1997	38.00	46.49***	0.31	42.80***	0.18	42.03***	0.15
Proxy for siblings in 1997	2.45	2.35***	-0.08	2.44	-0.01	2.36***	-0.08
Urban area (final state)	0.77	0.76*	-0.04	0.78	0.01	0.72***	-0.15
Urban area in 1997	0.64	0.61***	-0.07	0.63	-0.02	0.56***	-0.18
Black	0.25	0.18***	-0.15	0.18***	-0.16	0.13***	-0.27
Hispanic	0.18	0.12***	-0.16	0.15***	-0.08	0.15***	-0.09
Cognitive factor	-0.66	-0.11***	0.56	-0.15***	0.53	-0.45***	0.22
socioemotional factor	0.08	0.10	0.02	0.25***	0.18	0.04**	-0.04
Mechanical factor	0.11	0.20***	0.08	0.11	0.00	0.22***	0.10
Percentage	69.6%		9.6%		9.6%		14.0%

Note: Only simulated individuals who would choose to be high school graduates under uncertainty are considered. They are classified according to whether the net value of being a high school graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.17: Sensitive to Uncertainty: Two-year graduates.

	Obtains the Highest a 2y grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y dropout		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	12.97	13.52***	0.23	13.17***	0.09	12.93	-0.02	12.39**	-0.24
Single-parent home in 1997	0.31	0.22***	-0.19	0.28**	-0.07	0.32	0.04	0.23*	-0.16
Family income in 1997	48.50	55.68***	0.23	51.84***	0.11	50.22	0.05	42.07**	-0.20
Proxy for siblings in 1997	2.33	2.25**	-0.07	2.29	-0.04	2.43***	0.10	2.45	0.12
Urban area in 1997	0.63	0.62	-0.02	0.65*	0.05	0.68***	0.10	0.47***	-0.34
Urban area (final state)	0.76	0.78	0.05	0.79**	0.07	0.79**	0.08	0.75	-0.02
Black	0.10	0.09*	-0.06	0.09	-0.03	0.13*	0.07	0.11	0.01
Hispanic	0.14	0.09***	-0.15	0.13	-0.03	0.16	0.06	0.14	-0.01
Cognitive factor	-0.14	0.23***	0.40	0.14***	0.30	-0.20*	-0.06	-0.29*	-0.17
Socioemotional factor	-0.11	0.02***	0.12	0.03***	0.14	-0.12	-0.01	0.15***	0.26
Mechanical factor	0.04	-0.01	-0.04	-0.03**	-0.07	-0.02	-0.06	-0.13*	-0.16
Percentage	76.3%	8.8%		14.5%		8.0%		1.2%	

Note: Only simulated individuals who would choose to be two-year graduates under uncertainty are considered. They are classified according to whether the net value of being a two-year graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.18: Sensitive to Uncertainty: Four-year graduates - with Two-year College Enrollment.

	Obtains the Highest Value as a 4y grad. (2y)	Higher Value as a 4y grad. (direct)		Higher Value as a 4y dropout (2y)		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	13.36	14.38***	0.41	13.23	-0.05	13.70***	0.14	13.01	-0.14
Single-parent home in 1997	0.37	0.21***	-0.34	0.43**	0.11	0.25***	-0.25	0.28**	-0.19
Family income in 1997	56.71	65.87***	0.21	56.63	-0.00	58.06	0.03	49.09*	-0.18
Proxy for siblings in 1997	2.38	2.24*	-0.12	2.40	0.02	2.28*	-0.08	2.23	-0.13
Urban area in 1997	0.78	0.72**	-0.13	0.80	0.06	0.74**	-0.09	0.69**	-0.21
Urban area (final state)	0.84	0.84	-0.03	0.86	0.04	0.82*	-0.08	0.84	-0.00
Black	0.15	0.08***	-0.18	0.16	0.04	0.07***	-0.23	0.09*	-0.17
Hispanic	0.15	0.09**	-0.16	0.18	0.08	0.11***	-0.12	0.09*	-0.18
Cognitive factor	0.39	0.84***	0.54	0.16***	-0.28	0.49***	0.11	0.33	-0.08
Socioemotional factor	0.24	0.31	0.07	0.28	0.04	0.16*	-0.07	0.51***	0.27
Mechanical factor	-0.15	-0.36***	-0.23	-0.26***	-0.12	-0.04***	0.12	-0.09	0.06
Percentage	78.3%	3.8%		7.5%		9.1%		1.8%	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a two-year college, under uncertainty are considered. They are classified according to whether the net value of being a four-year graduate enrolling in two-year college is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.19: Heteroskedasticity Coefficients - Estimates of Standard Deviations of Idiosyncratic Shocks to Earnings, for Different Family Income Quartile Groups.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HS Grad. (initial)	0.100***	0.088***	0.109***	0.094***
	(0.005)	(0.004)	(0.005)	(0.004)
HS Grad. (final)	0.127***	0.172***	0.201***	0.097***
	(0.010)	(0.015)	(0.021)	(0.016)
2y Enrollee	0.135***	0.107***	0.109***	0.123***
	(0.010)	(0.008)	(0.009)	(0.011)
4y Enrollee	0.142***	0.113***	0.095***	0.129***
	(0.012)	(0.008)	(0.006)	(0.007)
2y Dropout	0.192***	0.129***	0.229***	0.132***
	(0.021)	(0.013)	(0.029)	(0.021)
2y Grad.	0.145***	0.247***	0.209***	0.163***
	(0.033)	(0.042)	(0.040)	(0.035)
4y Dropout	0.258***	0.142***	0.260***	0.289***
	(0.035)	(0.018)	(0.032)	(0.036)
4y Grad.	0.254***	0.255***	0.278***	0.325***
	(0.026)	(0.022)	(0.019)	(0.020)

Note: Standard errors in parenthesis.

Table 2.20: Comparing Results on Sensitivity to Uncertainty with and without Heteroskedasticity - Four-year Graduates - with Direct Enrollment.

	Higher returns as a 4y grad. (2y)		Higher returns as a 4y Dropout		Higher returns as a 2y Grad.		Higher returns as a HS Grad.	
	SMD	SMD	SMD	SMD	SMD	SMD	SMD	SMD
Mother's education in 1997	-0.14***	-0.14***	-0.20***	-0.23***	-0.17***	-0.17***	-0.43***	-0.41***
Single-parent home in 1997	0.04***	0.05***	0.13***	0.18***	-0.11***	-0.10***	0.09***	0.10***
Family income in 1997	-0.11***	-0.11***	-0.07***	-0.15***	-0.21***	-0.22***	-0.40***	-0.41***
Proxy for siblings in 1997	0.06***	0.06***	0.06***	0.07***	0.00	-0.00	0.04	0.05*
Urban area in 1997	0.06***	0.06***	0.03	0.02	-0.14***	-0.15***	-0.20***	-0.19***
Urban area (final state)	0.02	0.02	0.00	-0.01	-0.12***	-0.11***	-0.15***	-0.15***
Black	-0.03*	-0.03*	0.11***	0.13***	-0.15***	-0.15***	0.02	0.03
Hispanic	0.08***	0.09***	0.10***	0.11***	-0.05***	-0.04**	0.02	0.03
Cognitive factor	0.09***	0.08***	-0.34***	-0.32***	-0.05***	-0.06***	-0.26***	-0.27***
Socioemotional factor	0.16***	0.16***	-0.03	-0.02	-0.02	-0.01	0.11***	0.10***
Mechanical factor	-0.04***	-0.03*	-0.09***	-0.08***	0.15***	0.16***	0.18***	0.18***
Heteroskedasticity	Yes	No	Yes	No	Yes	No	Yes	No

Note: Stars indicate standard significance levels for a t-test on mean differences relative to the reference group: those reaching the highest ex-post net value. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the reference group, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.21: Comparing Results on Sensitivity to Uncertainty with and without Heteroskedasticity - High School Graduates.

	Higher returns as a 4yr Grad. (direct)		Higher returns as a 4yr Grad. (2y)		Higher returns as a 2yr Grad.	
	SMD	SMD	SMD	SMD	SMD	SMD
Mother's education in 1997	0.33***	0.34***	0.16***	0.16***	0.11***	0.11***
Single-parent home in 1997	-0.24***	-0.24***	-0.12***	-0.12***	-0.28***	-0.28***
Family income in 1997	0.31***	0.31***	0.18***	0.18***	0.15***	0.16***
Proxy for siblings in 1997	-0.08***	-0.08***	-0.01	-0.01	-0.08***	-0.07***
Urban area in 1997	-0.07***	-0.06***	-0.02	-0.02	-0.18***	-0.16***
Urban area (final state)	-0.04*	-0.03	0.01	0.02	-0.15***	-0.13***
Black	-0.15***	-0.16***	-0.16***	-0.17***	-0.27***	-0.27***
Hispanic	-0.16***	-0.16***	-0.08***	-0.07***	-0.09***	-0.07***
Cognitive factor	0.56***	0.55***	0.53***	0.52***	0.22***	0.19***
Socioemotional factor	0.02	0.00	0.18***	0.17***	-0.04**	-0.05***
Mechanical factor	0.08***	0.08***	0.00	0.02	0.10***	0.11***
Heteroskedasticity	Yes	No	Yes	No	Yes	No

Note: Stars indicate standard significance levels for a t-test on mean differences relative to the reference group: those reaching the highest ex-post net value. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the reference group, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.22: Comparing Results on Sensitivity to Uncertainty with and without Heteroskedasticity - Two-year Graduates.

	Higher returns as a 4y Grad. (direct)		Higher returns as a 4y Grad. (2y)		Higher returns as a 2y Dropout		Higher returns as a HS Grad.	
	SMD	SMD	SMD	SMD	SMD	SMD	SMD	SMD
Mother's education in 1997	0.23***	0.24***	0.09***	0.09***	-0.02	0.02	-0.24**	-0.17*
Single-parent home in 1997	-0.19***	-0.17***	-0.07**	-0.07**	0.04	0.10**	-0.16*	-0.09
Family income in 1997	0.23***	0.21***	0.11***	0.12***	0.05	0.08**	-0.20**	-0.19*
Proxy for siblings in 1997	-0.07**	-0.11***	-0.04	-0.04	0.10***	0.10**	0.12	0.13
Urban area in 1997	-0.02	0.01	0.05*	0.06*	0.10***	0.15***	-0.34***	-0.28***
Urban area (final state)	0.05	0.06	0.07**	0.07**	0.08**	0.07*	-0.02	-0.13
Black	-0.06*	-0.04	-0.03	-0.01	0.07*	0.13***	0.01	0.05
Hispanic	-0.15***	-0.14***	-0.03	-0.03	0.06	0.06	-0.01	-0.01
Cognitive factor	0.40***	0.41***	0.30***	0.30***	-0.06*	-0.12***	-0.17*	-0.14
Socioemotional factor	0.12***	0.10***	0.14***	0.14***	-0.01	-0.00	0.26***	0.20**
Mechanical factor	-0.04	-0.07*	-0.07**	-0.06**	-0.06	-0.08**	-0.16*	-0.21**
Heteroskedasticity	Yes	No	Yes	No	Yes	No	Yes	No

Note: Stars indicate standard significance levels for a t-test on mean differences relative to the reference group: those reaching the highest ex-post net value. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the reference group, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.23: Comparing Results on Sensitivity to Uncertainty with and without Heteroskedasticity - Four-year Graduates - with Two-year College Enrollment.

	Higher returns as a 4y grad. (direct)		Higher returns as a 4y Dropout		Higher returns as a 2y Grad.		Higher returns as a HS Grad.	
	SMD	SMD	SMD	SMD	SMD	SMD	SMD	SMD
Mother's education in 1997	0.41***	0.44***	-0.05	-0.12**	0.14***	0.11**	-0.14	-0.25***
Single-parent home in 1997	-0.34***	-0.32***	0.11**	0.15***	-0.25***	-0.24***	-0.19**	-0.12
Family income in 1997	0.21***	0.15**	-0.00	-0.07	0.03	0.00	-0.18*	-0.23**
Proxy for siblings in 1997	-0.12*	-0.10	0.02	0.05	-0.08*	-0.06	-0.13	-0.04
Urban area in 1997	-0.13**	-0.14**	0.06	0.04	-0.09**	-0.11**	-0.21**	-0.29***
Urban area (final state)	-0.03	-0.01	0.04	0.01	-0.08*	-0.12***	-0.00	-0.09
Black	-0.18***	-0.11*	0.04	0.06	-0.23***	-0.22***	-0.17*	-0.18*
Hispanic	-0.16**	-0.17***	0.08	0.11**	-0.12***	-0.12***	-0.18*	-0.16*
Cognitive factor	0.54***	0.54***	-0.28***	-0.25***	0.11***	0.12***	-0.08	-0.05
Socioemotional factor	0.07	0.05	0.04	0.06	-0.07*	-0.09**	0.27***	0.28***
Mechanical factor	-0.23***	-0.24***	-0.12***	-0.09**	0.12***	0.10**	0.06	0.01
Heteroskedasticity	Yes	No	Yes	No	Yes	No	Yes	No

Note: Stars indicate standard significance levels for a t-test on mean differences relative to the reference group: those reaching the highest ex-post net value. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the reference group, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.24: Sensitive to Uncertainty and Exposure to the Great Recession: Four-year graduate - Direct Enrollment.

	Obtains the Highest Value as a 4y grad. (direct)	Higher Value as a 4y grad. (2y)		Higher Value as a 4y dropout		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	14.69	14.31***	-0.15	14.19***	-0.20	14.28***	-0.16	13.63***	-0.42
Single-parent home in 1997	0.23	0.25***	0.05	0.30***	0.17	0.20***	-0.07	0.27***	0.09
Family income in 1997	77.63	70.38***	-0.12	72.63***	-0.09	64.96***	-0.22	54.66***	-0.40
Proxy for siblings in 1997	2.22	2.27***	0.05	2.27**	0.05	2.27***	0.05	2.26	0.04
Urban area (final state)	0.82	0.83**	0.03	0.82	-0.01	0.79***	-0.12	0.77***	-0.19
Urban area in 1997	0.72	0.74**	0.04	0.72	-0.00	0.64***	-0.17	0.62***	-0.23
Black	0.12	0.11**	-0.03	0.14***	0.08	0.07***	-0.15	0.10*	-0.06
Hispanic	0.09	0.09	0.02	0.11***	0.09	0.08**	-0.04	0.10	0.05
Exposure to the Crisis (first state)	0.00	0.00	0.02	0.00**	0.05	0.00	-0.00	0.00**	0.06
Exposure to the Crisis (final state)	0.68	0.67***	-0.05	0.67**	-0.05	0.69	0.01	0.64***	-0.19
Cognitive factor	0.49	0.60***	0.12	0.26***	-0.28	0.48	-0.01	0.32***	-0.21
Socioemotional factor	-0.04	0.14***	0.19	-0.06	-0.02	-0.05	-0.01	0.07***	0.11
Mechanical factor	0.03	-0.02***	-0.06	-0.02***	-0.06	0.18***	0.16	0.20***	0.18
Percentage	72.9%	13.8%		6.3%		11.3%		3.3%	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a four-year college, under uncertainty are considered. They are classified according to whether the net value of being a four-year graduate, enrolling directly in a four-year college, is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.25: Sensitive to Uncertainty and Exposure to the Great Recession: High School Graduates

	Obtains the Highest Value as a HS grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	11.88	12.67***	0.32	12.24***	0.15	12.22***	0.14
Single-parent home in 1997	0.55	0.42***	-0.28	0.48***	-0.15	0.42***	-0.27
Family income in 1997	36.92	44.70***	0.29	41.13***	0.16	40.26***	0.13
Proxy for siblings in 1997	2.49	2.37***	-0.10	2.42**	-0.05	2.42***	-0.06
Urban area in 1997	0.65	0.63**	-0.05	0.67	0.03	0.58***	-0.16
Urban area (final state)	0.78	0.76**	-0.05	0.78	0.02	0.74***	-0.12
Black	0.26	0.18***	-0.18	0.17***	-0.20	0.13***	-0.29
Hispanic	0.18	0.12***	-0.14	0.16**	-0.04	0.15***	-0.07
Exposure to the Crisis (first state)	0.00	0.00	-0.02	0.00	-0.00	0.00	-0.00
Exposure to the Crisis (final state)	0.60	0.62***	0.06	0.62***	0.07	0.64***	0.13
Cognitive factor	-0.65	-0.11***	0.53	-0.13***	0.51	-0.45***	0.20
Socioemotional factor	0.06	0.05	-0.01	0.23***	0.18	0.05	-0.00
Mechanical factor	0.10	0.18***	0.08	0.10	0.01	0.23***	0.12
Percentage	69.3%		9.3%		9.3%		14.7%

Note: Only simulated individuals who would choose to be high school graduates under uncertainty are considered. They are classified according to whether the net value of being a high school graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.26: Sensitive to Uncertainty and Exposure to the Great Recession: Two-year Graduates.

	Obtains the Highest a 2y grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y dropout		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	12.97	13.61***	0.27	13.27***	0.13	12.91	-0.03	12.65	-0.14
Single-parent home in 1997	0.33	0.23***	-0.22	0.29***	-0.10	0.39***	0.12	0.34	0.00
Family income in 1997	48.51	55.05***	0.21	52.62***	0.13	46.38*	-0.07	42.47**	-0.19
Proxy for siblings in 1997	2.37	2.30*	-0.06	2.36	-0.01	2.31	-0.05	2.25	-0.11
Urban area in 1997	0.63	0.59**	-0.08	0.65	0.04	0.68***	0.11	0.42***	-0.44
Urban area (final state)	0.76	0.76	-0.02	0.78**	0.06	0.78	0.05	0.73	-0.10
Black	0.12	0.07***	-0.14	0.09***	-0.09	0.16***	0.12	0.14	0.07
Hispanic	0.12	0.07***	-0.16	0.11*	-0.05	0.14	0.04	0.06**	-0.20
Exposure to the Crisis (first state)	0.00	0.00	-0.02	0.00	0.02	0.00	-0.00	0.01**	0.22
Exposure to the Crisis (final state)	0.67	0.67	0.01	0.67	-0.01	0.65*	-0.07	0.69	0.07
Cognitive factor	-0.12	0.26***	0.41	0.15***	0.29	-0.14	-0.02	-0.12	-0.00
Socioemotional factor	-0.06	0.06***	0.12	0.12***	0.17	-0.10	-0.05	0.17**	0.23
Mechanical factor	0.05	0.02	-0.03	-0.03**	-0.07	0.02	-0.03	-0.20***	-0.24
Percentage	75.8%	8.6%		14.1%		8.4%		1.3%	

Note: Only simulated individuals who would choose to be two-year graduates under uncertainty are considered. They are classified according to whether the net value of being a -twoyear graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.27: Sensitive to Uncertainty and Exposure to the Great Recession: Four-year graduate - Two-year College Enrollment.

	Obtains the Highest Value as a 4y grad. (2y)	Higher Value as a 4y grad. (direct)		Higher Value as a 4y dropout		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	13.31	14.53***	0.48	13.02**	-0.12	13.77***	0.18	12.95	-0.14
Single-parent home in 1997	0.38	0.22***	-0.32	0.44***	0.12	0.23***	-0.31	0.28**	-0.21
Family income in 1997	54.85	58.72	0.10	53.73	-0.03	57.42	0.06	50.28	-0.11
Proxy for siblings in 1997	2.40	2.22**	-0.16	2.42	0.02	2.32*	-0.07	2.29	-0.09
Urban area in 1997	0.77	0.76	-0.03	0.83***	0.15	0.72***	-0.12	0.64***	-0.31
Urban area (final state)	0.84	0.85	0.02	0.84	0.00	0.79***	-0.18	0.79*	-0.18
Black	0.14	0.10*	-0.12	0.20***	0.17	0.08***	-0.18	0.08*	-0.17
Hispanic	0.16	0.07***	-0.26	0.18	0.03	0.09***	-0.20	0.13	-0.09
Exposure to the Crisis (first state)	0.00	0.00**	0.13	0.00	-0.06	0.00	-0.01	0.00	-0.06
Exposure to the Crisis (final state)	0.66	0.70**	0.15	0.66	-0.00	0.67	0.05	0.64	-0.07
Cognitive factor	0.41	0.87***	0.56	0.16***	-0.31	0.44	0.04	0.40	-0.02
Socioemotional factor	0.27	0.57***	0.30	0.24	-0.03	0.22	-0.05	0.53***	0.27
Mechanical factor	-0.14	-0.25*	-0.12	-0.21*	-0.09	-0.02***	0.14	-0.13	0.01
Percentage	78.9%	3.7%		6.9%		8.7%		1.6%	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a two-year college, under uncertainty are considered. They are classified according to whether the net value of being a 4-year graduate, enrolling in a two-year college, is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.28: Sensitive to Uncertainty and Risk Preferences: Four-year graduates - with Direct Enrollment.

	Obtains the Highest a 4y grad. (direct)	Higher Value as a 4y grad. (2y)		Higher Value as a 4y dropout		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	14.72	14.37***	-0.14	14.21***	-0.20	14.33***	-0.16	13.53***	-0.47
Single-parent home in 1997	0.23	0.25***	0.05	0.29***	0.15	0.19***	-0.09	0.26**	0.07
Family income in 1997	78.16	71.53***	-0.11	71.69***	-0.11	66.42***	-0.20	53.25***	-0.43
Proxy for siblings in 1997	2.23	2.27**	0.04	2.26	0.04	2.25	0.02	2.31***	0.08
Urban area in 1997	0.71	0.74***	0.07	0.72	0.03	0.66***	-0.11	0.64***	-0.14
Urban area (final state)	0.82	0.83**	0.03	0.82	-0.02	0.79***	-0.11	0.79***	-0.12
Black	0.12	0.10***	-0.06	0.14***	0.07	0.08***	-0.13	0.13	0.05
Hispanic	0.08	0.11***	0.11	0.10***	0.07	0.07**	-0.04	0.08	0.00
Relative Risk Tolerance - Cat. 1	0.29	0.32***	0.06	0.34***	0.10	0.29	-0.02	0.39***	0.20
Relative Risk Tolerance - Cat. 2	0.28	0.24***	-0.10	0.29	0.02	0.23***	-0.11	0.24***	-0.09
Relative Risk Tolerance - Cat. 3	0.17	0.17	-0.01	0.17	-0.02	0.22***	0.13	0.13***	-0.11
Relative Risk Tolerance - Cat. 4	0.25	0.27**	0.04	0.20***	-0.11	0.26	0.02	0.24	-0.03
Cognitive factor	0.48	0.56***	0.10	0.25***	-0.27	0.43***	-0.06	0.33***	-0.18
Socioemotional factor	-0.08	0.08***	0.16	-0.02**	**0.05**	-0.07	0.01	-0.01**	0.07
Mechanical factor	0.03	-0.05***	**-0.08**	-0.03**	-0.06	0.13***	0.11	0.27***	**0.26**
Percentage	72.3%	14.1%		6.3%		11.8%		3.4%	
Std. Deviation of Net Value	1.36	1.33		0.98		0.89		0.24	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a four-year college, under uncertainty are considered. They are classified according to whether the net value of being a four-year graduate, starting in a four-year college, is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.29: Sensitive to Uncertainty and Risk Preferences: High School Graduates.

	Obtains the Highest Value as a HS grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	11.90	12.74***	0.34	12.30***	0.16	12.20***	0.12
Single-parent home in 1997	0.52	0.39***	-0.26	0.45***	-0.13	0.40***	-0.24
Family income in 1997	37.28	45.82***	0.33	42.15***	0.19	41.71***	0.17
Proxy for siblings in 1997	2.50	2.40***	-0.08	2.45*	-0.04	2.40***	-0.08
Urban area in 1997	0.67	0.63***	-0.09	0.66	-0.02	0.60***	-0.14
Urban area (final state)	0.78	0.77	-0.02	0.79	0.03	0.74***	-0.11
Black	0.26	0.18***	-0.16	0.18***	-0.17	0.16***	-0.22
Hispanic	0.18	0.13***	-0.13	0.16	**-0.04**	0.15***	-0.06
Relative Risk Tolerance - Cat. 1	0.54	0.45***	-0.18	0.49***	-0.10	0.47***	-0.15
Relative Risk Tolerance - Cat. 2	0.22	0.24***	0.06	0.19**	-0.05	0.20	-0.03
Relative Risk Tolerance - Cat. 3	0.08	0.11***	0.09	0.10***	0.06	0.14***	0.22
Relative Risk Tolerance - Cat. 4	0.16	0.20***	0.11	0.22***	0.15	0.19***	0.07
Cognitive factor	-0.60	-0.11***	0.48	-0.14***	0.45	-0.44***	0.16
Socioemotional factor	0.06	0.05	-0.01	0.23***	0.17	0.03	-0.03
Mechanical factor	0.12	0.16	**0.04**	0.06**	**-0.06**	0.22***	0.09
Percentage	69.1%	9.5%		9.5%		13.8%	
Std. Deviation of Net Value	0.24	0.54		0.66		0.52	

Note: Only simulated individuals who would choose to be high school graduates under uncertainty are considered. They are classified according to whether the net value of being a high school graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}_{(s_1,\dot{s})}} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.30: Sensitive to Uncertainty and Risk Preferences: Two-year graduates.

	Obtains the Highest a 2y grad.	Higher Value as a 4y grad. (direct)		Higher Value as a 4y grad. (2y)		Higher Value as a 2y dropout		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	12.98	13.61***	0.27	13.21***	0.10	12.83	-0.06	12.70	-0.12
Single-parent home in 1997	0.32	0.23***	-0.20	0.28***	-0.10	0.37**	0.09	0.25*	-0.17
Family income in 1997	48.75	55.33***	0.20	52.12***	0.10	47.33	-0.04	46.77	**-0.06**
Proxy for siblings in 1997	2.34	2.26**	-0.07	2.29	-0.05	2.39	**0.04**	2.22	-0.12
Urban area in 1997	0.64	0.63	-0.02	0.66*	0.05	0.69***	0.11	0.45***	-0.39
Urban area (final state)	0.77	0.78	0.04	0.79**	0.07	0.79	0.06	0.68***	**-0.26**
Black	0.12	0.09***	-0.09	0.11	-0.04	0.17***	**0.17**	0.07*	**-0.16**
Hispanic	0.14	0.10***	-0.12	0.15	0.02	0.15	0.01	0.08*	**-0.17**
Relative Risk Tolerance - Cat. 1	0.40	0.31***	-0.17	0.39	-0.02	0.44**	0.09	0.41	0.02
Relative Risk Tolerance - Cat. 2	0.18	0.19	0.01	0.19	0.01	0.21**	0.08	0.21	0.06
Relative Risk Tolerance - Cat. 3	0.20	0.23*	0.07	0.18	-0.04	0.15***	-0.13	0.18	-0.05
Relative Risk Tolerance - Cat. 4	0.22	0.27***	0.13	0.25**	0.06	0.20	-0.06	0.21	-0.03
Cognitive factor	-0.15	0.17***	0.35	0.10***	0.27	-0.17	-0.02	-0.11	0.04
Socioemotional factor	-0.09	-0.07	**0.02**	-0.00***	0.09	-0.10	-0.01	-0.09	-0.00
Mechanical factor	0.02	-0.00	-0.02	-0.06***	-0.08	0.01	-0.01	-0.07	-0.09
Percentage	74.8%	9.5%		15.0%		8.0%		1.2%	
Std. Deviation of Net Value	0.95	1.01		1.09		0.73		0.22	

Note: Only simulated individuals who would choose to be two-year graduates under uncertainty are considered. They are classified according to whether the net value of being a two-year graduate is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1, \dot{s})) = \sum_{\tilde{s} \in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1}, \tilde{s}))\right]$, where $\overrightarrow{s}(s_1, \dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.31: Sensitive to Uncertainty and Risk Preferences: Four-year graduates - with Two-Year College Enrollment.

	Obtains the Highest a 4y grad. (2y)	Higher Value as a 4y grad. (direct)		Higher Value as a 4y dropout		Higher Value as a 2y grad.		Higher Value as a HS grad.	
	Mean	Mean	SMD	Mean	SMD	Mean	SMD	Mean	SMD
Mother's education in 1997	13.37	14.49***	0.45	13.13**	**-0.10**	13.81***	0.18	13.20	-0.07
Single-parent home in 1997	0.37	0.23***	-0.29	0.45***	0.16	0.23***	-0.29	0.33	**-0.08**
Family income in 1997	56.21	67.85***	0.27	56.23	0.00	58.49	0.05	46.98**	-0.22
Proxy for siblings in 1997	2.37	2.13***	**-0.21**	2.32	-0.04	2.24***	-0.12	2.14**	**-0.20**
Urban area in 1997	0.76	0.72	-0.10	0.76	0.00	0.72**	-0.10	0.65***	-0.25
Urban area (final state)	0.84	0.84	-0.01	0.83	-0.03	0.82**	-0.09	0.78**	**-0.21**
Black	0.14	0.08***	-0.18	0.18**	**0.11**	0.07***	-0.19	0.12	**-0.04**
Hispanic	0.17	0.09***	-0.22	0.20	0.07	0.12***	-0.13	0.10**	-0.19
Relative Risk Tolerance - Cat. 1	0.40	0.23***	-0.35	0.42	0.04	0.34***	-0.12	0.42	0.04
Relative Risk Tolerance - Cat. 2	0.19	0.19	0.01	0.19	0.00	0.17	-0.04	0.10**	-0.23
Relative Risk Tolerance - Cat. 3	0.13	0.17*	0.12	0.11	-0.06	0.13	0.00	0.12	-0.04
Relative Risk Tolerance - Cat. 4	0.29	0.42***	0.28	0.29	0.01	0.36***	0.16	0.37**	0.19
Cognitive factor	0.38	0.77***	0.47	0.15***	-0.27	0.47***	0.12	0.38	0.01
Socioemotional factor	0.23	0.27	0.03	0.17	-0.06	0.12***	**-0.12**	0.15	**-0.08**
Mechanical factor	-0.18	-0.30**	-0.14	-0.31***	-0.15	-0.11**	0.08	-0.26	-0.09
Percentage	77.8%	4.2%		7.3%		9.4%		1.7%	
Std. Deviation of Net Value	1.25	1.27		0.98		1.08		0.27	

Note: Only simulated individuals who would choose to be four-year graduates, starting in a two-year college, under uncertainty are considered. They are classified according to whether the net value of being a four-year graduate, starting in a two-year college, is the highest (column 1) or not. Net value is calculated as: $NV(\overrightarrow{s}(s_1,\dot{s})) = \sum_{\tilde{s}\in \overrightarrow{s}(s_1,\dot{s})} \left[PV(Y(\tilde{s})) - PV(C(\tilde{s}^{-1},\tilde{s}))\right]$, where $\overrightarrow{s}(s_1,\dot{s})$ is the schooling trajectory starting at the common initial node, transitioning through s_1 (the first choice), and leading to the final state $\dot{s}$. Stars indicate standard significance levels for a t-test on mean differences relative to the group in column 1: * p<0.10, ** p<0.05, *** p<0.01. SMD is the standardized mean difference that uses the standard deviation of the group in column 1, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Table 2.32: Percentage of Individuals Achieving the Highest Net Value Under Policy Simulation.

Schooling Path	Group	Status quo	Policy
2y Graduates	Always-takers	76.26%	83.69%
	Compliers	48.03%	63.63%
2y Dropouts	Always-takers	73.04%	75.12%
	Compliers	36.89%	49.31%
All	All	67.93%	67.33%

Note: The simulated data contains 100 replications of the data (106,800 observations in total). The Policy Simulation considers an annual $16,500 subsidy for a two-year college, which covers the total costs of attending a two-year college. Always-takers are individuals who would choose the same two-year path in both the status quo and the policy simulation. Compliers are those who would not choose the analyzed two-year path in the status quo but would do so under the policy.

Table 2.33: Two-year College Subsidy: Differences in Characteristics between Compliers and Never-takers by Schooling Choice.

	4y graduates		4y dropouts		2y dropouts		HS graduates	
	Never-takers Mean	Compliers SMD	Never-takers Mean	Compliers SMD	Never-takers Mean	Compliers SMD	Never-takers Mean	Compliers SMD
Mother's education in 1997	14.42	-0.31***	13.44	-0.09**	12.76	0.03	12.02	0.14***
Single-parent home in 1997	0.26	-0.09***	0.44	-0.19***	0.51	-0.28***	0.52	-0.29***
Family income in 1997	72.26	-0.29***	59.02	-0.17***	49.75	0.03	38.93	0.11***
Proxy for siblings in 1997	2.26	-0.00	2.39	-0.04	2.51	-0.11***	2.45	-0.08***
Urban area in 1997	0.73	-0.18***	0.75	-0.22***	0.79	-0.17***	0.64	-0.14***
Urban area (final state)	0.83	-0.18***	0.82	-0.13***	0.84	-0.14***	0.77	-0.16***
Black	0.12	-0.12***	0.23	-0.20***	0.23	-0.20***	0.23	-0.24***
Hispanic	0.10	-0.00	0.15	-0.01	0.20	-0.04	0.17	-0.10***
Cognitive factor	0.51	-0.21***	0.05	-0.25***	-0.27	0.01	-0.60	0.18***
Socioemotional factor	0.02	-0.06**	-0.02	-0.02	-0.07	-0.01	0.09	-0.12***
Mechanical factor	-0.01	0.09***	-0.13	-0.05	-0.07	0.07**	0.14	0.02
Percentage	93.1%	4.1%	90.6%	5.1%	92.8%	7.2%	86.2%	4.7%

Note: Only individuals choosing being 2-year graduates are considered in the complier groups. Stars indicate standard significance levels for a t-test on mean differences relative to the never-takers making the same choice in the status quo. SMD is the standardized mean difference that uses the standard deviation of the never-takers group, instead of the pooled standard deviation. The SMD can be used to measure the magnitude of the difference across characteristics. Factors are standardized to facilitate interpretation. Family income is measured in thousands.

Chapter 3: Observed and Unobserved Variables in Educational Treatment Effects

With Sergio Urzúa

3.1 Introduction

Decades of research have provided a detailed understanding of how unobservable factors shape heterogeneity in the returns to higher education (Belzil and Hansen, 2002; Belzil, Hansen and Liu, 2022; Carneiro, Heckman and Vytlacil, 2011; Carneiro, Hansen and Heckman, 2003; Cassagneau-Francis, 2022; Chen, 2008; Heckman, Humphries and Veramendi, 2018; Heckman, Stixrud and Urzua, 2006; Prada and Urzúa, 2017). Of course, observed characteristics also play a crucial role in elucidating heterogeneous responses, as they determine schooling choices and potential outcomes. Moreover, they have recently received increased attention in the treatment effects literature, as the functional specification of the outcome equations can be crucial to securing a causal interpretation (Blandhol et al., 2022). However, dissecting the interaction between unobservables and observable dimensions, which are often overlooked in existing literature, is necessary to untangle the factors determining the magnitudes of treatment effects.

This chapter explores the interplay between observed and unobserved variables and proposes a decomposition analysis to evaluate their relative importance in determining the treatment effects of postsecondary schooling decisions. We demonstrate that observable characteristics

primarily influence both the level and slope—where the latter represents the diverse compensations—of marginal treatment effects for certain groups and margins of choice. Our focus on the marginal treatment effect is driven by its crucial role in shaping other treatment effects and effective policy interventions (Heckman and Vytlacil, 2007, 2001). By identifying individuals at the margin of indifference, we pinpoint those most likely to respond to incentives introduced by policies, as these individuals require minimal subsidies or incentives to alter their decisions.

Our framework employs a static Roy model with latent cognitive, socioemotional, and mechanical abilities. Previous literature has shown that all these are essential in determining college returns and decisions (Belzil, Hansen and Liu, 2022; Prada and Urzúa, 2017). In this model, individuals can choose between i) staying with a high school diploma, ii) obtaining a two-year degree, or iii) obtaining a four-year degree. We focus on the impact of these decisions among those indifferent between schooling alternatives, decomposing the contribution of unobserved and observed dimensions. Most of the literature studying postsecondary returns and considering heterogeneity in these latent abilities have focused on analyzing only men (e.g., Carneiro, Hansen and Heckman, 2003; Eisenhauer, Heckman and Mosso, 2015; Heckman, Humphries and Veramendi, 2018; Prada and Urzúa, 2017). We focus on highlighting the differences between women and men as we separately estimate our model for each group (see some exceptions: Belzil, Hansen and Liu, 2022; Heckman, Stixrud and Urzua, 2006).

Our identification strategy follows literature standards for Roy models. We rely on a measurement system that imposes structure and interpretation on the latent abilities and exclusion restrictions that affect choice equations but not earnings. Our primary source of information is the National Longitudinal Survey of Youth 1997 (NLSY97), which contains detailed information on earnings, postsecondary schooling trajectories, test scores, and background characteristics, all

essential to estimate our model. This data source has been widely employed to study schooling decisions or returns to abilities (Arcidiacono et al., 2023; Belzil, Hansen and Liu, 2022; Deming, 2017; Luo, Hellerstein and Urzúa, 2023). The NLSY97 follows cohorts born between 1980 and 1984 that are slightly older than those analyzed by Mountjoy (2022), who also estimate marginal treatment effects of two-year and four-year college education, allowing us to have a benchmark to compare the magnitudes that we obtain. Limiting the number of schooling choices to three and imposing a static framework enable us to focus on analyzing all possible pairwise comparisons between schooling choices and decomposing marginal treatment effects (MTE) while having well-populated evaluation points of indifference. See the first chapter of this dissertation to focus instead on a dynamic version of this model, which has option values and examines more schooling decisions, including dropping out.

We contribute to three strands of the literature. First, we contribute to the literature that analyzes the different components of an MTE. We follow previous work focusing on decomposing the MTE in multinomial settings. Where more than two alternatives are available, the MTE can be expressed as a weighted average of the MTEs obtained from all the pair-wise comparisons between choices. Thus, we examine the MTE for individuals who are at different margins of indifference depending on the individual's next-best alternative (e.g., Heckman, Urzua and Vytlacil, 2006; Mountjoy, 2022). In addition, we propose a definition of the MTE that integrates over the distribution of observed characteristics for the in-sample compliers at each point of indifference.[1] This distinction allows us to decompose the MTE into the observables and each ability's contributions. The practice of decomposing parameters into observable and unobservable components

[1]Marginal treatment effects are usually defined as conditional functions of characteristics or abilities instead of integrating over them.

is a long-standing tradition in Labor Economics, dating back to Oaxaca-Blinder decompositions (Angrist, Pathak and Walters, 2013; Blinder, 1973; Oaxaca, 1973). These methods have been extended to treatment effect parameters, with several papers proposing methodologies or estimates for decomposing these parameters into systematic and idiosyncratic variations. (Ding, Feller and Miratrix, 2019; Djebbari and Smith, 2008; Heckman, Smith and Clements, 1997). Moreover, Blandhol et al. (2022) develop a decomposition to diagnose if the two-stage least squares estimate is level-dependent on outcomes and, hence, not rich in covariates. In contrast to previous work, we focus on analyzing MTEs and further decomposing unobservable components considering the role of latent abilities, an essential driver of heterogeneous schooling returns.

Second, we contribute to the articles that analyze the effect of higher education when more than two choices are available (e.g, Ferreyra, Galindo and Urzúa, 2022; Mountjoy, 2022). In particular, we can contribute to the literature that characterizes and analyzes the next-best alternatives. For instance, Kirkeboen, Leuven and Mogstad (2016) and Heinesen et al. (2022) rely on administrative data from centralized admission systems to identify the next-best alternative for students applying to different fields and postsecondary institutions. The structure of the model allows us to fully characterize the ranking of preferences without requiring detailed data on individual preferences.

Finally, we also contribute to the literature that analyzes the role of latent abilities on schooling choices by documenting the empirical consequences of modeling the ordered nature of socioemotional tests. Most of the available socioemotional tests use a Likert scale. Therefore, the psychological tests usually employed to derive noncognitive ability distributions ask respondents to declare which statement, each associated with an integer, best describes their personality or behavior. Consequently, the different values reported for these tests only contain information about

the order of preferences as they are not cardinal measures. Previous work using measurement systems usually models these tests as if they were cardinal test scores (see Attanasio et al., 2020; Hansen, Heckman and Mullen, 2004, for some exceptions). In this chapter, we show that the estimated distribution of the socioemotional latent ability is different if the ordered nature is considered. Assuming cardinality causes the estimated distribution to depend heavily on one test, the one informing the most about the latent ability. This dependency will increase with the number of mixtures determining the degree of flexibility of the ability's estimated distribution. Hence, the higher the flexibility of the distribution of the latent variable, the higher the over-dependence on this test. However, a common limitation in studies utilizing the NLSY97 to analyze socioemotional abilities is the timing of data collection, which often occurs either after individuals have made significant postsecondary schooling decisions or after completing them. Consequently, the interpretation of findings related to this ability dimension must be approached cautiously, as observed tests may be influenced by the educational experiences individuals experience during college. As in the second chapter of this dissertation, the implicit assumption in interpreting the lack of sorting observed for socioemotional abilities is that they remain stable from high school graduation into the mid- or late-twenties—when these measures are collected in the NLSY97.

As a preview of our results, we find different ability distributions and returns to ability for women and men. We observe that latent abilities assume crucial and distinctive roles depending on both the schooling decision and the group. Notably, the correlation between cognitive and mechanical abilities among men stands at 0.46, while it nearly doubles for women, reaching 0.86. Moreover, the socioemotional ability determines women's earnings associated with a high school diploma but not men's. However, our decomposition analysis shows that unobserved abilities are not always the primary factor that explains the level and slope of the MTE. Cognitive ability pre-

dominantly shapes the observed heterogeneity in men's marginal treatment effects. Conversely, observed factors are crucial in determining the level and slope of women's marginal treatment effects, with mechanical and cognitive abilities playing a comparatively minor role. In addition, we examine each observed variable's effect on MTEs. This further decomposition shows heterogeneous effects in terms of variables such as the number of children, urban residency, and region of residency, revealing changes in the composition of those at the margin of indifference.

We show, aligned with previous results by Mountjoy (2022), that the MTE of a two-year college education is only positive for those whose next-best alternative is staying with a high school diploma. In other words, incentivizing students to switch from four- to two-year colleges generates, on average, reduced earnings at the margin of indifference. At the same time, we would observe positive effects if these incentives were provided to those who would stay as high school graduates in the absence of a policy. On the other hand, the MTE of a four-year college education is positive for all groups. However, it is usually higher for those who would switch from being a high school graduate to attaining a four-year college degree. These results underscore the importance of understanding the ranking of preferences, as the next-best alternative can determine the level and sign of the marginal effect. We show that for those who decide to stay with a high school diploma, the most common second-best alternative is obtaining a four-year college degree for both men and women. We also show that 10.9% of women and 8.3% of men ranked getting a four-year college as their first best and attaining a two-year degree as their second best. Within these fractions, those closer to the margin of indifference would exhibit a negative effect if they were incentivized to get a two-year college degree.

The following section introduces our model and the MTE in a simplified setting, considering only two sectors or alternatives. Section 3.3 explains the decomposition into observed and

unobserved components and discusses the practical implementation of the MTE and its decomposition. Section 3.4 extends the discussed methodology to a framework with three sectors and details the further decomposition considering all pairwise comparisons of different margins of indifference. Section 3.5 unifies all these elements in a static Roy model with latent abilities. Then, Section 3.6 discusses the estimation method and describes our data and sample in detail. This section also discusses the goodness of fit of our model and the empirical consequences of incorporating the ordered nature of socioemotional measures in the measurement system's assumptions. Section 3.7 presents our main results, and Section 3.8 discusses our main conclusions.

3.2 Basic Model: Two-sector case

First, we examine a Roy model with only two sectors, where a specific sector is denoted with i ($i \in \{0, 1\}$). This framework has been used extensively to bridge the treatment effect and structural econometrics literature. In this model, potential outcomes (Y_0, Y_1) can be decomposed in terms of their mean, conditional on observed characteristics X, and individual deviations from the mean or unobserved components (U_0, U_1), as follows:

$$Y_1 = \mu_1(X) + U_1, \tag{3.1}$$

$$Y_0 = \mu_0(X) + U_0. \tag{3.2}$$

Y_i denotes the outcome that agent i receives upon selecting sector i. Please note the omission of individuals' subscripts for notation simplicity.

A choice model dictates how individuals choose one of the available sectors. A latent variable D^* captures the utility derived from choosing sector 1 while normalizing the utility of

sector 0 to zero. Consequently, we define the following binary indicator that takes the value corresponding to the chosen sector:

$$D = \begin{cases} 1 \text{ if } D^* = \mu_c(Z) - V \geqslant 0 \\ 0 \text{ otherwise.} \end{cases} \tag{3.3}$$

This expression means that individuals choose the sector that generates the highest utility, which is determined as a mean function of observed characteristics Z and an unobserved component V. We assume that:

$$U_1 \not\perp\!\!\!\perp U_0 \not\perp\!\!\!\perp V,$$

where $\not\perp\!\!\!\perp$ denotes no independence; the unobserved components are permitted to be correlated. Given the definition of D, the binary indicator, we can conveniently express the observed outcome Y as follows:

$$Y = Y_1 D + Y_0 (1 - D),$$

This expression encapsulates the central challenge of causal inference, which is fundamentally a missing data problem. For each individual unit, only one of either Y_0 or Y_1 is observable, with the observed outcome contingent upon the individual's choice. Notice that:

$$\begin{aligned} Y &= Y_1 D + Y_0 (1 - D) \\ &= \mu_0(X) + \beta D + U_0, \end{aligned}$$

where $\beta = Y_1 - Y_0$. This implies a distribution of gains, meaning that the effect of the treatment is heterogeneous, with β varies across units even after accounting for X. Consequently,

the response to treatment, or the choice of D, is partly shaped by idiosyncratic unobserved heterogeneity, a factor that influences even individuals who appear observationally identical (see Heckman, Urzua and Vytlacil (2006) for a more detailed discussion).

In this study, we will focus on two treatment parameters:

$$\Delta^{MTE}(x,v) = E\left(Y_1 - Y_0 \mid X = x, V = v, D^* = 0\right), \tag{3.4}$$

$$\Delta^{TT}(x) = E\left(Y_1 - Y_0 \mid X = x, D = 1\right). \tag{3.5}$$

The first equation corresponds to the marginal treatment effect (MTE) parameter, which measures the mean gain in outcomes for persons or units who would be indifferent between treatment or not when $V = v$ and $X = x$. The second equation corresponds to the treatment on the treated (TT) parameter, which measures the mean gain for individuals who receive treatment (or choose sector 1), given $X = x$.

Define $P(Z)$ as the probability of receiving treatment given Z, or in the lenses of a discrete choice model, of choosing sector 1 given Z. Then $\Pr(Z) \equiv \Pr(D = 1 \mid Z) = F_V(\mu_c(Z))$, where $F_V(\cdot)$ denotes the distribution function of V. If we assume that $(X, Z) \perp\!\!\!\perp (U_1, U_0, V)$, the MTE can be estimated over the support of P and is additive separable in X and V.

3.3 Practical Implementation

The MTE can be empirically identified using the Local Instrumental Variables (LIV) estimator. Let $U_D = F_V(V)$, which follows a uniform distribution on the $[0, 1]$ interval. Then, the

LIV estimator is:

$$\frac{\partial}{\partial P(z)} E\left(Y \mid X = x, P(Z) = P(z)\right)\Big|_{P(z)=u_D} = E(Y_1 - Y_0 \mid X = x, U_D = u_D). \tag{3.6}$$

The left-hand side of this equation provides an expression for the MTE based on only observable variables (Y, X, Z). The LIV parameter can be estimated for any $P(z)$ within the support of $P(Z)$ and defines a treatment effect for those with a given unobserved propensity to participate (u_D) that is equal to $P(z)$. Note that the expression on the right-hand side is equivalent to equation 3.4, using u_D instead of v for determining the evaluation point of unobservables and having $P(z) = u_D$ as the point of indifference to satisfy the equality. Observe that a high level of $P(z)$ identifies the MTE for a high level of $U_D = u_D$, meaning that it identifies the effect for individuals whose unobservables make them less likely to choose sector 1. Recall that $P(z)$ is a monotonic transformation of $\mu_c(z)$, thus, high levels of $\mu_c(z)$ would be required to compensate for high levels of v under indifference $(\mu_c(z) - v = 0)$.

Following Carneiro, Heckman and Vytlacil (2010), consider the introduction of a metric function $q(\cdot, \cdot)$ to capture the distance between $P(Z)$ and U_D. This function empirically defines indifference between sectors. Therefore, the MTE can be re-expressed as follows:

$$\Delta^{MTE}\left(X, u_D; \epsilon\right) = E(Y_1 - Y_0 \mid X = x, q(P(z), u_D) < \epsilon),$$

where ϵ denotes a user-defined tolerance threshold. As discussed by Carneiro, Heckman and Vytlacil (2010), different metrics will yield different estimates and identify distinct individuals at the indifference margin. However, the metric can be selected in a fashion such as the change

in the decision rule has a policy change interpretation.

Note that the MTE considered so far is an expression conditional on X, the observed variables affecting sector-specific outcomes. However, conditioning on X might be empirically infeasible to satisfy if X contains continuous variables. Therefore, we consider instead an MTE averaged over the distribution of X. For a given ϵ:

$$\begin{aligned}\Delta^{MTE}(u_D;\epsilon) &= \int \Delta^{MTE}(x,u_D;\epsilon)\, dF_{X|U_D=u_D,q(P,U_D)<\epsilon}(x) \\ &= E(Y_1 - Y_0 \mid U_D = u_D, q(P,U_D) < \epsilon).\end{aligned}$$

Then, every point of indifference involves integrating over a distinct relevant distribution ($F_{X|U_D=u_D,q(P,U_D)<\epsilon}$). Note that no assumption required for estimating the MTE precludes the possibility that Z and X are correlated over the set defined by $q(P,u_D) < \epsilon$. Therefore, the contribution of X to the MTE might change as one evaluates different values of $(u_D, P(z))$. We propose the following decomposition to examine the extent to which this correlation with observed variables or with unobserved components (U_1, U_0) explains the MTE:

$$\begin{aligned}\Delta^{MTE}(u_D;\epsilon) &= \int [\mu_1(x) - \mu_0(x) + U_1 - U_0]\ dF_{X|U_D=u_D,q(P,U_D)<\epsilon}(x) \\ &= \int [\mu_1(x) - \mu_0(x)]\ dF_{X|U_D=u_D,q(P,U_D)<\epsilon}(x) \\ &\quad + \int [U_1 - U_0]\ dF_{X|U_D=u_D,q(P,U_D)<\epsilon}(x) \\ &= \beta_X(U_D = u_D, q(P(Z),U_D) < \epsilon) \\ &\quad + \beta_{u_D}(U_D = u_D, q(P(Z),U_D) < \epsilon).\end{aligned} \tag{3.7}$$

The first term captures how much of the MTE is explained by observed factors ($\mu_1(x) -$

$\mu_0(x)$), and the second term captures how much of the MTE is explained by unobserved factors ($U_1 - U_0$), that in our specific application will refer to the role of abilities. It is crucial to recognize that the integration over the distribution of X, conditional on each indifference point, means the sample for each u_D may vary. Consequently, this decomposition also reveals how the characteristics influencing sector selection or treatment (Z, V) relate to the outcome components.

We examine this decomposition in a multinomial setting, introduced in the following section.

3.4 Unordered model: HS, 2YC, and 4YC,

This section introduces a generalization of the previously described model, expanding the choice framework to allow individuals to select from a broader range of alternatives beyond the binary options considered initially. Let $\mathcal{J}$ be the set of all sectors under consideration, with no predetermined order of preference between elements. Consequently, this model acknowledges that individual preferences will lead to varied rankings of these options, with no inherent hierarchy among them. Additionally, let C_j determine the utility derived from selecting sector $j \in \mathcal{J}$:

$$C_j = \varphi_j(Z_j) - V_j, \tag{3.8}$$

and, similarly, define Y_j as the outcome associated with selecting sector j:

$$Y_j = \mu_j(X_j) - U_j, \tag{3.9}$$

Then, we can define the discrete choice model governing sector selection as follows:

$$D_{\mathcal{J},j} = \begin{cases} 1 & \text{if} \quad C_j \geqslant C_k \quad \forall k \in \mathcal{J} \\ 0 & \text{otherwise.} \end{cases}$$

where $D_{\mathcal{J}_j}$ is an indicator variable defined for each sector j, taking the value of one exclusively when the utility from sector j, denoted by C_j, surpasses that of all other considered sectors.

Define $C_{\mathcal{J}}$ as the highest level of utility achievable within the choice set $\mathcal{J}$, represented as:

$$C_{\mathcal{J}} = \max_{j \in \mathcal{J}} \{C_j\} = \sum_{i \in \mathcal{J}} D_{\mathcal{J},j} C_j. \tag{3.10}$$

Given that individuals select only the sector yielding the highest utility, the econometrician is limited to observing:

$$Y_{\mathcal{J}} \equiv \sum_{j \in \mathcal{J}} D_{\mathcal{J},j} Y_j, \tag{3.11}$$

which is the outcome associated with the utility-maximizing sector.

Following Heckman, Urzua and Vytlacil (2006), we can use these elements to define the MTE in a multinomial setup. The main challenge when more than two sectors or alternatives are available is that we do not have a clear counterfactual to calculate the relative change in outcomes, while in the binary setup, there is only one choice left for comparisons. To address this, we consider two distinct choice sets defined by the next-best alternative. First, we define $\mathcal{K} = \{k\}$, a singleton set with only alternative k. Then, we define $\mathcal{L} = \mathcal{J} \setminus \{k\}$, which is the

choice set with all available sectors but k. These two sets allow us to define the following MTE:

$$\Delta^{MTE}_{\mathcal{K},\mathcal{L}}(x, u_{D_\mathcal{K}}) = E\left[Y_\mathcal{K} - Y_\mathcal{L} \mid X = x, C_\mathcal{K} = C_\mathcal{L}\right]. \tag{3.12}$$

This MTE measures the average difference in potential outcomes for individuals indifferent between option k and the next-best alternative–the choice individuals would have selected if option k were unavailable. Note that if we consider a model with three sectors, set $\mathcal{L}$ would encompass two distinct choices. We explore this scenario in more detail in the following subsection.

3.4.1 Three-sector MTE

In our specific application, we study the treatment effects of post-secondary educational choices. Agents choose one among three different choices. They could stop their education after high school graduation, staying only with a high school diploma (HS); they may pursue a two-year college degree (2YC); or they may enroll in a four-year college program to obtain the respective degree (4YC). These distinct sectors define a specific set $\mathcal{J} = \{\text{HS, 2YC, 4YC}\}$ containing only three elements. Therefore, each MTE will be defined as a weighted average of two pairwise MTEs. To exemplify this idea, let's explicitly derive the MTE for being a four-year graduate that is defined using the sets $\mathcal{K} = \{\text{4YC}\}$ and $\mathcal{L} = \{\text{HS, 2YC}\}$. Then we can express

equation 3.12 as follows:

$$\begin{aligned}\Delta^{MTE}_{4YC,\mathcal{L}}(x, u_{D_{4YC}}) =& \Pr\left(C_{2YC} > C_{HS} | X = x, u_{D_{4YC}}, C_{4YC} = C_{2YC}\right) \\ & \times E\left[Y_{4YC} - Y_{2YC} | X = x, u_{D_{4YC}}, C_{4YC} = C_{2YC}\right] \\ & + \Pr\left(C_{2YC} \leqslant C_{HS} | X = x, u_{D_{4YC}}, C_{4YC} = C_{HS}\right) \\ & \times E\left[Y_{4YC} - Y_{HS} | X = x, u_{D_{4YC}}, C_{4YC} = C_{HS}\right].\end{aligned} \tag{3.13}$$

Then, the MTE for being a four-year graduate is determined by the probability that having a two-year degree would be preferred over a high school degree and being indifferent between a four- or two-year college degree, multiplied by the MTE for the binary case where staying as a high school graduate is not an option. This result is added to the probability that having a high school diploma would be preferred over a two-year college degree and being indifferent between a four-year college degree or a high school diploma, multiplied by the binary MTE where attaining a two-year college degree is no longer an option. These probabilities can be re-expressed as weights, and using Mountjoy (2022)'s nomenclature, we obtain:

$$\begin{aligned}\Delta^{MTE}_{4YC,\mathcal{L}}(x, u_{D_{4YC}}) =& \omega_{4YC}(x, u_{D_{4YC}}) \times \boldsymbol{MTE}_{4YC \leftarrow 2YC}(x, u_{D_{4YC}}) \\ & + (1 - \omega_{4YC}(x, u_{D_{4YC}})) \times \boldsymbol{MTE}_{4YC \leftarrow HS}(x, u_{D_{4YC}}),\end{aligned} \tag{3.14}$$

where the $k \leftarrow j$ subscript denotes the groups of individuals being indifferent between k and j, or who would switch from j to k if a policy aimed to increase (reduce) the utility (costs) of option k were implemented. Using the same rationale, we can equivalently define the MTE for attaining

a two-year degree as follows:

$$\begin{aligned}\Delta^{MTE}_{2YC,\mathcal{L}}(x, u_{D_{2YC}}) =& \omega_{2YC}(x, u_{D_{2YC}}) \times \boldsymbol{MTE}_{2YC \leftarrow 4YC}(x, u_{D_{2YC}}) \\ &+ (1 - \omega_{2YC}(x, u_{D_{2YC}})) \times \boldsymbol{MTE}_{2YC \leftarrow HS}(x, u_{D_{2YC}}).\end{aligned} \tag{3.15}$$

We will apply the decomposition into unobservables and unobservables, as shown in equation 3.7, to each of the pairwise MTEs in equations 3.14 and 3.15.

3.5 Roy Model with latent abilities

We employ a parametric generalized Roy model with latent abilities to analyze the returns to the three postsecondary choices that were explained in the previous section. Roy models have been extensively used to analyze returns to education (Heckman, Humphries and Veramendi, 2018; Heckman, Stixrud and Urzua, 2006; Prada and Urzúa, 2017) as well as in the marginal treatment effects literature (Carneiro, Heckman and Vytlacil, 2010; Heckman and Vytlacil, 2007, 2005; Heckman, Urzua and Vytlacil, 2006). In this model, individuals make schooling choices $j \in \mathcal{J} = \{\text{HS, 2YC, 4YC}\}$ to maximize their utility. Utility from choosing j is given by $C_j = Z_j'\gamma_j - V_j$ and earnings from choosing j by $Y_j = X_j'\beta_j + U_j$. V_j and U_j are unobserved from the perspective of the econometrician but not from the perspective of the decision maker. They have the following structure:

$$\begin{aligned} V_j &= \theta' \lambda_j^c + \varepsilon_j, \\ U_j &= \theta' \lambda_j^y + \epsilon_j \qquad \text{for } j \in \mathcal{J}, \end{aligned}$$

where θ is a vector of latent abilities that is predetermined before making any postsecondary decision. ε_j and ϵ_j are normally distributed and independent errors; where $\theta \perp\!\!\!\perp \{\varepsilon_j, \epsilon_j\}_{j=\{HS,2YC,4YC\}}$ and $\{\varepsilon_{j'}, \epsilon_{j'}\} \perp\!\!\!\perp \{\varepsilon_j, \epsilon_j\}$ for j' and j in {HS,2YC,4YC}. Despite the assumptions on the error terms, note that θ creates correlation across all unobserved components.

Moreover, we assume that $(X, Z) \perp\!\!\!\perp \{U_j, V_j\}_{j=\{HS,2YC,4YC\}}$. This condition guarantees non-parametric identification of all the MTE components that will be decomposed (Carneiro, Hansen and Heckman, 2003). Nonetheless, in practice, and relying on parametric identification, weaker assumptions can be considered. Despite all the assumptions on independence, X and Z may still be correlated. This fact will be crucial to interpret results in section 3.7

3.5.1 Identification of Latent Abilities

θ is a vector of latent abilities, $\theta = [\theta_c, \theta_s, \theta_m]$, encompassing cognitive (θ_c), socioemotional (θ_s), and mechanical (θ_m) dimensions. Previous studies have highlighted the importance of these dimensions in influencing post-secondary choices and their subsequent returns (Belzil, Hansen and Liu, 2022; Heckman, Stixrud and Urzua, 2006; Prada and Urzúa, 2017). We model abilities using a measurement system and factor variables following previous literature. The measurement system enables the factor variables to inherit the intended interpretation of the latent abilities and facilitates their identification. The latent variables resulting from this process aim to capture inherent abilities and their development within a specific environment with distinct resources until individuals are in high school and ready to determine their optimal post-secondary investments. The main idea behind the measurement system is to use tests related to each dimension to recover the free-of-measurement-error latent abilities. We impose the following structure

for the measurement system:

$$
\begin{aligned}
c_r &= Q_c'\eta_{c_r} + \theta_c\lambda_{c_r}^c + \varepsilon_{c_r} && \text{for } r = 1, ..., R \\
s_l^* &= Q_s'\eta_{s_l} + \theta_s\lambda_{s_l}^s + \varepsilon_{s_l} && \text{for } l = 1, ..., L \\
m_p &= Q_m'\eta_{m_p} + \theta_m\lambda_{m_p}^m + \theta_c\lambda_{m_p}^c + \varepsilon_{m_p} && \text{for } p = 1, ..., P.
\end{aligned} \tag{3.16}
$$

On the left-hand side of the system, we find test scores associated with cognitive (c_r), socioemotional (s_l^*), and mechanical traits (m_p). The main intuition behind considering a measurement system is to treat these tests only as noisy measures of each ability. Therefore, we impose structure and use factor variables to capture the information from several tests left after removing measurement errors. Q_c, Q_s, and Q_m are observed variables that affect test performance. Controlling for them allows us to remove any effect from background and family student characteristics that should not affect the actual ability and, hence, could generate non-classical measurement error. ε_{c_r}, ε_{s_l}, and ε_{m_p} are independent and normally distributed errors, capturing the fact that test scores are also subject to random error. $\eta_{c_r}, \eta_{s_l}, \eta_{m_p}, \lambda_{c_r}^c, \lambda_{s_l}^s, \lambda_{m_p}^m$, and $\lambda_{m_p}^c$ are parameters to be estimated. Note that for each type of test, there are several measures, each generating a different equation: R cognitive, L socioemotional, and P mechanical equations.

We impose several restrictions to achieve identification.[2] First, we restrict the relationship between test scores and θ. As the system shows, the mechanical measures inform about cognitive and mechanical abilities, while socioemotional (mechanical) measures are exclusively dedicated to informing about socioemotional (mechanical) abilities. Moreover, θ_m and θ_c are allowed to be correlated, while θ_s is assumed to be independent of other abilities. These assumptions are intro-

[2]See Carneiro, Hansen and Heckman (2003) for a deeper discussion about the identification of measurement systems.

duced after conducting an exploratory factor analysis on the observed measures.[3] Furthermore, we impose $\lambda^c_{c1} = \lambda^s_{s1} = \lambda^m_{m1} = 1$ to set the scale of the factors to the scale of the first measure in each system of equations. Consistent with standard practice in the field, we also set $\lambda^c_{m_P} = 0$ to ensure that there is at least one dedicated measure for the mechanical ability, which helps identify the correlation between θ_c and θ_m.

In contrast to most of the previous literature analyzing abilities and returns to schooling, we derive θ_s from an ordered system. Observed socioemotional measures s_l are not cardinal, as they use a Likert scale. Therefore, respondents rank how much their personality aligns with a given trait or behavior. Previous work usually treats these measures as cardinal. Instead, we model the ordered nature of each question and assume that s^*_l, the associated latent variables, follow a normal process. Therefore, the socioemotional system is estimated as an Ordered Probit. We introduce standard assumptions to achieve identification in such a system. First, Q_s does not contain a constant term. Second, the variance of all the error terms associated with socioemotional measures is assumed to be one ($Var(\varepsilon_{s_l}) = 1$ for $l = 1, ..., L$). With these assumptions, we can estimate the cutoffs of the latent variables that generate the different levels in the observed measures (Muthén, 1984). Later, in subsection 3.6.7, we describe the empirical consequences of deviating from assuming cardinality.

3.6 Estimation - CMLE

The model is estimated using Conditional Maximum Likelihood Estimation (CMLE). This procedure defines two stages. In the first stage, we estimate the parameters associated with the

[3]The exploratory factor analysis is available upon request. We obtain the same conclusions using oblique or orthogonal rotations.

distribution of latent abilities and test scores. In the second stage, fixing the distribution of abilities, we get estimates for the parameters affecting earnings and schooling choices. As test scores are ideally observed before making any postsecondary decision and θ is ideally measuring endowments before college, this two-step procedure ensures that the factor variables are primarily identified based on theoretically proposed relationships with test scores rather than being influenced by postsecondary decisions and earnings.

To describe in detail the estimation procedure, consider the likelihood function associated with the model explained in Section 3.5:

$$\int_{\underline{\Theta}} \left\{ \prod_{t \in \mathbf{T}} f(t|B,\theta;\delta) \prod_{j \in \mathcal{J}} [f(Y_j|B,\theta;\delta)\text{Pr}(D_{\mathcal{J},j}=1|B,\theta;\delta)]^{D_{\mathcal{J},j}} \right\} dF_\theta(\theta), \tag{3.17}$$

where $\mathbf{T}$ is set of test scores, B represents the set of explanatory variables, and δ the vector of all parameters. In addition, $\underline{\Theta}$ denotes the support of θ and $F_\theta(\cdot)$ is the joint cumulative distribution of θ.

The choice probabilities ($\text{Pr}(D_{\mathcal{J},j} = 1|B,\theta;\delta)$) do not have closed-form solution when more than two options are available to choose from. Our application considers three sectors, so we use the smoothed accept–reject method to estimate choice probabilities considering 100 evaluation points.

The distribution of the factors is allowed to follow a flexible distribution using mixtures of normal distributions as follows:

$$\theta_i \sim \sum_{j=1}^{h_i} p_j^i N(\mu_j^i, \sigma_j^{i2}) \qquad \text{for } i = c, s, u \tag{3.18}$$

where μ_j^i and σ_j^{i2} denote the means and variances for each component j of each factor θ_i. θ_u denotes the uncorrelated component of the mechanical system, as $\theta_m = \alpha\theta_c + \theta_u$. As shown by Prada and Urzúa (2017), α can be identified if we assume that one of the mechanical measures is a mechanical-dedicated test score, meaning it can only inform about the mechanical ability. Using Likelihood Ratio tests, we choose h_i, the number of mixture components. Furthermore, we restrict the mean of each factor to zero to allow the identification of the intercepts ($\sum_{j=1}^{h_i} p_j^i \mu_j^i = 0$). We solve the high-order integral over θ using Monte Carlo Simulation and 100 Halton draws per mixture-ability dimension pair.

To fully understand the two stages in the estimation problem, consider a partition of δ into δ_M and δ_R. δ_M contains all the parameters related to equations 3.16 and 3.18. Therefore, δ_M also includes all the parameters of the measurement system, including variances of errors when relevant, and all the parameters of the measurement system and mixtures of the factors. δ_R, on the other hand, contains all parameters related to utility and outcomes. In step one, the following likelihood function is maximized:

$$\int_{\underline{\Theta}} \left\{ \prod_{t \in \mathbf{T}} f(t|B, \theta; \delta_M) \right\} dF_\theta(\theta). \tag{3.19}$$

In the second step, we maximize the following function:

$$\int_{\underline{\Theta}} \left\{ \prod_{t \in \mathbf{T}} f(t|B, \theta; \hat{\delta_M}.\delta_R) \prod_{j \in \mathcal{J}} [f(Y_j|B, \theta; \delta_R)\text{Pr}(D_{\mathcal{J},j} = 1|B, \theta; \delta_R)]^{D_{\mathcal{J},j}} \right\} d\hat{F}_\theta(\theta), \tag{3.20}$$

taking as given $\hat{\delta_M}$ and $\hat{F}_\theta$. To incorporate the uncertainty from both steps into the standard errors, we consider a one-iteration last step where the Hessian matrix is calculated. In this last

step, all parameters are jointly estimated without constraints.

3.6.1 Data

We analyze data from the National Longitudinal Survey of Youth 1997 (NLSY97), a longitudinal study that follows individuals born between 1980 and 1984 and living in the United States during the first round (1997-1998). We focus on the cross-sectional sample of 6,748 men and women representative of the selected cohorts.[4] This data set offers rich information on background characteristics, annual earnings, postsecondary choices, and test scores. To measure cognitive and mechanical abilities, we use the Armed Services Vocational Aptitude Battery (ASVAB) test that is also available in the NLSY79 and has been extensively used to measure these abilities in previous studies (see Heckman, Urzua and Vytlacil, 2006, Prada and Urzúa, 2017, and Belzil, Hansen and Liu, 2022). The ASVAB test was administered from the summer of 1997 through the spring of 1998 when participants were at most 18 years old. Following previous literature, we consider six ASVAB components as cognitive measures: math knowledge, word knowledge, paragraph comprehension, numerical operations, coding speed, and arithmetic reasoning. We use mechanical comprehension, electronics, shop information, and auto information for the mechanical measures. Although we use the same measures available in the NLSY79, one difference is worth discussing. Shop information and auto information are available as one single measure in the longitudinal study of 1979, while separated in the NLSY97.

In assessing the dimensions of socio-emotional abilities, the National Longitudinal Survey of Youth 1997 (NLSY97) makes use of the Ten-Item Personality Inventory (TIPI) Scale, administered in round 12 (2009). This scale asks participants to self-evaluate their compatibility with

[4]We exclude the supplemental samples designed to oversample Hispanic, Latino, and Black populations.

various attributes. It is an effective tool for measuring the Big Five personality traits: extroversion, agreeableness, conscientiousness, emotional stability, and openness. A useful feature of the TIPI is its dual-question format for each trait, formulated in contrasting ways, which helps counteract the common survey issue of agreement bias. Thus, we adjust the order of the opposing questions for each trait and then compute their average, obtaining only one measure per trait.

In addition to the NLSY97 dataset, we incorporate data from the Integrated Postsecondary Education Data System (IPEDS) and the Current Population Survey (CPS) to construct geographic variables. IPEDS provides information on tuition across two- and four-year institutions, while CPS supplies data on wage rates and unemployment rates for various demographic groups. We will elaborate on the specific definitions of these variables later when outlining our empirical specification.

To define our sample, we exclude high school dropouts, focusing on individuals with a high school diploma or a GED certificate, which are prerequisites for pursuing postsecondary education. We include only those who had not begun their college education when they took the ASVAB test, ensuring that the cognitive and mechanical measures are unaffected by postsecondary education. In addition, earnings are measured when individuals are 28 to 30 years old, excluding those still in college at this age or with insufficient data in this age range. Furthermore, we omit observations with missing data for the variables considered in our specifications.[5] These criteria result in a sample comprising 1,181 men and 1,202 women. It is worth noting that Mountjoy (2022) focuses on individuals whose projected high school graduation year was between 2000 and 2004, just a few years later than the projected graduation years in the NLSY97. Ad-

[5]We perform imputations for earnings and the number of children. This imputation process is particularly beneficial for addressing missing information arising from the biannual survey format of the NLSY97 post-2011.

ditionally, earnings are measured over ages 28–30 in both studies. These decisions ensure some degree of comparability between his sample and ours.

Table 3.1 presents the summary statistics by group. We present the mean of the main variables employed in the analysis for men and women but also further divide each group depending on their postsecondary educational attainment. The proportion of Black and Hispanic individuals decreases as the level of education increases, particularly among men. The data from 1997 reveal consistent urban residency among the groups, except for two-year college graduates, who are at least ten percentage points more likely to have lived in rural areas. The proportion of individuals residing in the Southern United States in 1997 remains relatively stable across all educational groups, varying around 30%. The prevalence of individuals from single-parent homes declines with higher education, as does the number of siblings. As expected, family income and the mother's schooling in 1997 positively correlate with educational attainment.

Upon examining the cohorts within the data, it is observed that among men, the 1983 birth cohort is marginally overrepresented, whereas the 1980 cohort is marginally underrepresented. Similarly, for women, there is a slight overrepresentation of the 1981 cohort and a slight underrepresentation of the 1984 cohort. This pattern of representation remains consistent across the educational groups analyzed.

Current residency patterns, observed when individuals are between 28 and 30 years old, show a decline in rural living across all groups. This shift is most apparent among men with two-year degrees, a group that no longer shows a marked rural presence—an observation that contrasts their teenage years. The only exception to this trend is women with two-year degrees, who persist in urban living at a rate unchanged since 1997, with 58% residing in cities. Women show a higher tendency to live in the South across all educational categories, whereas the distribution of current

residency for men is more balanced across regions.

The table also underscores disparities in earnings and family choices. Men's earnings significantly outpace women's across all education levels, but the gap narrows with higher education. Regarding family choices, the data show that women generally have more children and are more frequently married than men. The average number of children for both men and women declines as educational attainment increases. The data also show that the proportion of individuals married is highest among those with two-year degrees.

The final row of Table 3.1 presents the total number of individuals in each subgroup. The samples consist of 1,181 men and 1,204 women. Among these, high school graduates represent 59.86% of men and 51.82% of women. Those with two-year college degrees account for 8.21% of men and 8.22% of women. Lastly, individuals with four-year college degrees make up 31.92% of the male cohort and 39.95% of the female cohort. The cohorts from the NLSY97, which started their college education in the early 2000s, exhibit a trend documented in national statistics: women attend and graduate from college at higher rates than men.

3.6.2 Raw measures

Figures 3.2 and 3.3 display the cognitive and mechanical abilities distributions among the analyzed groups. In these figures, solid blue and dashed orange lines represent the distributions for women and men, respectively. The most significant group differences are observed for numerical operations, coding speed, and arithmetic reasoning. Women usually score relatively higher in numerical operations and coding speed. Yet, men's distributions show a thicker right tail in these areas, meaning they are more likely to get top scores.

Conversely, men tend to outperform women in arithmetic reasoning, particularly for scores near and above the overall mean. The disparities in other cognitive measures, math and word knowledge and paragraph comprehension, are comparatively less pronounced. Figure 3.3 indicates that, in mechanical measures, men consistently outperform women, showcasing larger disparities compared to cognitive measures. While both groups have similar scores at the lower end of the distribution, men's scores are predominantly higher, evident from their right-shifted distributions and thick right tails.

Figure 3.4 shows the raw socio-emotional measures. These measures combine the two questions measuring the same trait, and the histograms present the total count of answers for each value. Blue bars display the responses for women, while orange bars represent men's responses. The data shows that women generally exhibit higher levels of agreeableness, extroversion, and conscientiousness, as illustrated in panels A, B, and C. Conversely, men tend to display greater emotional stability and a slightly higher openness to new experiences, as evident in panels D and E.

In general, the substantial differences in the raw ability measures observed between women and men support the separate estimation of the model for each group.

3.6.3 Point estimates

The empirical specification presented in Table 3.2 delineates the variables included in each equation. All types of equations consider cohort, race, and ethnicity dummies. Schooling choice equations (Schooling) and measurement system equations (TIPI and ASVAB tests) incorporate additional variables designed to capture individuals' backgrounds during their teenage years be-

fore they make any college decisions. These variables encompass family income, years of schooling of the mother, and dummy indicators for residing in the South, living in urban areas, and being raised in single-parent households. All these variables were measured in 1997, the first year of the study, and when survey participants were between 12 and 17 years old. The number of siblings is also included in these equations. However, the NLSY97 started collecting this information only in 2011.

Schooling choice equations measure the utility of different sectors. We need to normalize one of the sectors to have zero utility to achieve identification in discrete choice models. We designate staying with a high school diploma (HS) as this alternative. The schooling choice equations also include three regional variables that are measured when individuals are 17 years old: average public tuition, unemployment relative to high school graduates, and wage rates relative to relative to high school graduates. Sector-specific in nature, these variables capture variations pertinent to either two-year or four-year college graduates or institutions. Acting as exogenous cost-shifters, they account for variations influencing schooling choices while remaining independent of individual characteristics. Unlike the schooling choice equations, the measurement system equations do not include regional variables. Instead, they contain information about the years of schooling of the student when they took each respective test, whether the ASVAB test or the TIPI scale test. Consistent with previous literature, the inclusion of these variables helps mitigate heterogeneity in derived abilities by accounting for differences in accumulated schooling when test scores are observed.

The earnings equations encompass information contemporary to the time earnings are observed, which typically falls between ages 20 and 30 for individuals. They incorporate dummies for the region of current residency, urban area residence, and for being married. Moreover, we

also consider the number of biological children in the household.[6]

In Table 3.3, we present reduced form estimates that depart from the structural framework outlined in earlier sections. We use OLS estimations with earnings, measured in tens of thousands and in 2010 dollars, as the dependent variable in these specifications. We include dummies for schooling choices, with staying with a high school diploma as the omitted category. Additionally, we control for all variables mentioned in the empirical specification. To control for abilities, we include the standardized mean of test scores, creating one index for each type of measure: cognitive, mechanical, and socioemotional. We present specifications with and without ability proxies. Furthermore, estimates are presented separately for men and women. These results indicate that postsecondary decisions significantly impact annual earnings at age 30. Specifically, obtaining a four-year college degree increases annual earnings by between $13,280 and $17,610, and a two-year college degree increases earnings by between $5,840 and $9,400, relative to individuals who do not attain any further schooling degree after high school. Although estimates vary across groups, Wald tests on the differences between women and men suggest that the effects are statistically equal across groups.[7] These results also suggest that test scores are relevant in explaining earnings, except for the socioemotional ability's impact on men's earnings and the mechanical ability's impact on women's earnings.

In Table 3.4, we compare the estimated effects of abilities on schooling choices and earnings using OLS (Panel A) with the estimates for the same effects using structural estimation of the proposed Roy model (Panel B). Estimates related to the school choice equation refer to the point estimates of the utility derived from each sector. This table demonstrates that the conclusions

[6]Controlling for these variables implies that our model assumes fertility and marriage choices as exogenous.
[7]See Table 3.19.

drawn from these two methodologies differ. In most cases, using reduced-form techniques tends to underestimate the effect of abilities, both in terms of the absolute value of the effect and the statistical significance level. Additionally, there are notable differences between the estimates for women and men, regardless of the specific method considered. Although, in the case of the structural estimates, women's and men's estimates come from two distinct models, we test whether the effects of abilities are different across groups. We confirm significant statistical differences between both groups, especially regarding earnings effects.[8]

We have demonstrated that the conclusions drawn from the reduced-form estimation differ from those obtained from the structural model. Additionally, interpreting reduced-form estimates requires caution due to several factors. Firstly, there is selection bias, as individuals who choose different schooling paths are not randomly selected and could have made a choice based on unobservables. Secondly, test scores may be susceptible to measurement error, and actual abilities likely influence schooling decisions and earnings. These factors introduce bias into reduced-form estimates. Consequently, we will focus on the results derived from the structural model, which align with the discussion presented in section 3.5. The point estimates from the structural model are displayed from Table 3.5 to Table 3.14.

Tables 3.5 and 3.10 present the point estimates for the utility of sectors 2YC and 4YC, with sector HS normalized to zero utility. Similar variables influence utility for both men and women, ultimately shaping their schooling choices. Notably, living with both parents, family income, and the mother's years of schooling all positively impact the likelihood of choosing a four-year college degree. These factors are indicative of long-term credit constraints and correlate with investments that facilitate ability development, thereby fostering readiness for college enrollment.

[8] See Table 3.20 for the t-statistics from these tests.

Additionally, cognitive ability positively influences the likelihood of pursuing a four-year degree, while a negative effect is observed for mechanical ability, although only marginally significant for men. All these findings align with previous literature. However, a notable difference between women and men is that significant cohort effects influence the utility of women attaining a four-year college degree, which is not observed among men.

Fewer variables statistically influence the utility of two-year college degrees. Residing in an urban area decreases the utility of a two-year degree for both groups, although this effect is only marginally significant for men. Additionally, living with both parents increases the likelihood of attaining this degree for both groups. Notably, maternal years of schooling increase the likelihood of women obtaining a two-year college degree, whereas cognitive ability only increases this likelihood for men.

Tables 3.6 and 3.11 present the point estimates related to the earnings equations for men and women, respectively. Several differences between the groups are worth highlighting. Firstly, being black increases the earnings of male high school graduates, while neither race nor ethnicity plays a role in determining women's earnings. Secondly, the number of children decreases women's earnings as four-year or high school graduates, while for men, having more children seems to increase earnings as four-year graduates weakly. For men, being married increases earnings in all sectors, but this variable does not statistically affect women's earnings. Cognitive ability increases earnings for four-year graduates in all cases. However, there are several differences in how abilities define earnings between groups. Cognitive ability increases the earnings of female high school graduates but not men's.

Similarly, socioemotional ability increases the earnings of female high school graduates but does not affect men's earnings. Finally, mechanical ability increases earnings for all sectors

except for attaining a four-year degree for men. For women, this ability decreases the earnings of a two-year college degree.

Tables 3.7 and 3.12 display the point estimates of the cognitive system for men and women, respectively. Across both groups, the loadings, which are the coefficients associated with the factor variable, are similar. The tests with the highest loadings are arithmetic reasoning, paragraph comprehension, and mathematical knowledge. Additionally, maternal education emerges as a crucial factor that increases cognitive scores for both women and men. However, some observed variables affect cognitive test scores differently across groups. Specifically, for men, coming from a two-parent household and family income seem to have less impact. In contrast, these characteristics consistently play crucial roles for women in all tests.

The estimates for the socioemotional system are shown in Tables 3.8 and 3.13. Once again, the loadings are similar across groups. The tests with the highest loadings are related to emotional stability and agreeableness, while the lowest loadings are for extroversion. These results need to be considered when interpreting the derived socioemotional factor variable. The point estimates for the mechanical system are displayed in 3.9 and 3.14. Despite mechanical measures coming from the same test as the cognitive measures, there are differences in terms of the role of observed characteristics. Mother's years of schooling continue to be an important explanatory factor but to a lesser extent than in the case of the cognitive system. Coming from a two-parent household only increases the mechanical knowledge and electronics information scores.

Interestingly, family income is not a significant factor except for men, where higher parental income decreases the shop information test scores. Loadings between groups differ for this system. The highest mechanical loading for men is associated with the auto and shop information tests, while for women, it is only the loading associated with auto information. Additionally,

cognitive ability decreases the auto information score for women while having a null effect for men.

3.6.4 Marginal Densities

Figure 3.5 illustrates the marginal densities of latent abilities. Panel A presents the densities for men, while Panel B displays those for women.[9] All three densities show variations between men and women, supporting the decision to estimate separate models for each group. The cognitive and mechanical abilities depicted in blue and green exhibit a higher variance for men. In the case of cognitive ability, the higher variance is mainly explained by a thicker left tail, while for mechanical ability, men exhibit a thicker right tail. Therefore, a higher proportion of men have exceptionally high mechanical endowments and very low cognitive levels relative to women. The socioemotional densities are normally distributed but have a slightly higher variance for women. Refer to Figure 3.35 in the Appendix to directly compare ability types across groups.

The most notable distinction, however, lies in the correlation between cognitive and mechanical abilities. For men, we estimate a correlation of 0.46, which aligns with findings from a similar system estimated using the ASVAB test in the NLSY79 dataset, focusing solely on men's information (Prada et al., 2017). Conversely, for women, the estimated correlation almost doubles, reaching 0.86. This substantial difference carries significant implications for interpreting the results presented in this article. Specifically, women's mechanical ability appears to be highly dependent on cognitive ability, while men do not observe such dependency. Consequently, inferring that women's mechanical ability is more closely related to the ability required to succeed in

[9]Recall that the number of mixtures determining the distribution of the factor is chosen using likelihood ratio tests. We stop adding additional mixture components when likelihood ratio tests do not reject that the model's fit is equivalent to one using fewer mixtures.

STEM fields is plausible. In contrast, for men, the captured latent mechanical ability appears less reliant on cognitive endowments.

3.6.5 Variance Decomposition of the Measurement System

Figure 3.1 illustrates the variance decomposition of test scores within our measurement system to explain the relative contributions of observed variables (in darker blue), latent factors or abilities (in medium blue), and the error term (in light blue). Panel A and B present the decomposition for men and women, respectively. A consistent pattern across both groups is the lower proportion of variance explained by observed variables in socio-emotional measures; a trend also noted in studies using NLSY datasets. The variance attributable to abilities is relatively small for most socio-emotional measures, except for emotional stability. Notably, women's cognitive and mainly mechanical scores show a higher relative contribution of the error term. Additionally, mechanical measures for women exhibit lower variability, which is explained by abilities relative to men.

The presence of a significant error component across all measures for both groups underscores the importance of utilizing inferred distributions of unobserved abilities instead of relying solely on raw measures in our analysis.

3.6.6 Goodness of Fit

Measures

Figures 3.6-3.9 display the goodness of fit of the mechanical and cognitive predicted measures relative to the observed measures. Each figure follows a similar structure: a solid, light blue

line represents the empirical Cumulative Distribution Function (CDF) of the observed measure, while a dashed, black line depicts the empirical CDF of the simulated measure—the measure predicted by the model post-estimation. We generate our simulated data using 1,000 replications of the original sample. Moreover, atop each graph, the p-value from a Kolmogorov-Smirnov test is displayed within parentheses. The test's null hypothesis proposes that both depicted CDFs come from the same distribution.

Figures 3.6 and 3.7 display the goodness of fit of cognitive measures for men and women, respectively. While the null hypothesis is rejected at a 95% confidence level for paragraph comprehension in both groups and for word knowledge and coding speed in men, none of them reject the null hypothesis at a 99% confidence level. Figures 3.8 and 3.9 depict the goodness of fit for the mechanical measures. In this case, all but one measure, mechanical comprehension, fails to reject the null under standard significance levels for both groups. Despite rejecting the Kolmogorov-Smirnov test at conventional significance levels, the empirical CDFs of the simulated measures closely resemble those of the observed measures in all cases.

Schooling Choices

Table 3.15 presents the goodness of fit of schooling choices on the left side. The first two columns display the fractions of individuals who choose each of the sectors, first for the simulated data and then for the observed data. Panel A shows these results for men at the top of the table, while Panel B displays these fractions for women. The fractions for men in each sector, both in the simulated and observed data, are very close. However, there is a slight overestimation of those staying as high school graduates by 1.7 percentage points, fully compensated by an

underestimation of four-year graduates by the same magnitude. The same pattern applies to women, but the difference is larger, ranging from 3.5 to 3.7 percentage points. Although the fit for women is not as good as for men, in all cases, the fraction of individuals in each sector in the simulated data closely resembles those in the observed data.

Earnings

The second part of Table 3.15 presents some results describing the goodness of fit of earnings. The right side of this table once again compares summary statistics, now focusing on the mean and variance, between the simulated and observed earnings data, which, as a reminder, are measured in tens of thousands. For all sectors and groups, simulated earnings closely match the mean and variance of observed data.

Figure 3.10 presents additional information about the goodness of fit of earnings. This figure compares the density of observed (solid, light blue) and simulated (black, dashed) earnings. Additionally, the p-value of a Kolmogorov-Smirnov test is displayed in parenthesis above each graph. The goodness of fit is excellent for female and male two-year graduates, as the null hypothesis of simulated and observed earnings having the same distribution is not rejected in these cases. Although the null hypothesis is rejected for other sectors and groups, the simulated earnings can still replicate the general pattern observed in earnings.

3.6.7 Ordered vs Continuous System

This section discusses the empirical consequences of modeling or ignoring the ordered nature of socioemotional measures in the measurement system. To do so, we compare the results

using two different assumptions or systems. Under the ordered system, we assume each socioemotional measure follows an Ordered Probit process, aligned with the assumptions considered in Section 3.5. This assumption captures the ordered nature of the measures surveyed using Likert scales. The second system, which we call a continuous system, assumes that the observed measures are cardinal. There, we assume that each test follows a normal distribution. Previous literature usually imposes this last assumption.

Table 3.16 presents the estimated loadings, or coefficients associated with the latent socioemotional ability, for men and women under different assumptions. Panel A shows the results after considering an ordered system, and Panel B shows the estimates from assuming a continuous system. We also show these estimates for models considering different numbers of mixtures, defining the distribution of the latent ability. Therefore, each column within a panel shows the results of one estimation of the measurement system. We can see that most loadings are relatively constant when we increase the number of mixtures, except in one case. This pattern is observed for stability in Panel B, which corresponds to the case where we ignore the ordered nature of the measures. Stability is the measure that has the highest correlation with the latent derived ability in all cases, as the loading is the highest. However, this table shows that under the continuous system, when the number of mixtures to model the distribution of the ability increases, the loading becomes much higher, especially in comparison to other loadings.

Number of Mixtures

Figures 3.11 and 3.12 display men's and women's socioemotional densities for different mixture specifications. Each specification assumes a different number of mixtures. We can see

that the estimated densities are very different under a continuous and ordered system if we condition on the number of mixtures. This pattern is exhibited for both men and women.

However, someone could argue that the model with a higher number of mixtures could have better goodness of fit and, hence, be the "right" model. The legends in Figures 3.11 and 3.12 show p-values of a likelihood-ratio test comparing a given specification with the specification that uses only one additional mixture component. We can see that for men, the likelihood-ratio tests suggest using just one mixture—a normally distributed latent ability—under the ordered system. In contrast, the tests reject using even three mixtures for the continuous system. A similar pattern is observed for women in Figure 3.12, although for them, the model with two mixtures is rejected at 95% of confidence against the model that uses three mixtures under the ordered system. For the continuous system, a specification using three mixtures has the same fit as one using four.

Figure 3.13 compares the ordered and continuous system's goodness of fit for men. Figure 3.14 presents the results for women. We compare the CDFs of the observed (in solid, light blue) and simulated measures. Dashed black corresponds to CDFs of the predicted (or simulated) measures obtained under an ordered system, while solid red represents the predicted measures assuming a continuous system. We use one mixture for the ordered systems following the results of the likelihood-ratio tests. For the continuous system, we use four mixtures for men and three for women. We can see that the measures under the ordered system perfectly fit the observed data in all cases, while the ones derived from a continuous system do not.

Finally, Figures 3.15-3.18 show the variance decomposition of the socioemotional system under all specifications considered. Each color represents a different assumption. Dark blue corresponds to the decomposition obtained after assuming an ordered system, while light blue shows the results from assuming a continuous system. Each plot displays the result for a given

measure or test, and each bar shows the decomposition of specifications using a given number of mixtures. Figure 3.15 shows the fraction of the test variance explained by the variance of the latent variable for men. We can observe that the fraction remains stable for all measures when we assume an ordered system. However, the fraction of the variance explained by the ability quickly increases to almost one in the case of the stability tests. The same pattern is observed for women in Figure 3.15.

Figures 3.17-3.18 present the relative participation of the error term in each of the socioemotional measures. Aligning with previous figures, we can see that the error variance drops quickly to almost zero for the continuous system and the stability measure. For the other measures, we do not see any unexpected behavior.

This section concludes that choosing between an ordered or continuous assumption for socioemotional measures holds significant implications, as the resulting distributions exhibit notable disparities. Adopting a continuous framework leads to a distribution heavily influenced by the test with the highest loading, a dependency exacerbated by increasing the number of mixtures. Given this trend and the superior fit observed with an ordered system, we opt for adopting an ordered approach.

3.7 Main Results

3.7.1 Ranking of Preferences

Analyzing preference ranking when more than two options are available is crucial to predicting the potential impact of policy interventions. In the following subsection, we will examine all the pairwise comparisons of treatment effect parameters. When designing policies targeting

a specific sector, such as subsidizing two-year college tuition, understanding the likelihood of preferring a two-year college degree as the second option will inform how we should weigh the different calculated treatment effect pairs.

Table 3.17 presents the percentage of individuals by ranking of preferences for women and men. For both groups, the most preferred ranking, with more than 31% of women and men preferring this option, is staying as a high school graduate in the first place and obtaining a four-year college degree in second place. However, the second most preferred ranking differs between men and women. The second most preferred ranking for women, preferred by 25% of women, is having to get a four-year college degree as the first option and to stay with a high school diploma as the second best. Around 30% of men prefer staying as a high school graduate, and as their second preference, they would prefer attaining a two-year degree. For both groups, the least preferred ranking is achieving a two-year degree as the first preference and a four-year degree as the second preference.

The percentage of individuals ranking each alternative first, second, or third place is displayed in Table 3.18. Here, we can see that the most common least preferred degree or sector is a two-year college degree, with 58.7% of women and 53.3% ranking it as their third option. This table also shows that the most common second-best option differs between groups. For men, the most common second preferred degree is a two-year college degree (38.5%), while for women, it is a four-year one (36.6%). Evidence from these two tables can indicate the proportion of individuals that might *potentially* react when introducing incentives to attend one sector in the higher education system. However, not all of them will respond in the incentivized direction. For example, although we know that the second most preferred ranking among men is first getting a high school diploma, followed by attaining a two-year degree, this fact does not necessarily translate

into a scenario where providing a subsidy for a two-year college results in all these male high school graduates obtaining such a degree. Their reaction will depend on how well the subsidy can offset the differences in utility between these two options.

3.7.2 Treatment Effects

We are analyzing three postsecondary schooling alternatives: $\mathcal{J} = \{\text{HS, 2YC,4YC}\}$. This section will focus on analyzing two sets of treatment effect parameters:

$$\Delta^{MTE}_{\mathcal{K},\mathcal{L}}(x, u_{D_\mathcal{K}}) = E\left[\Delta_{\mathcal{K},\mathcal{L}} \mid X = x, C_\mathcal{K} = C_\mathcal{L}\right] \tag{3.21}$$

$$\Delta^{TT}_{\mathcal{K},\mathcal{L}}(x) = E\left[\Delta_{\mathcal{K},\mathcal{L}} \mid X = x, C_\mathcal{K} > C_\mathcal{L}\right]. \tag{3.22}$$

The first equation corresponds to the Marginal Treatment Effect, which was discussed in Sections 3.3, 3.4, and 3.5, and the second equation refers to the Treatment on the Treated (TT) effect. As a reminder, $\mathcal{K} = \{k\}$ and $\mathcal{L} = \mathcal{J} \setminus \{k\}$ is the choice set with all available option but k. We will focus on characterizing the MTE and TT parameters for each sector k, using the second-best sector as a reference point.

Tables 3.17 and 3.18 presented evidence of heterogeneous preferences. There is no single hierarchy that satisfies everyone's preferences. Therefore, for each set $\mathcal{K}$ considered, there will be individuals selecting each element in $\mathcal{J}$ as their second-best. For this reason, we consider the

following further decomposition of the MTE (and their TT equivalencies):

$$\begin{aligned}\Delta^{MTE}_{4YC,\mathcal{L}}(x,u_{D_{4YC}}) =& \omega_{4YC}(x,u_{D_{4YC}}) \times \textit{MTE}_{4YC\leftarrow 2YC}(x,u_{D_{4YC}}) \\ &+ (1-\omega_{4YC}(x,u_{D_{4YC}})) \times \textit{MTE}_{4YC\leftarrow HS}(x,u_{D_{4YC}}). \\ \Delta^{MTE}_{2YC,\mathcal{L}}(x,u_{D_{2YC}}) =& \omega_{2YC}(x,u_{D_{2YC}}) \times \textit{MTE}_{2YC\leftarrow 4YC}(x,u_{D_{2YC}}) \\ &+ (1-\omega_{2YC}(x,u_{D_{2YC}})) \times \textit{MTE}_{2YC\leftarrow HS}(x,u_{D_{2YC}}).\end{aligned} \tag{3.23}$$

Finally, each MTE on the right-hand side of these equations will also be decomposed into observable and unobservable contributions, as follows:

$$\Delta^{MTE}(u_{D_{\mathcal{K}}}) = \beta_{X|q(P_{\mathcal{K}}(Z),u_{D_{\mathcal{K}}})\approx 0} + \beta_{u_D|q(P_{\mathcal{K}}(Z),U_{D_{\mathcal{K}}})\approx 0} \tag{3.24}$$

Marginal Treatment Effects

Figures 3.19-3.28 present our estimates of the Marginal Treatment Effects and their decomposition. We first analyze a set of results for men, followed by the results for women.

Figure 3.19 displays the Marginal Treatment Effects for men. Panel A considers the MTE for a two-year college education (k =2YC), and Panel B for a four-year college education (k =4YC). The results of estimating equation 3.21 for different values of unobservables are represented with a solid, black line. Note the unobservables considered for each sector vary. We use the difference between the unobserved component of the sector being analyzed relative to the other non-zero utility sector. Recall that the utility of being a high school graduate is normalized to zero to achieve identification. The other lines in this figure reflect the different components of the system of equations 3.23. The red and blue line shows the MTE considering specific inflows

of individuals, each representing men with different second-best alternatives. Red shows the inflow of individuals who would move from the other college sector, while blue captures the effect for those who would no longer stay with a high school diploma. The dashed, gray line shows the weights, which are the fraction of individuals with the other college sector as the second-best alternative.

For calculating the MTEs, we use the absolute value of the difference of utilities to define the distance between sectors. We use a tolerance level ϵ of 0.25. Reducing the tolerance level ϵ to 0.1 generates similar but noisier results (see Section 3.3 for more details about the practical implementation). The smaller the ϵ, the smaller the set of simulated individuals used to calculate each point of the graphs. We only show estimates for points of indifference with at least 0.25% of the simulated sample. Even without imposing this restriction, there would be unobserved component values where the calculation of the MTE is unfeasible.

Panel A in Figure 3.19 examines the MTE results for a two-year college education. Therefore, we can interpret these results as those of a policy that would reduce the costs of attending two-year college, attracting individuals from the other two sectors into two-year college institutions. We can see that the overall MTE associated with two-year college policies (black line) is usually positive. Still, it can be negative, especially for values of unobservables, where more four-year graduates are likely to react to such policies (higher values of the differentiated unobservables). A higher weight is associated with a negative overall MTE because the red MTE–measuring the effect on four-year graduates who would decide to get a two-year college degree because of the policy–is negative (ranging from -$7,013 to -$19,835). In contrast, the red MTE, measuring the impact for high school graduates, is positive (ranging from $9,560 to -$238).

The results on Panel A in Figure 3.19 can be compared with those by Mountjoy (2022), who

considers an IV estimation and MTE decomposition of reducing the distance to two-year college institutions. Figure 3.36 in the Appendix shows his equivalent estimates. However, we need to take some precautions before conducting any comparisons. His results should be multiplied by four, as his estimation uses quarterly earnings, while ours considers an annual earnings frequency. Moreover and most importantly, the scale on the x-axis on both graphs is incomparable. We can not translate our unobservable components scale into distance to college institutions, as we do not have access to this type of information. The MTE calculated from those who would choose to attain only a high school diploma in the absence of a policy is within the confidence intervals calculated by Mountjoy (2022), although his point estimates are smaller. MTE for the inflow of students who would switch from a four-year degree to a two-year degree is also negative but, in our case, larger in magnitude. Additionally, Mountjoy (2022) obtains a flat MTE while we estimate a downward-slopping MTE. Other previous studies find a downward slope and argue this is an expected pattern (e.g., Carneiro, Heckman and Vytlacil, 2011). The reason is that those with high values for unobservables have a low probability of selecting the analyzed sector; hence, they probably have little to gain. Those with low levels of unobservables already have a very high likelihood of participating; thus, those are likely the ones that can benefit the most from selecting that sector. However, we will see that we obtain a positive slope for women for the pairwise MTEs. As Mountjoy (2022) estimates come from pooling both groups, an effect that nets out across groups could explain the flat MTEs in his study while reconciling the differences with our estimates.

Panel B in Figure 3.19 shows the estimates for the MTE of a four-year college. Note the red MTE, which is the effect for individuals who would switch from attaining a two-year college degree to getting a four-year college degree ($4yg \leftarrow 2yg$), is very similar to the negative of the

red MTE in Panel A but with an inverted x-axis, which analyzes the inflow from four-year college into two-year college ($2yg \leftarrow 4yg$). Ultimately, both calculate the average difference between college earnings for the same group: those indifferent between a four-year college degree and a two-year college degree. The only difference relies on what the second-best alternative is. As a consequence, we see that this MTE ranges from \$20,580 to \$7,056. The blue MTE, calculated for those who would switch from staying as high school graduates to getting a four-year college, also exhibits positive values that closely follow those switching from a two-year college education (red MTE18), ranging from \$18,154 to \$11,308. In fact, for high values of unobservables ($V_{4yg} - V_{2yg}$), which is precisely when there is a lower proportion of those indifferent between a high school diploma and a four-year college degree (gray dashed line), the MTE for the inflow of high school graduates is higher than the overall MTE (black line). As in the case of Panel A, all MTEs in Panel B also have a negative slope.

Figure 3.20 decomposes men's MTE for those who would switch to get a two-year college from a four-year college degree (2y $\leftarrow$ 4y), applying equation 3.24. The graph on the left shows the MTE as a solid line and how much is explained by each component cumulatively in the bars. Dark blue shows the cumulative explanation of observed characteristics. Light blue shows the part of the MTE explained by cognitive abilities, red by socioemotional, and green by mechanical abilities. On the right, lines represent each component's isolated contribution, without adding up, using the same color code. These graphs show that the MTE observed for those switching from a four-year to a two-year college education is mainly explained by cognitive ability and observed characteristics. We can see that the slope observed in the MTE is inherited from cognitive ability. The cognitive component of the MTE even becomes positive for low levels of the unobservables—those who are more likely to participate. However, the component explained by

observables, although almost flat, is negative (varying from -$8,465 to -$10,676), generating a total MTE that is also negative.

Figure 3.21 decomposes the MTE that would be relevant for policies targeting the two-year college sector and attracting those who, in the absence of the policy, would havestayed with a high school degree (2y ← HS for men). The decomposition shows a similar pattern to that observed in Figure 3.20. Observed characteristics and cognitive ability mainly explain the MTE. The cognitive ability provides the slope, while the effect driven by observed characteristics is mostly stable across different levels of unobservables (around $5,000). The main difference relative to results shown in Figure 3.20 is that the MTE and the effect of observables are both positive.

We could further decompose the observed effect of the MTE into how much each observed characteristic explains. Given the functional form assumed for earnings, note that the coefficients are fixed. As a consequence of this assumption, any change in the contribution of each observed component is explained by a change in the composition of those at the margin of indifference for each evaluation point of unobservables. The same interpretation applies to changes in the contribution of abilities, as the loadings are also fixed. These changes in composition highlight the interplay between observable variables and unobservables.

Figure 3.22 shows each observed variable's contribution to the two-year college MTE for men. Panel A shows this decomposition for those indifferent between a two-year college degree and a four-year college degree (2y ← 4y). We can see that the main driver of levels is urban residency. The relative importance of the different characteristics changes, too. Urban residency and cohort effects are less relevant for higher values of unobservables, while region dummies and the number of children become more important. All these three variables have a negative

contribution to the MTE. Panel B displays the decomposition for those indifferent between a two-year college degree and staying as a high school graduate (2y ← HS). For this case, the constant term provides the highest contribution by far. The relative contributions of different characteristics do not vary much, except for the region of residency effects that have a negative impact and increase relevance for high values of unobservables (less likelihood of participation), becoming more negative.

To wrap up the analysis of men, Figure 3.23 shows the MTE decomposition in terms of observed factors and abilities for the inflow of those switching from staying as high school graduates to attaining a four-year college degree (4y ← HS). The same pattern observed for the previous decompositions for men still holds. The level of the total MTE is mainly explained by observed characteristics that are relatively stable around $15,000, exhibiting a slight negative slope (from $16,226 to $14,419). The cognitive contribution mainly explains the MTEs slope.

Figures 3.24-3.28 show the MTE estimations for women. We will see some patterns that are common across most of the graphs. Firstly, the role of observed characteristics is stronger for women. Secondly, some MTEs have a positive slope that seems to be explained by the effect of observed characteristics. Lastly, abilities play a less critical role relative to men's estimations, but mechanical is the most important ability to explain female MTEs.

Figure 3.24 displays the Marginal Treatment Effects for women. Panel A shows the MTE for the two-year college sector (2YC), and Panel B for the four-year college sector (4YC). There is one outstanding difference relative to Figure 3.19, which includes the equivalent results for men. In the first place, we observe that women's MTEs do not have a pronounced downward slope. The aggregate MTE has a small but negative slope, similar to results found by Mountjoy (2022) who pooled men and women in one estimation. Women's results are closer to those obtained

by Mountjoy (2022); our point estimates are within his confidence intervals and, in most cases, close to his point estimates. We can see that the MTEs that characterize the comparison between a four-year college degree and a two-year college degree (red lines in both panels) and between a high school degree and a two-year college degree (blue line) are upward-sloping. A change in the weights mainly explains the negative slope in the overall MTE.

Panel A in Figure 3.24 shows that the overall MTE of a two-year college education (black line) is positive and primarily stable at approximately $2,500 for most of the unobservables support, approaching zero for high values of the unobservables (low probability of choosing a two-year college degree). It ranges from $3,377 to $838. The MTE for the inflow of those switching a high school diploma for a two-year college degree (blue line) is also relatively flat at $8,000 (varying from $7,780 to $10,302). The MTE for the inflow of four-year graduates (red line) has an upward slope and is negative, ranging from -$12,082 to -$3,243. A negative MTE means that if we were to create an incentive for women who, in the absence of a policy, decide to get a four-year college degree to get a two-year college degree instead, they would get lower earnings on average than in the four-year college sector. The upward slope means that those with higher values of unobservables and hence with a low likelihood of selecting a two-year college degree would receive higher earnings in that sector (2YC), although still lower than those with a four-year college education, given the negative MTE. We will explore the drivers of this pattern in the upcoming, more detailed decompositions.

Panel B in Figure 3.24 displays the MTE for women and a four-year college education. The patterns of each curve are very similar: a slight downward slope for the total MTE, an almost flat MTE for the inflow of high school graduates, and an upward-sloping MTE for those who would switch their two-year college degrees. However, the levels are always positive and higher. The

total MTE (black line) and the MTE for the inflow of female high school graduates (blue line) start above $15,000 and fluctuate slightly around this value (to $14,892 and to $18,583, respectively). The MTE for those switching a two-year college degree (red line) ranges from $5,043 to $12,062.

Figure 3.25 decomposes the MTE for women switching from four-year to two-year college (2y ← 4y). We can see that there are two main contributors to this MTE: observed variables and mechanical ability, although the former plays a more important role. In contrast to men's decomposition, cognitive ability is not relevant anymore, and ability effects do not explain the slope. The positive slope in the MTE is driven by a positive slope observed for the observables' contribution to the MTE. Figure 3.26 shows the results from decomposing the MTE of the inflow of women switching a high school diploma for a two-year college degree. Observables and mechanical ability are also the main explanatory factors behind the estimated MTE, but cognitive ability contributes a small degree to the MTE for this inflow. The effect solely explained by the mechanical ability has a negative slope that ends up offset by the positive slope of the observables and cognitive effects.

Decomposing the MTE in terms of the contribution of each observable variable allows us to determine which specific variable explains the positive slope observed in previous figures. Figure 3.27 decomposes the MTE into observables for women in the two-year college sector. In Panel A, we have the results from decomposing the MTE resulting from the inflow of women changing a four-year college degree (2y ← 4y). The upward-sloping MTE is explained by an increased positive contribution of the variable counting the number of children when the level of unobservables increases, or in other words when the likelihood of choosing a two-year college degree over a four-year college decreases. To understand this result better, recall that the difference between earnings coefficients is always constant, as the coefficients are also fixed. For

this particular case, the difference in earnings coefficients between these two sectors is positive $(-0.33-(-0.69)=0.36)$. Therefore, since the contribution of the number of children has a positive contribution to the MTE and its related effect increases with high values of unobservables, we conclude that women who are less likely to choose a two-year college degree over a four-year college degree (high differences in unobservables) have more children than those with higher probability. For men, we observed an increased contribution of this variable, too, but negative, in favor of the earnings someone with a four-year college degree would receive. Urban residency continues to play an important negative role, and actually, its contribution is also reduced when the level of unobservables increases. However, we observed the same pattern for the role of urban residency for this men's pairwise MTE, which, in contrast, exhibited a negative slope.

Panel B in Figure 3.27 decomposes the MTE for women who would move from the high school sector to the two-year college sector into each observed component contribution. This MTE is almost flat with a slightly positive slope, and the contribution of different observable variables is mostly stable. However, the positive contribution of region dummies increases slightly for higher values of unobservables. Relative to men's decomposition, the constant term plays a lesser role, and the residency region's effects have a positive rather than negative contribution. Additionally, cohort dummies are not relevant factors explaining this MTE for women, but they were for men. For this margin of decision (2YC-HS), the number of children, a crucial factor in Panel A, does not explain the MTE effect.

Finally, Figure 3.28 shows that the MTE for women who would switch from the high school sector to attaining a four-year college degree, which has a slightly positive slope, is almost entirely explained by variation in observable components. Figure 3.38 in the Appendix shows a negative and decaying effect of the number of children, explaining the change in slope. Addi-

tional graphs in the Appendix show the decomposition into observables and abilities of other pairwise MTEs that we decided not to discuss because they are very similar by construction to reflections of the MTEs already described.

Effects of Treatment on the Treated

The following paragraphs will consider the effects of TT by quintiles of unobserved ability, showing substantial heterogeneity in returns. We will highlight which groups, depending on their ability endowments, would gain from switching their choice. However, it is interesting to contrast these results with those obtained when calculating MTEs. We will see that the TTs and MTEs will sometimes exhibit opposing signs for the same margin of comparison. These results suggest that those at the margin of indifference might not be the same with the specific ability endowments that would benefit from switching their schooling choice.

Figures 3.29-3.34 present the effects of treatment on the treated. Negative TTs could mean opportunities for intervening, as a negative TT indicates a person would have earned more in their second-best alternative than the chosen one. Nevertheless, negative TTs will not contain information on whether individuals who could get higher earnings in sectors rather than the chosen are likely to react to a policy affecting their utility. Their likelihood to respond will depend on whether these individuals are close to indifferent between sectors.

Figure 3.29 presents the effects of obtaining a four-year college education (4YC) for men. This group can be divided into two categories: those whose next-best alternative is a two-year college degree (Panel A) and those whose next-best option is a high school diploma (Panel B). Each group is divided into quintiles based on cognitive, socioemotional, and mechanical abilities.

We calculate the average earnings difference between the 4YC sector and the next-best alternative for each quintile pair, normalizing by the mean of the next-best alternative. The results are presented using heat maps, where warmer colors represent higher earnings. The rest of the effects of TT are displayed in the same fashion.

In Panel A of Figure 3.29, we analyze four-year graduates who would opt to get a two-year college degree if the option of obtaining a four-year college degree were not available. There is a high probability of obtaining a high TT, especially for those with high cognitive and socioemotional endowments but low mechanical endowments, where the average earnings can even be 144% higher. However, belonging to the first cognitive quintile has a negative TT, where those who are also in the highest quintile of mechanical abilities can earn 34% less with a four-year college degree than if they had obtained a two-year college degree. Belonging to the second cognitive quintile and the highest mechanical quintile can still generate earnings that are 9% lower in comparison.

We see a very different panorama in Panel B, where we consider those who, if obtaining a four-year college education were not an option, would choose to stay with a high school diploma. For all quintile pairs, men earn more as four-year graduates on average, with 11% to 86% higher earnings. However, as expected, the difference relative to the earnings obtained with a high school diploma grows larger with cognitive ability and smaller with mechanical ability. This result aligns with previous findings in the literature showing that those with higher mechanical and low cognitive endowments are more likely to have positive returns from staying as a high school graduate (Montoya-Agudelo, 2024; Prada and Urzúa, 2017).

Figure 3.30 shows the normalized TT for women pursuing a four-year college degree. Regardless of the next-best alternative, female four-year graduates earn, on average, higher than

they would have if they had chosen other sectors. Some quintile pair estimations are shown in black, meaning there is no TT estimation for that specific group. The absence of a TT arises from the high correlation between mechanical and cognitive abilities for women, causing some quintile pairs to be unpopulated and making the TT calculation unfeasible. Relative to a two-year degree (Panel A), women have higher returns if they have high mechanical and cognitive endowments but low socioemotional ability. Their earnings can be as much as 83% higher. However, their relative returns are not as high as those for male four-year graduates shown in Figure 3.29.

Panel B shows the normalized TT effects for female four-year graduates who would have preferred to stay with a high school diploma if being a four-year graduate was not an option. As in the case of men, we can see that all of the effects are positive; however, for women, they are higher. These returns range from 52% to 166%. As in Panel A, the TT effects are higher for female four-year graduates with high socioemotional and lower cognitive ability. However, mechanical ability is irrelevant in determining returns relative to a high school diploma.

The TT effects for those choosing to attain a two-year college degree are shown in Figures 3.31 and 3.32 for men and women. Before interpreting the results, note that these effects are not just the negative of the TT effects displayed for the two previous figures, as the schooling decisions are different. Panel A in Figure 3.31 shows the TT effects for male two-year graduates relative to the earnings that would have been observed had they chosen a four-year college education instead. The effects are usually negative, meaning male two-year graduates usually would have fared better with a four-year degree. Some of them, however, do earn more with their actual choice: those with low cognitive and socioemotional abilities but high mechanical abilities. For these individuals, the return to a two-year college degree is 4%-33% relative to a four-year college degree.

Panel B in Figure 3.31 shows the TT effects for men with a two-year college degree, whose next-best would be stopping their schooling after graduating from high school. In contrast to Panel A, these effects are usually positive, although negative for some cases. Specifically, negative TT effects are observed for male two-year graduates with high socioemotional and cognitive abilities but low mechanical abilities. Therefore, if these individuals had stayed with a high school diploma instead, their earnings would have been higher. Their actual earnings can be as low as 21% lower.

Figure 3.32 shows the TT effects for women holding a two-year degree. Panel A reveals that women whose second-best option is obtaining a four-year college degree would have higher earnings if they received a four-year degree. Average returns are as low as -44%. Positive returns are only observed for those in the lowest cognitive and socioemotional ability quintiles, and the maximum average is just 14%. Panel B compares the earnings of a two-year degree relative to the earnings of a high school diploma for two-year graduates. All but one quintile pair group exhibit positive returns. They increase with lower ability endowments in all dimensions. These returns are also higher than those observed for men, reaching an average return of 132% for the lowest socioemotional and cognitive quintiles.

Figures 3.33 and 3.34 display the TT results for men and women without college degrees. Generally, we see negative returns except for a handful of men with a two-year college degree as their next-best alternative (Panel B in Figure 3.33), high cognitive and socioemotional abilities, and low mechanical abilities. For men whose second-best is getting a four-year college degree (Panel A in Figure 3.33), average returns do not vary much with abilities, ranging from -0.14 to -0.47. We see even lower returns for women with the same preferences (Panel A in Figure 3.34), with relative TT effects lower than 50% in many cases. For female high school graduates whose

second best is getting a two-year college degree, we also see that returns are usually negative, with only a few cases at the top of the mechanical quintile showing positive but low returns. For this group, the lowest returns are observed with women with the lowest endowments in all three abilities.

3.8 Conclusions

While policies targeting postsecondary education can yield positive outcomes, understanding the heterogeneity of individual returns and responses is crucial for maximizing their impact. In this study, we focus on analyzing the effects of marginal treatment effects (MTE) of three higher education choices. We use a Roy model, accounting for unobserved factors influencing earnings and decisions, specifically cognitive, socioemotional, and mechanical abilities, all well-documented sources of heterogeneity in schooling choices. We propose a decomposition of the MTE, elucidating the respective contributions of observed and latent ability components. Additionally, we estimate the model separately for women and men, focusing on describing how responses and treatment effects vary between these two groups.

Our decomposition analysis shows that unobserved abilities are not always the primary factor that explains the level and slope of the MTE. For men, unobserved abilities are the main driver of a downward-sloping MTE pattern, although observables also play an important but constant role. On the other hand, for women, the primary driver is observables, with mechanical and cognitive abilities playing only a minor role. Additionally, women's pairwise MTEs exhibit an upward slope mainly driven by the observables' contribution.

A closer look at each observed variable's effect reveals that the contributions of variables

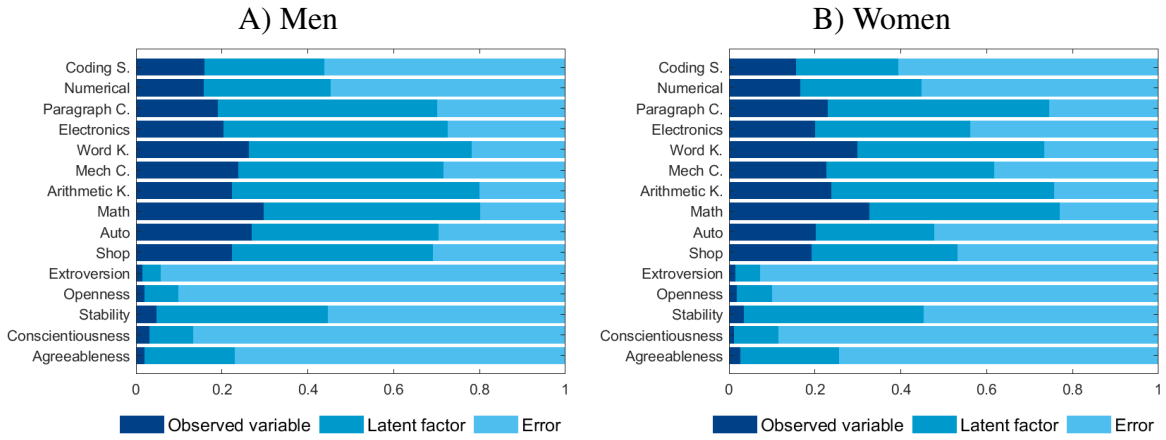
such as the number of children and type or region of residency change through the support of unobservables. These changes in contributions are explained by a change in the composition of individuals who are indifferent when the level of unobservables changes to determine different indifference evaluation points. Therefore, this interaction between unobservables and observed variables determining earnings (X) arises from the fact that individuals who are indifferent at each evaluation point differ in terms of the observed variables that determine the educational choice (Z). These observed variables that determine choices also vary to satisfy the different points of indifference. Therefore, the relation between X and Z is key to understanding the interplay between observables and unobservables in shaping MTEs.

To conclude, we stress the importance of studying MTEs. When examining the treatment effects associated with attaining a two-year college degree, we find, aligned with previous literature, that the direction of the effect, whether positive or negative, depends on the alternative sector that an individual considers their second-best option. We observe that MTEs are positive for both women and men who would transition from staying with a high school diploma to pursuing a two-year college degree, although they are higher for women. Compared to the earnings potential associated with obtaining a four-year college degree, the MTEs for two-year college degrees are negative. On the other hand, we find evidence of gains in switching from a four-year college degree to a two-year college degree for both men and women with low cognitive abilities and high mechanical abilities when we examine the effects of treatment on the treated (TT). This fact contrasts with the negative MTE and highlights the importance of analyzing marginal effects when designing policy interventions: Although some individuals would benefit from attending a two-year institution instead of a four-year college, they are not necessarily the individuals who are at the margin of indifference. Those at the margin of indifference, who would react to minimal

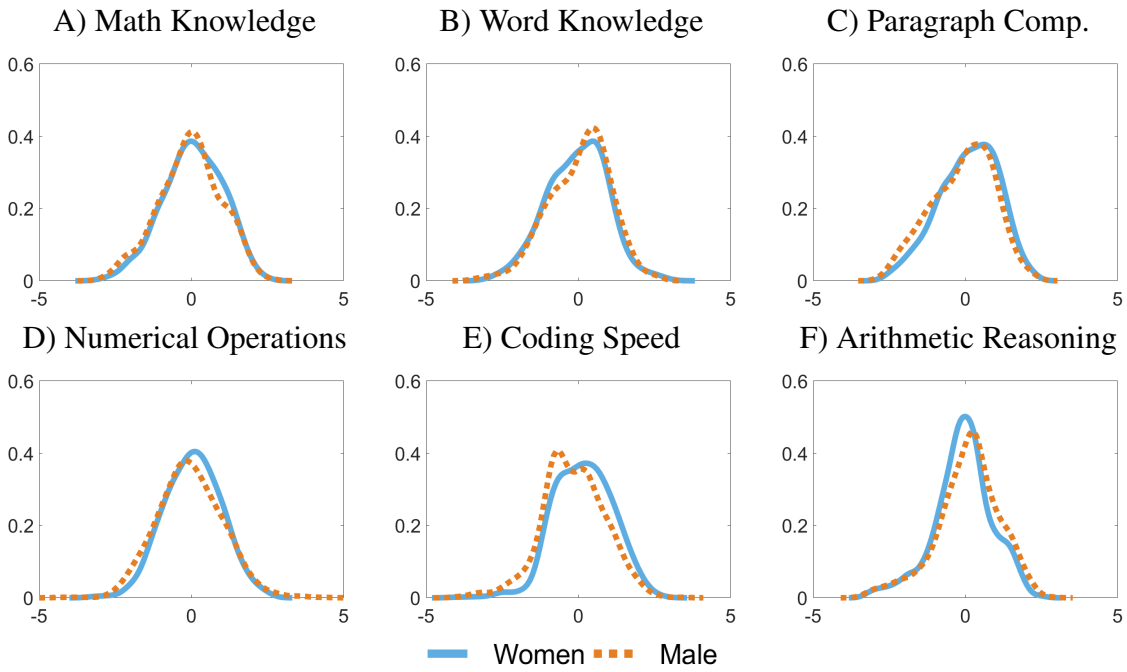
incentives, exhibit negative effects.

3.9 Figures and Tables

Figure 3.1: Variance Decomposition

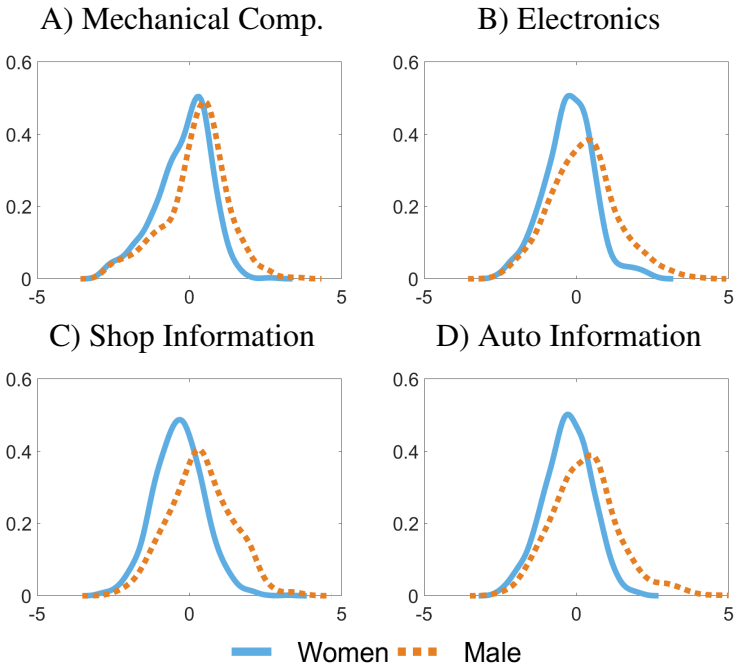


Note: The simulated data contains 1,000 replications of the sample. Coding S. = coding speed, Numerical = numerical operations, Paragraph C. = paragraph comprehension, Electronics = electronics information, Word K. = word knowledge, Mech C. = mechanical comprehension, Arithmetic K. = arithmetic reasoning, Math = math knowledge, Auto = auto information, Shop = shop information. The number of mixtures for each factor is based on Likelihood Ratio Tests comparing the fit in the measurement system. Cognitive factors have three mixtures, socioemotional factors have one mixture, and the uncorrelated components of the mechanical factors have two mixtures.



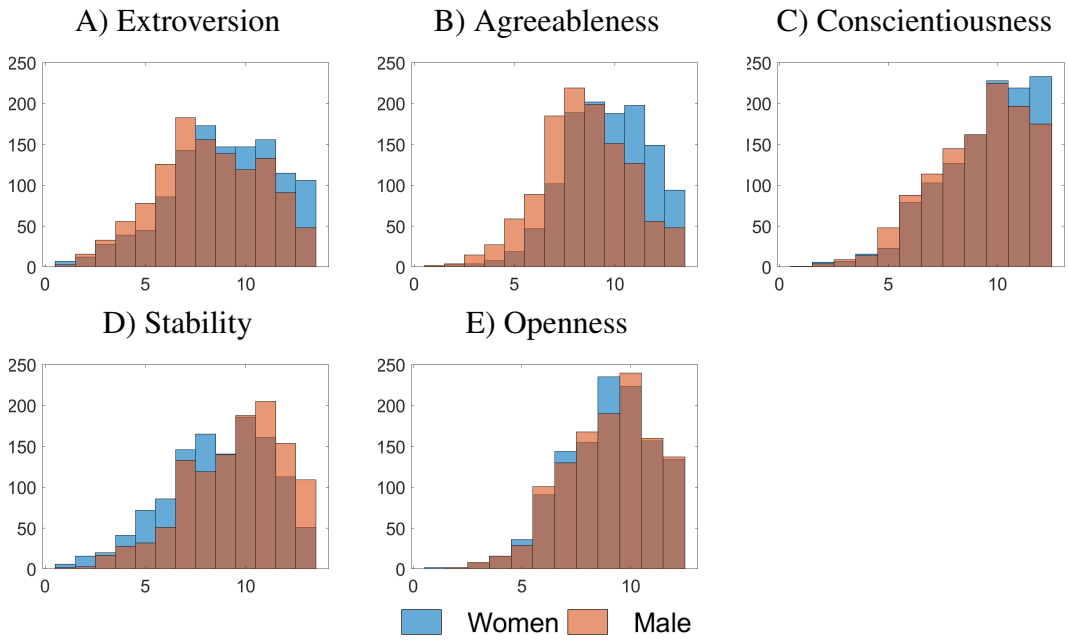
Note: Comparison between the densities of men's measures (orange, dashed line) and women's measures (blue, solid line). All measures are standardized in the pooled sample. Cognitive measures come from the ASVAB test, administered between 1997 and 1998. The simulated data contains 1,000 replications of the sample.

Figure 3.2: Raw Cognitive Measures



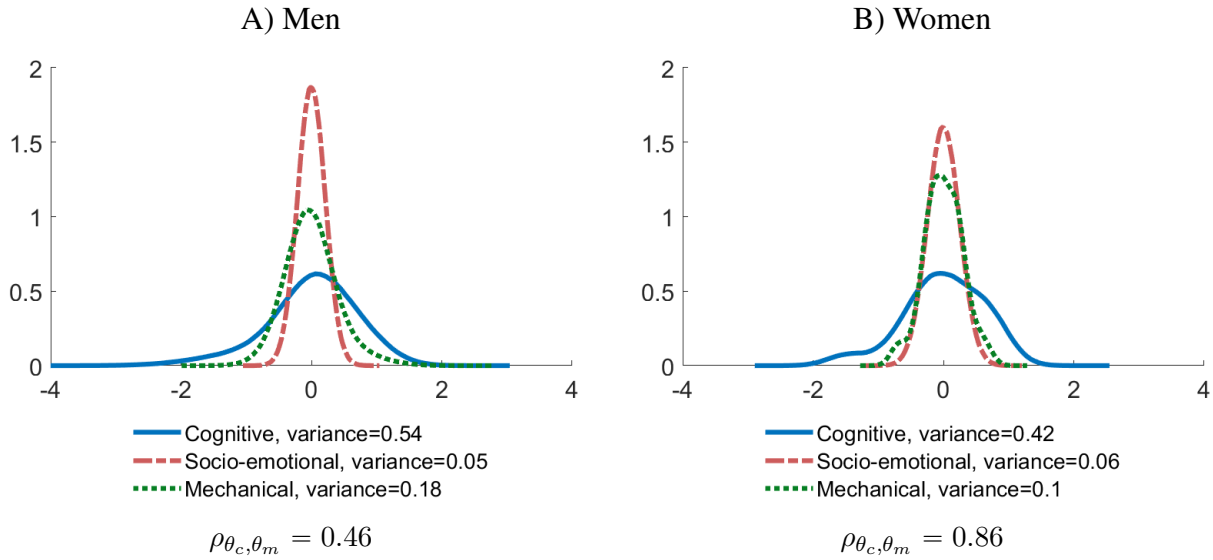
Note: Comparison between the densities of men's measures (orange, dashed line) and women's measures (blue, solid line). All measures are standardized in the pooled sample. Mechanical measures come from the ASVAB test, administered between 1997 and 1998. The simulated data contains 1,000 replications of the sample.

Figure 3.3: Raw Mechanical Measures



Note: Comparison between the densities of men's measures (orange bars) and women's measures (blue bars). All measures are standardized in the pooled sample. Socioemotional measures come from the TIPI scale, administered in 2008. Each big trait has two questions, which allows to control for acquiescence. The simulated data contains 1,000 replications of the sample.

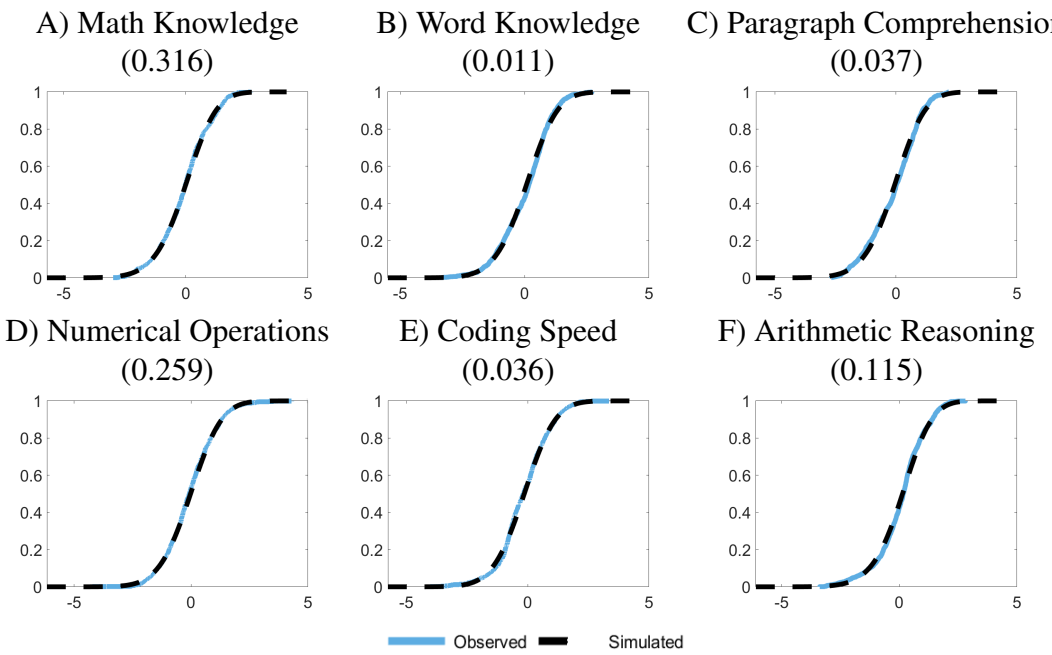
Figure 3.4: Raw Socio-emotional Measures



$\rho_{\theta_c,\theta_m} = 0.46$ $\rho_{\theta_c,\theta_m} = 0.86$

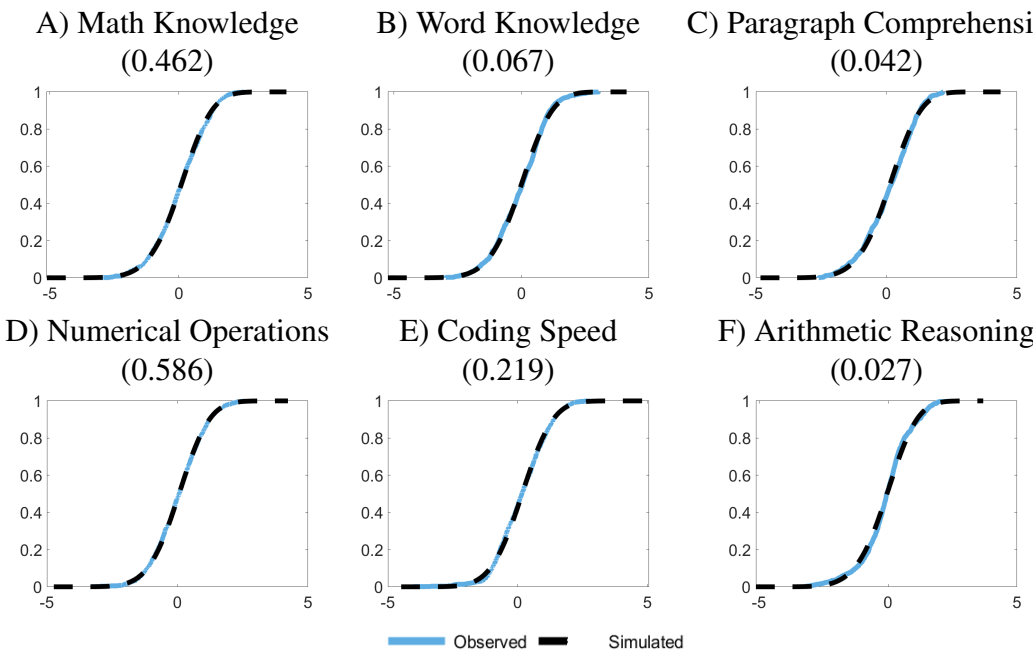
Note: The simulated data contains 1,000 replications of the sample. The number of mixtures for each factor is based on Likelihood-Ratio Tests comparing the fit in the measurement system. Cognitive factors have three mixtures, socioemotional factors have one mixture, and the uncorrelated components of the mechanical factors have two mixtures.

Figure 3.5: Latent Abilities' Marginal Densities.



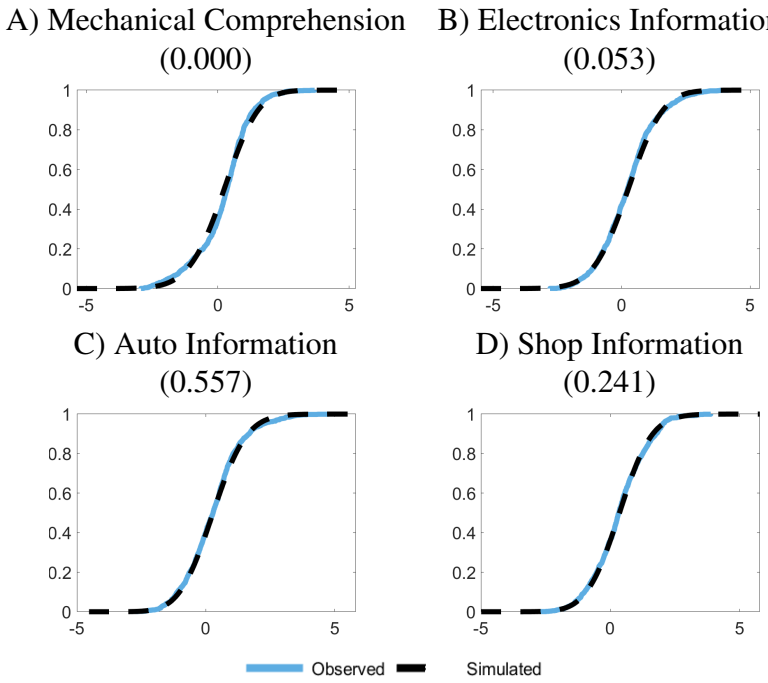
Note: Comparison between the CDF of the observed data (blue, solid line) and the CDF of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. The simulated data contains 1,000 replications of the sample.

Figure 3.6: Goodness of Fit: Cognitive System - Men.



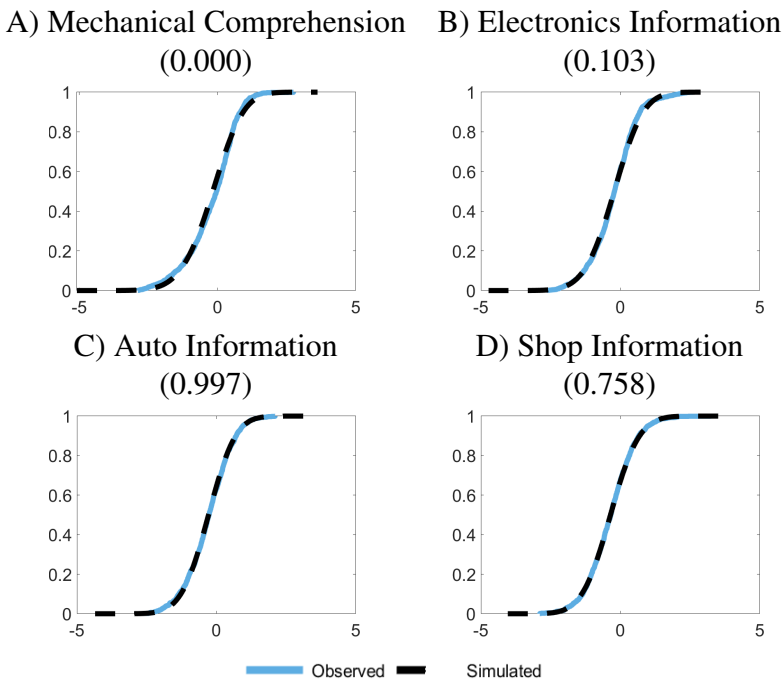
Note: Comparison between the CDF of the observed data (blue, solid line) and the CDF of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. The simulated data contains 1,000 replications of the sample.

Figure 3.7: Goodness of Fit: Cognitive System - Women.



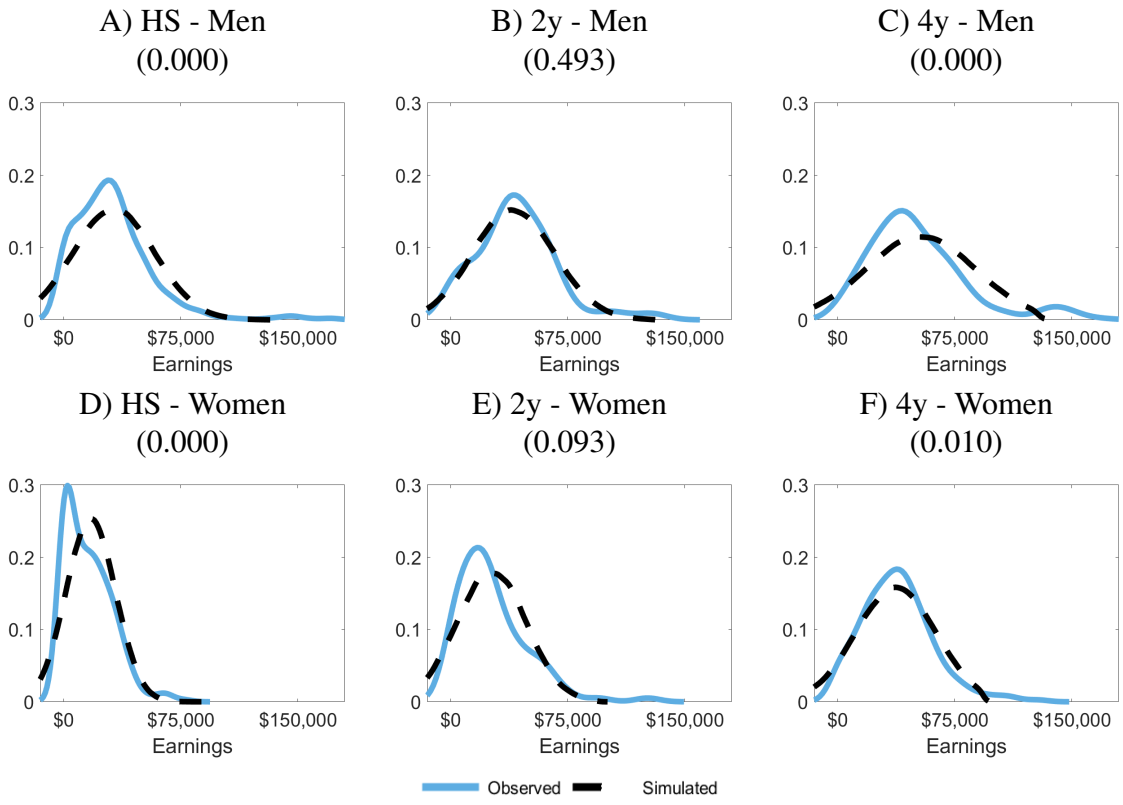
Note: Comparison between the CDF of the observed data (blue, solid line) and the CDF of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. The simulated data contains 1,000 replications of the sample.

Figure 3.8: Goodness of Fit: Mechanical System - Men.



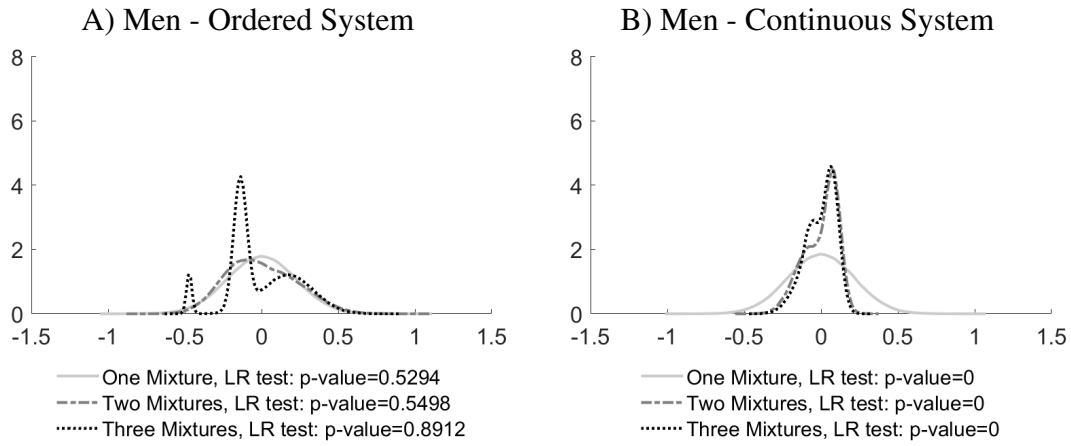
Note: Comparison between the CDF of the observed data (blue, solid line) and the CDF of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. The simulated data contains 1,000 replications of the sample.

Figure 3.9: Goodness of Fit: Mechanical System - Women.



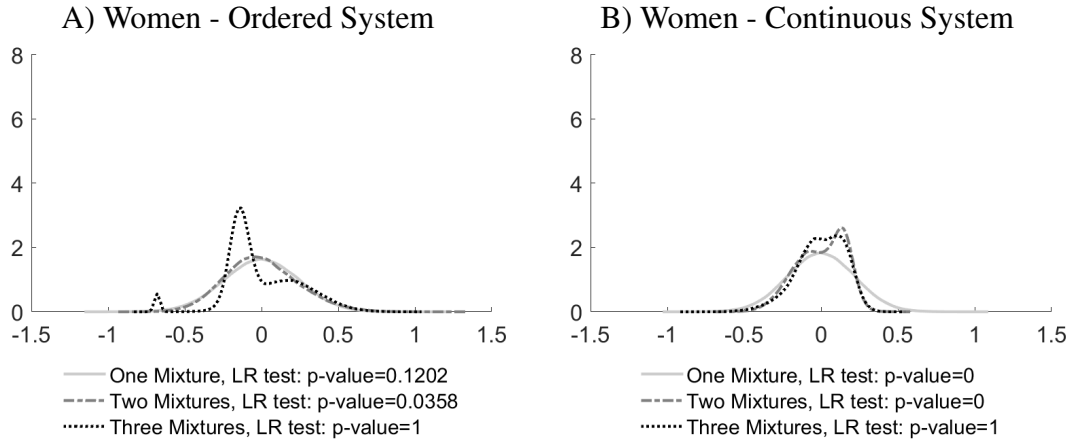
Note: Comparison between the densities of the observed data (blue, solid line) and the densities of the simulated data (black, dashed line). The p-value from a Kolmogorov–Smirnov test is shown in parenthesis at the top of each graph. Values in the bottom and top 0.5% of the unconditional distribution are not considered. The simulated data contains 1,000 replications of the sample.

Figure 3.10: Goodness of fit: Earnings



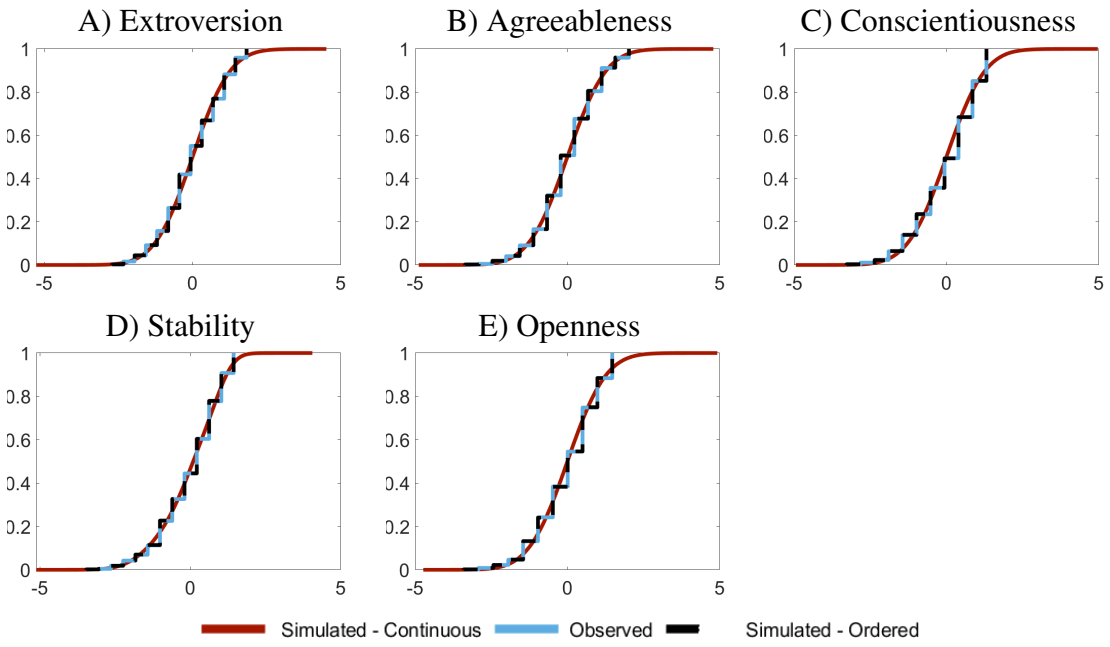
Note: Comparison of socioemotional factor distribution densities under different mixture assumptions (ordered and continuous). P-values from Likelihood-Ratio tests inform our choice of mixtures: one for the ordered system and four for the continuous system. Each p-value test considers the plotted assumption (restricted model) relative to a model where one additional mixture is considered. We consider a multi-start algorithm for each specification.

Figure 3.11: Socio-emotional ability distributions under different specifications - Men



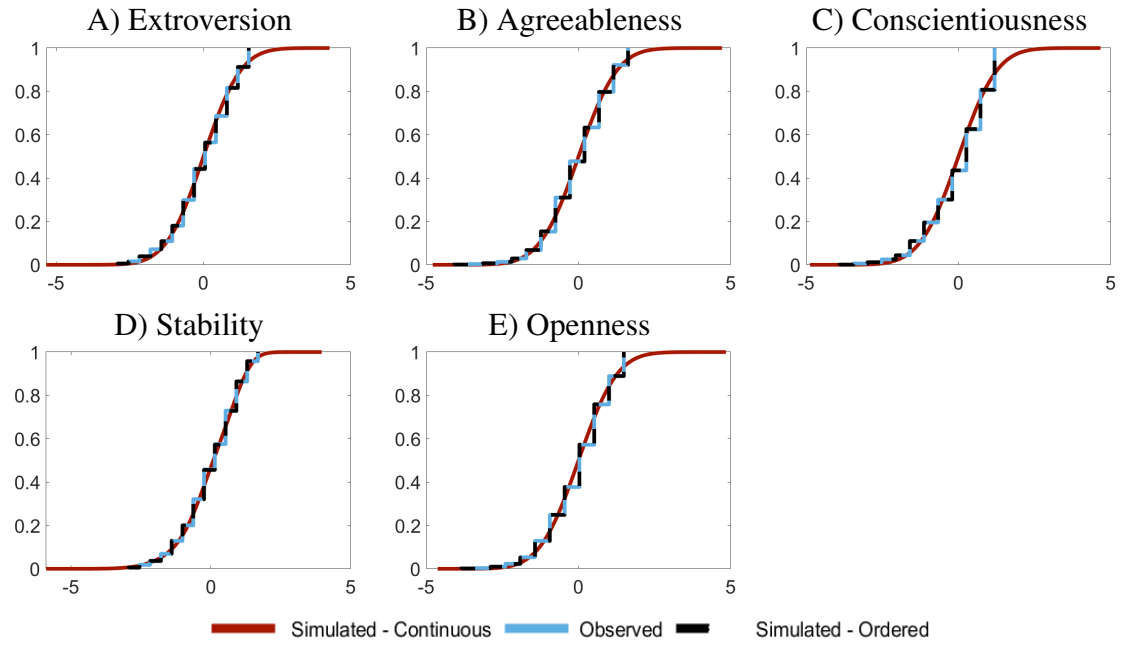
Note: Comparison of socioemotional factor distribution densities under different mixture assumptions (ordered and continuous). P-values from Likelihood-Ratio tests inform our choice of mixtures: one for the ordered system and three for the continuous system. Each p-value test considers the plotted assumption (restricted model) relative to a model where one additional mixture is considered. We consider a multi-start algorithm for each specification.

Figure 3.12: Socio-emotional ability distributions under different specifications - Women



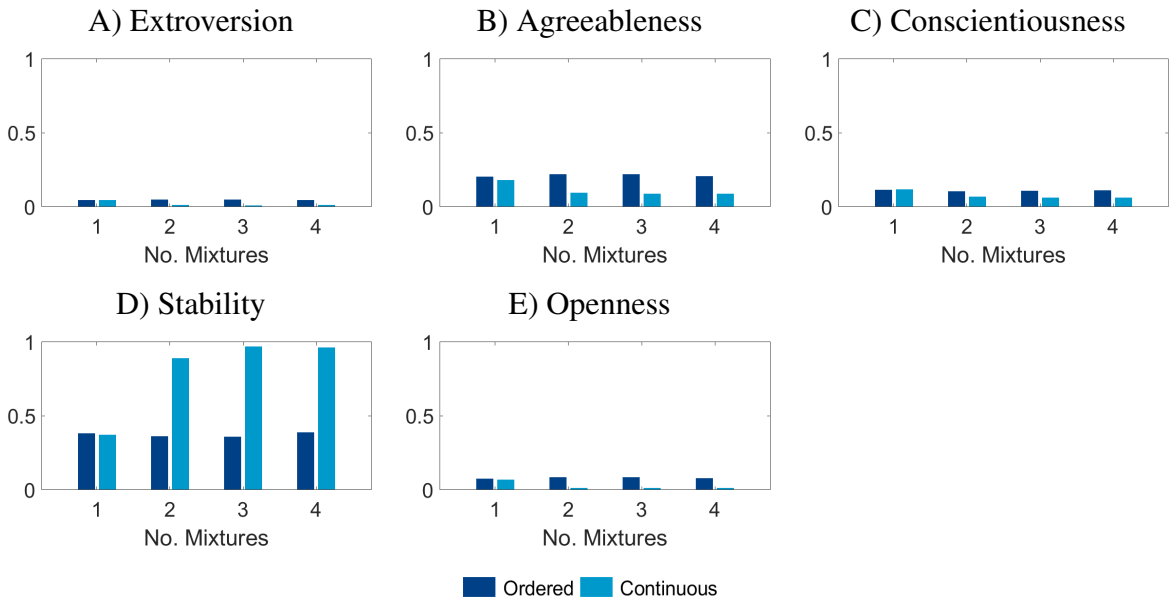
Note: Comparison between the CDFs of the observed data (blue, solid line), the CDFs of the simulated data assuming an ordered system (black, dashed line) and a continuous system (red, solid line) for men. Ordered system assumes one normal mixture for the socioemotional factor, while the continuous measure uses four mixtures. The simulated data contains 1,000 replications of the sample.

Figure 3.13: Predicted socio-emotional measures under different specifications - Men



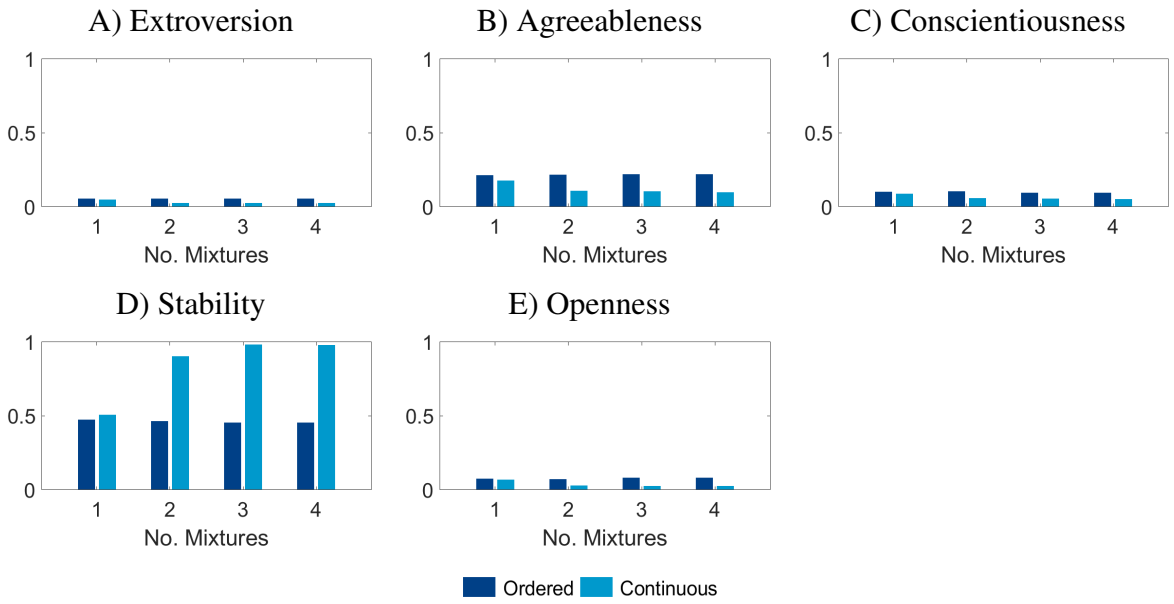
Note: Comparison between the CDFs of the observed data (blue, solid line), the CDFs of the simulated data assuming an ordered system (black, dashed line) and a continuous system (red, solid line) for men. Ordered system assumes one normal mixture for the socioemotional factor, while the continuous measure uses three mixtures. The simulated data contains 1,000 replications of the sample.

Figure 3.14: Predicted socio-emotional measures under different specifications - Women



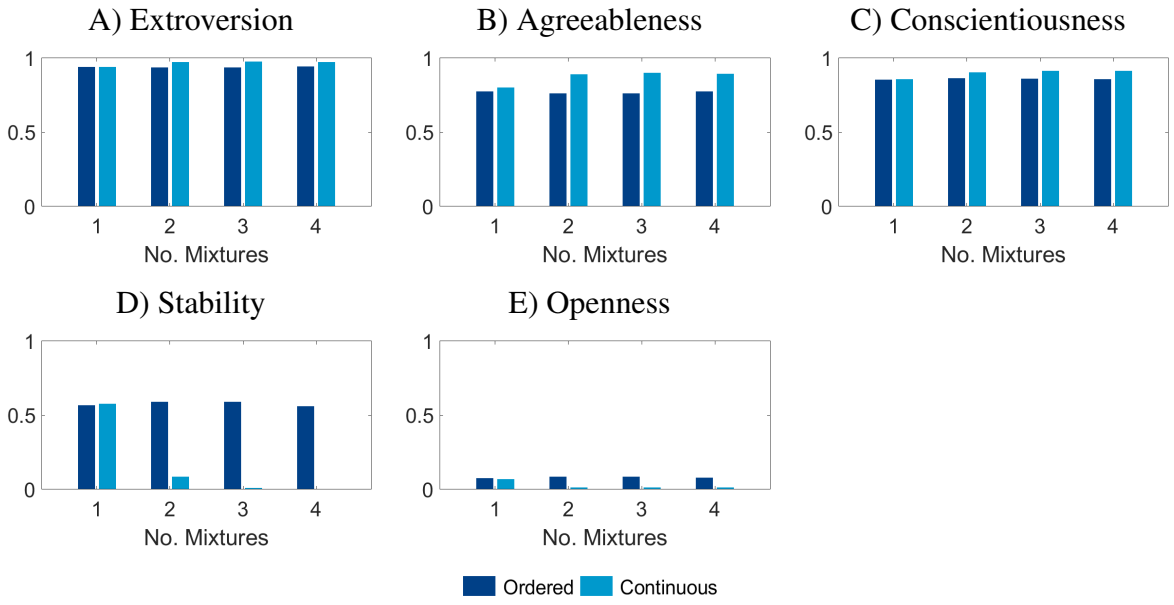
Note: We present what fraction of the variance of each measure is explained by the variance of the socioemotional factor. Darker blue represents the specifications where we consider the ordered nature of the measures, while light blue represents those assuming continuous measures.

Figure 3.15: Ability's contribution to socio-emotional measure by specification - Men



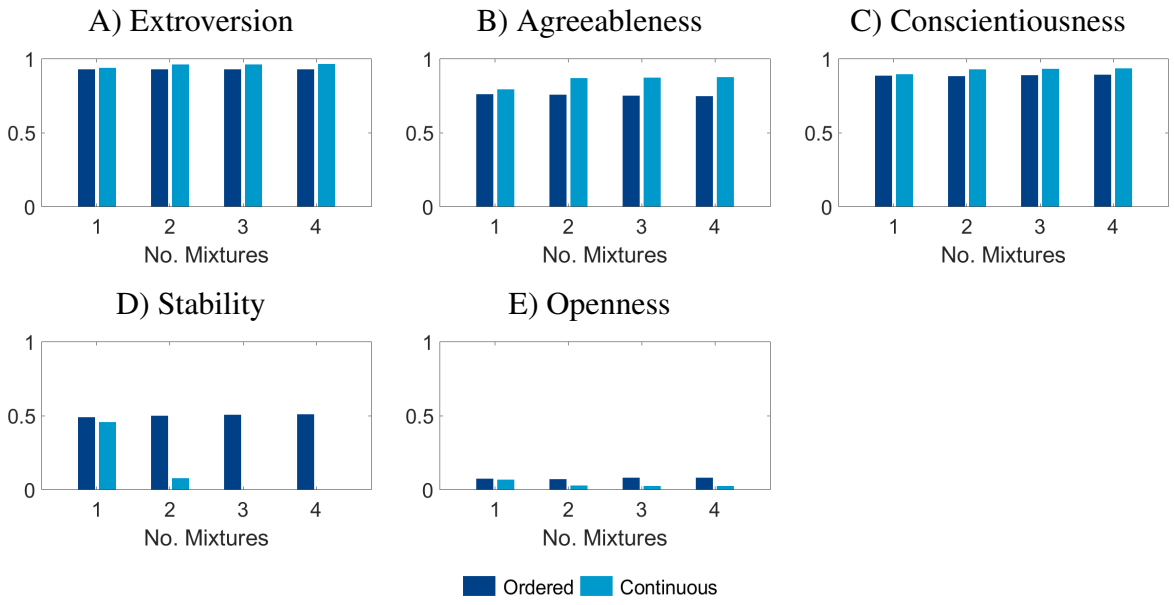
Note: We present what fraction of the variance of each measure is explained by the variance of the socioemotional factor. Darker blue represents the specifications where we consider the ordered nature of the measures, while light blue represents those assuming continuous measures.

Figure 3.16: Ability's contribution to socio-emotional measure by specification - Women



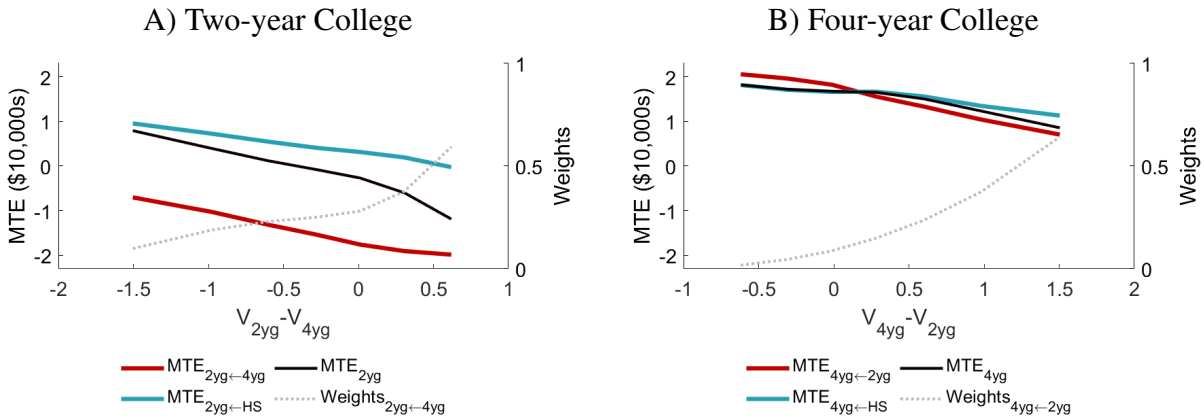
Note: We present what fraction of the variance of each measure is explained by the error term. Darker blue represents the specifications where we consider the ordered nature of the measures, while light blue represents those assuming continuous measures.

Figure 3.17: Error term's variance by socio-emotional measure and model specification - Men



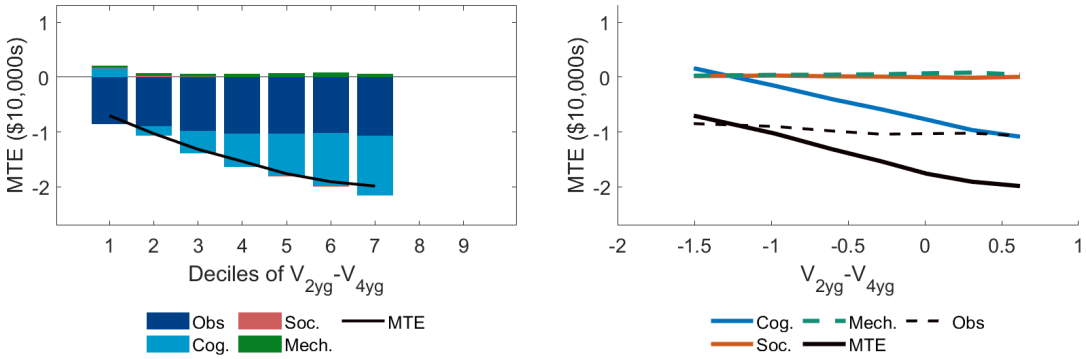
Note: We present what fraction of the variance of each measure is explained by the error term. Darker blue represents the specifications where we consider the ordered nature of the measures, while light blue represents those assuming continuous measures.

Figure 3.18: Error term's variance by socio-emotional measure and model specification - Women



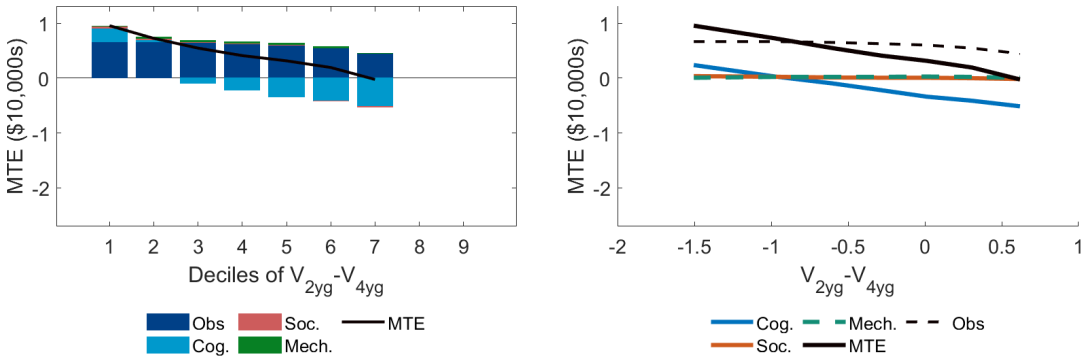
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.19: Marginal Treatment Effect for Four- and Two-year College - Men



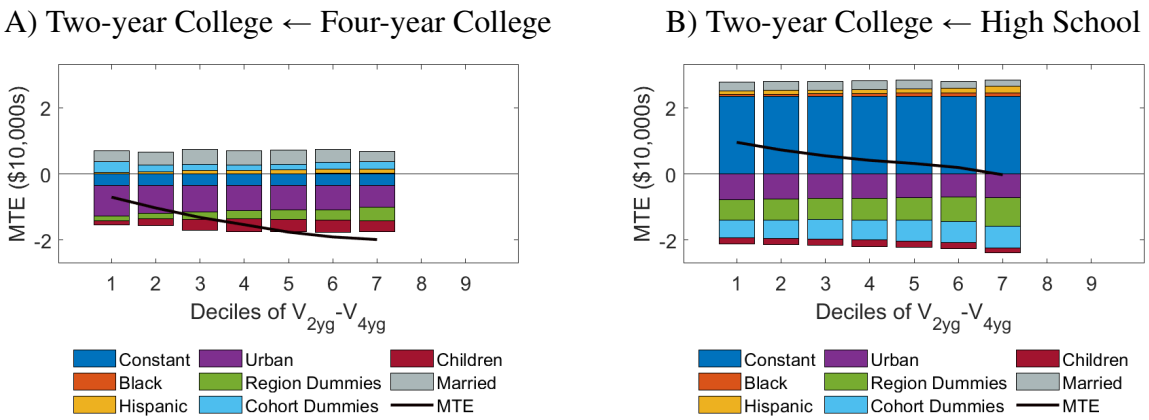
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.20: MTE Decomposition of Four-year Graduates Inflow into Two-year College - Men



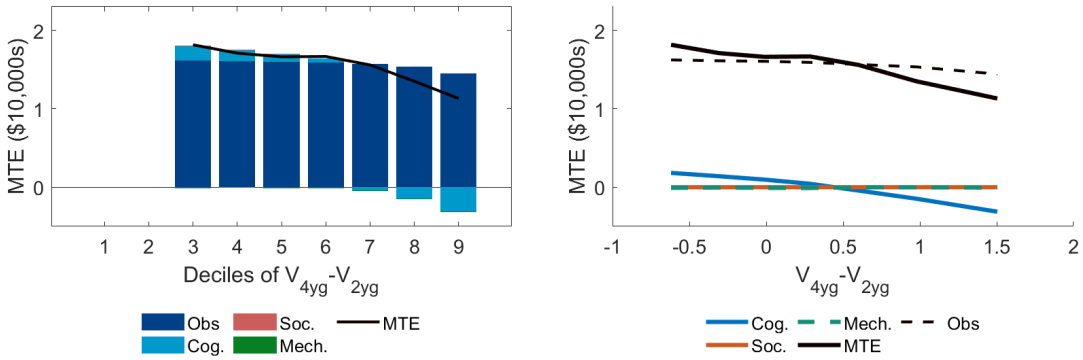
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.21: MTE Decomposition of High School Graduates Inflow into Two-year College - Men



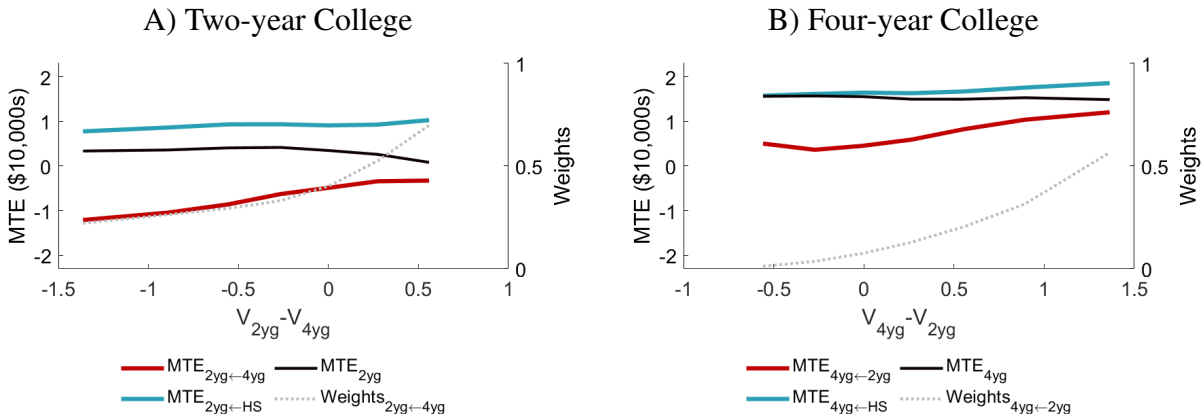
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.22: MTE Decomposition of Observables for Two-year College - Men



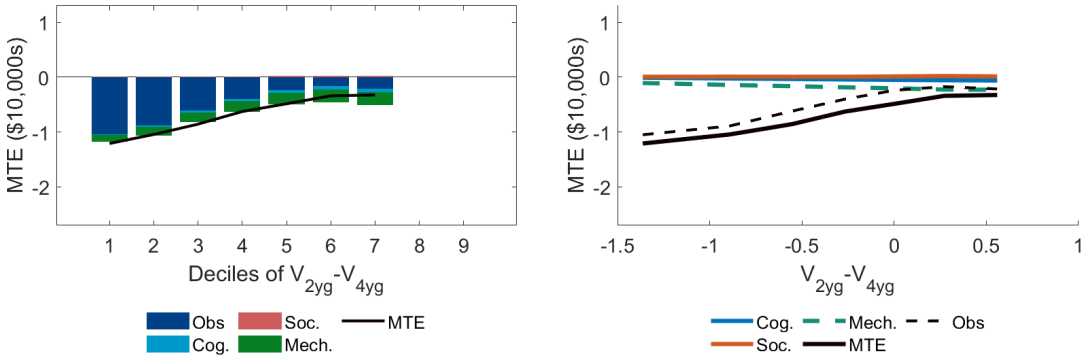
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.23: MTE Decomposition of High School Graduates Inflow into Four-year College - Men



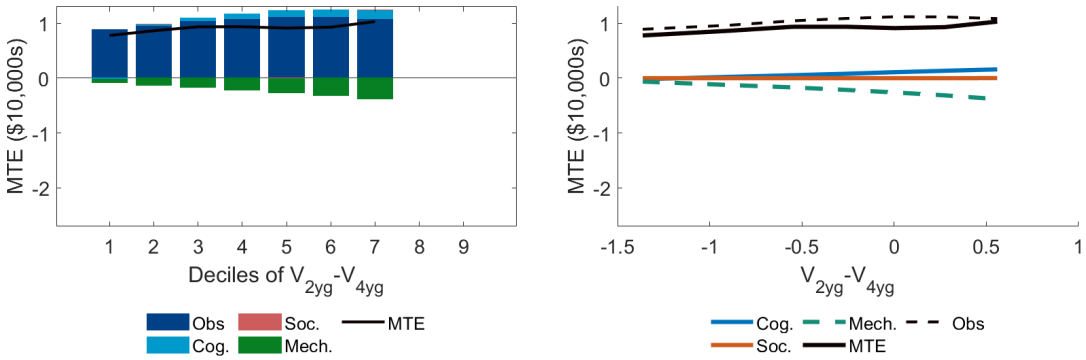
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.24: Marginal Treatment Effect for Four- and Two-year College - Women



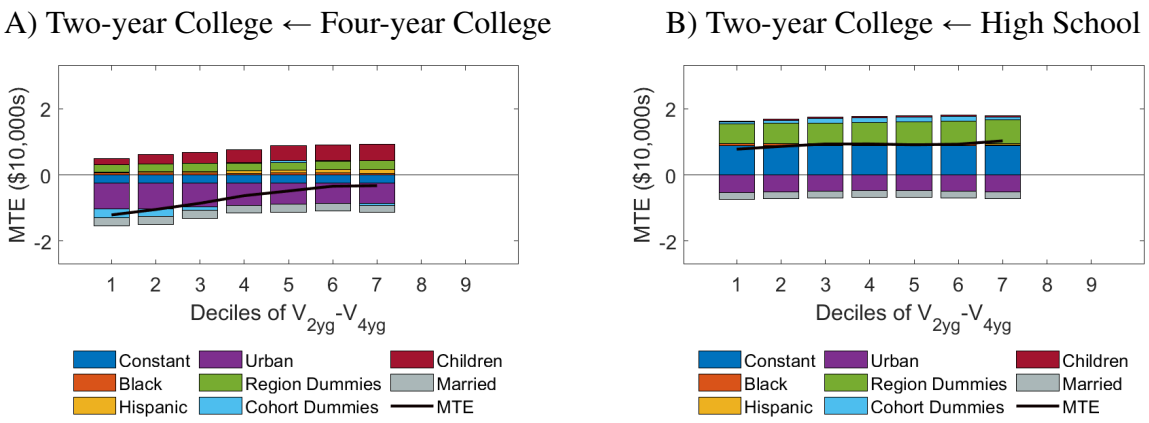
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.25: MTE Decomposition of Four-year Graduates Inflow into Two-year College - Women



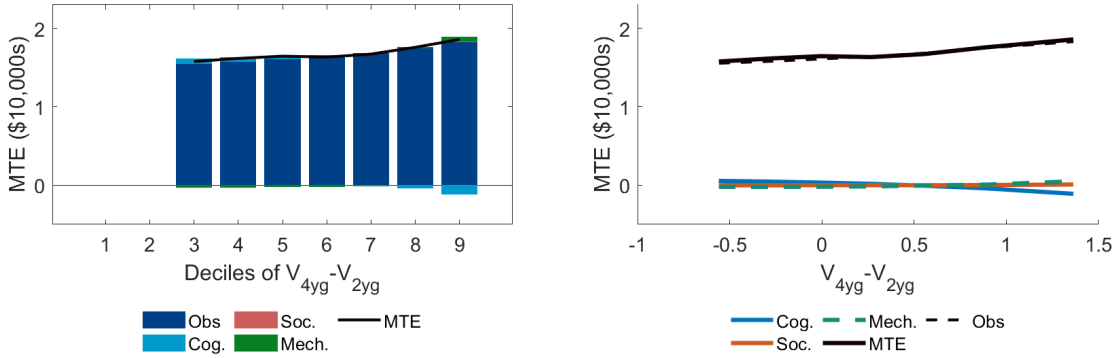
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.26: MTE Decomposition of High School Graduates Inflow into Two-year College - Women



Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

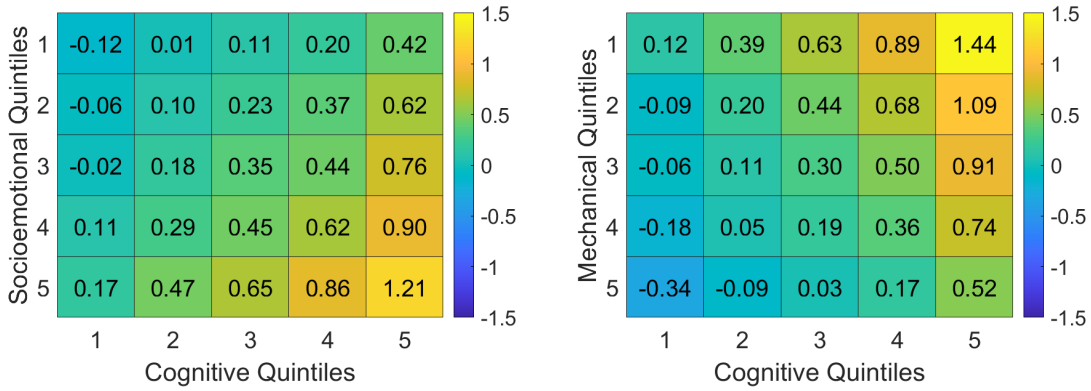
Figure 3.27: MTE Decomposition of Observables for Two-year College - Women



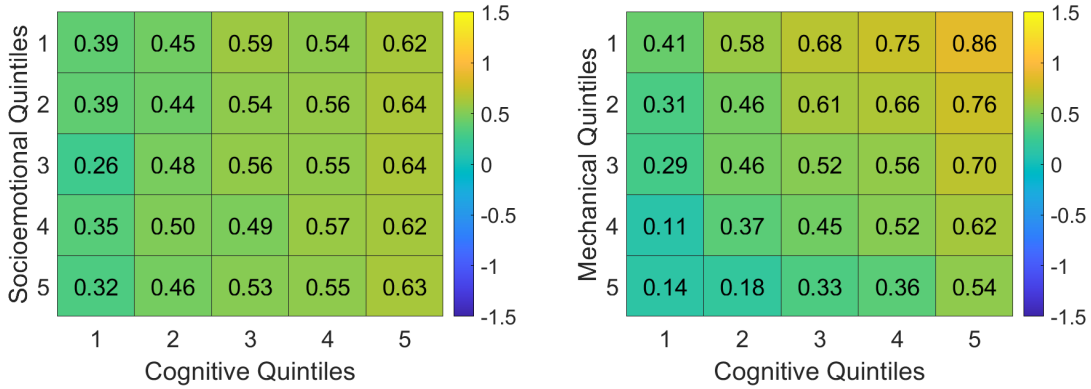
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.28: MTE Decomposition of High School Graduates Inflow into Four-year College - Women

A) Four-year College Relative to Two-year College



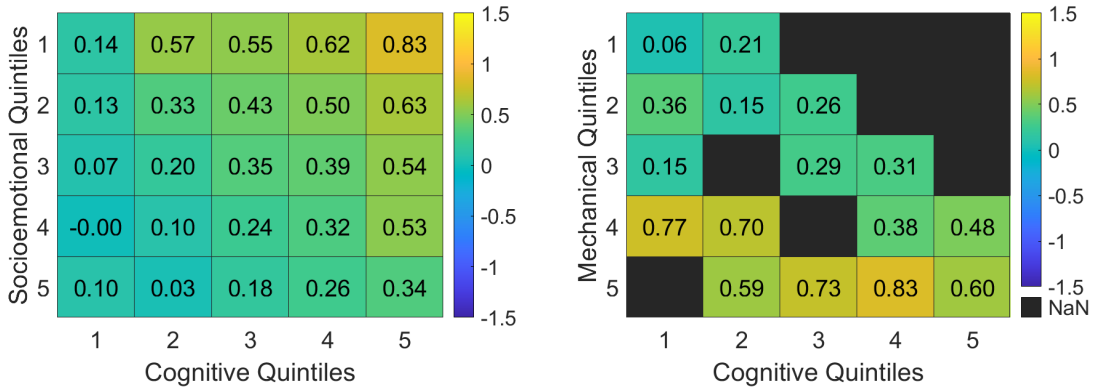
B) Four-year College Relative to High School



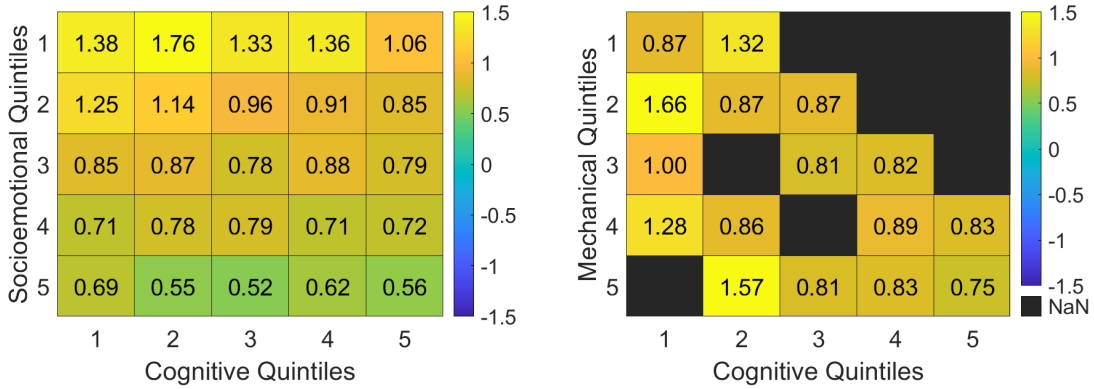
Note: The simulated data contains 1,000 replications of the sample. We compute the average treatment effect relative to the next-best alternative, normalized by the mean of the next-best alternative at each grid point

Figure 3.29: Treatment on the Treated for Four-Year Graduates - Men

A) Four-year College Relative to Two-year College



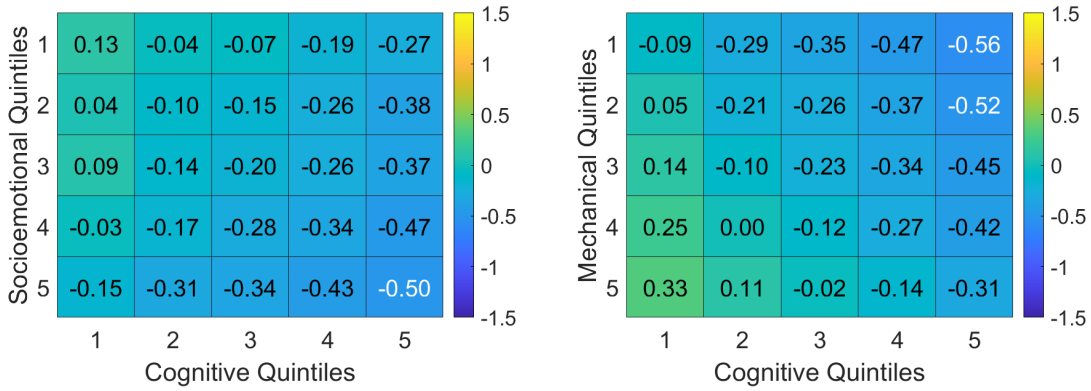
B) Four-year College Relative to High School



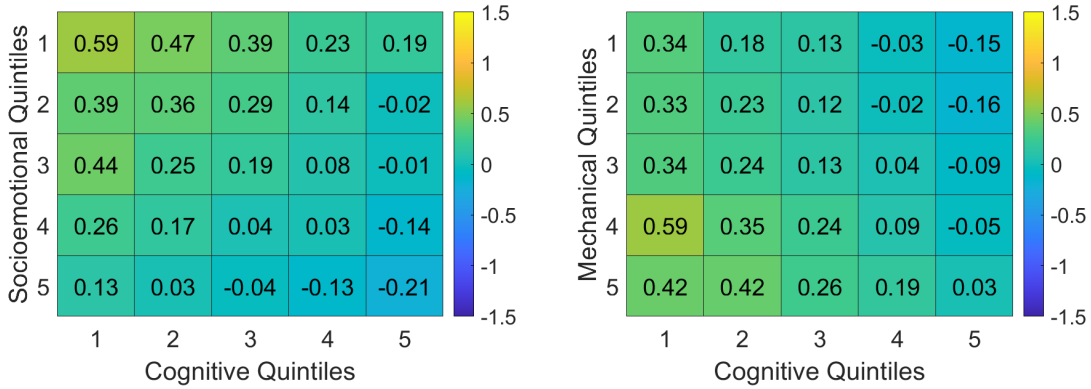
Note: The simulated data contains 1,000 replications of the sample. We compute the average treatment effect relative to the next-best alternative, normalized by the mean of the next-best alternative at each grid point

Figure 3.30: Treatment on the Treated for Four-Year Graduates - Women

A) Two-year College Relative to Four-year College



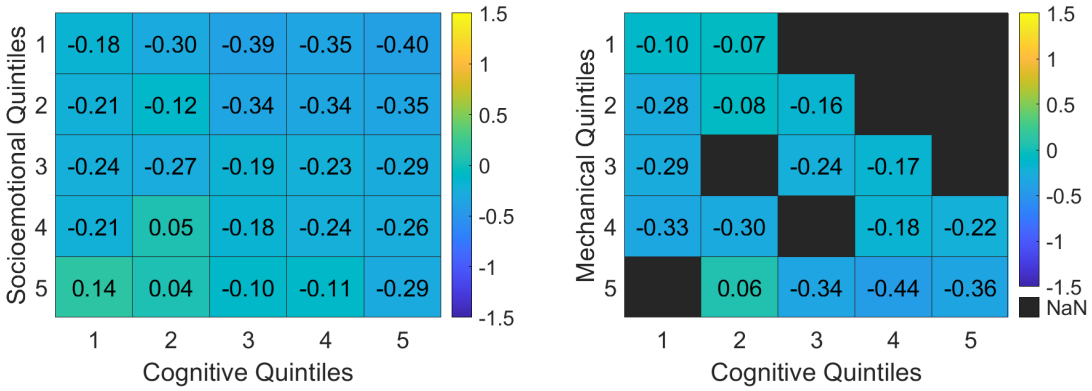
B) Two-year College Relative to High School



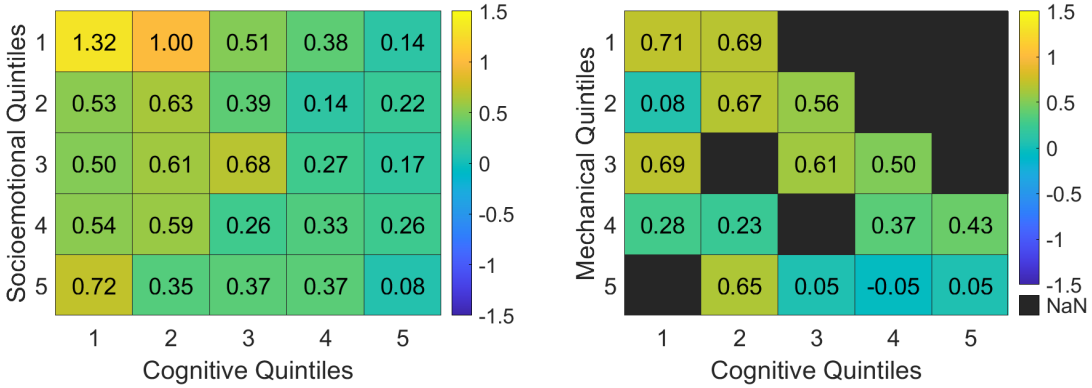
Note: The simulated data contains 1,000 replications of the sample. We compute the average treatment effect relative to the next-best alternative, normalized by the mean of the next-best alternative at each grid point

Figure 3.31: Treatment on the Treated for Two-Year Graduates - Men

A) Two-year College Relative to Four-year College



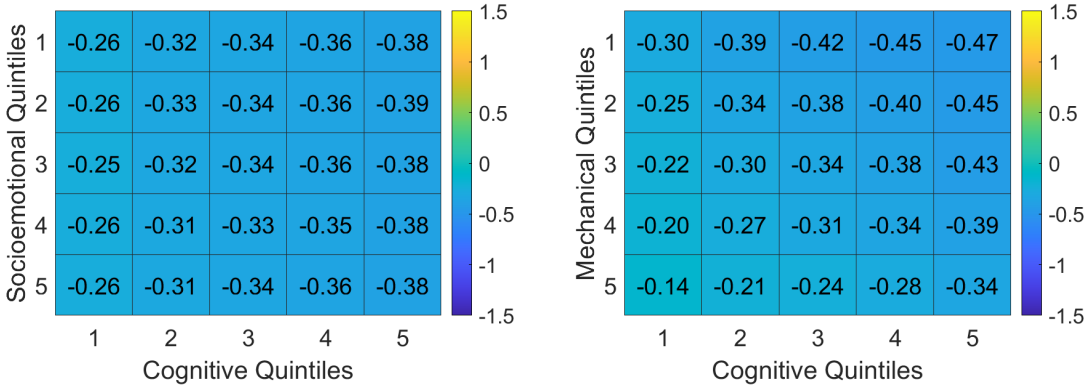
B) Two-year College Relative to High School



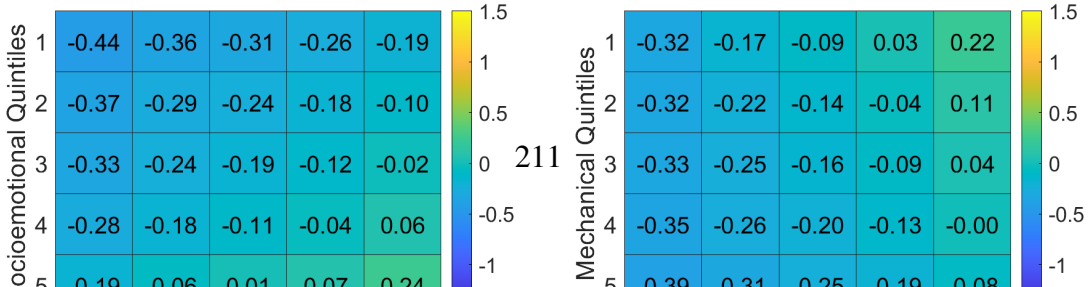
Note: The simulated data contains 1,000 replications of the sample. We compute the average treatment effect relative to the next-best alternative, normalized by the mean of the next-best alternative at each grid point

Figure 3.32: Treatment on the Treated for Two-Year Graduates - Women

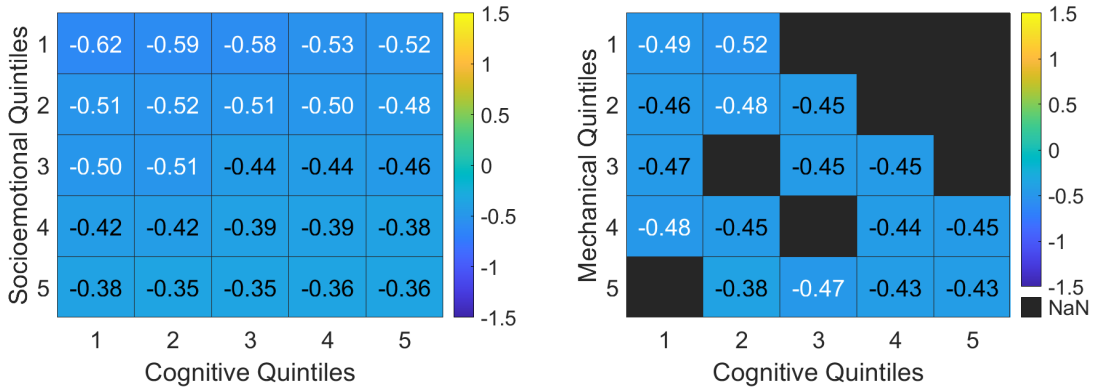
A) High School Relative to Four-year College



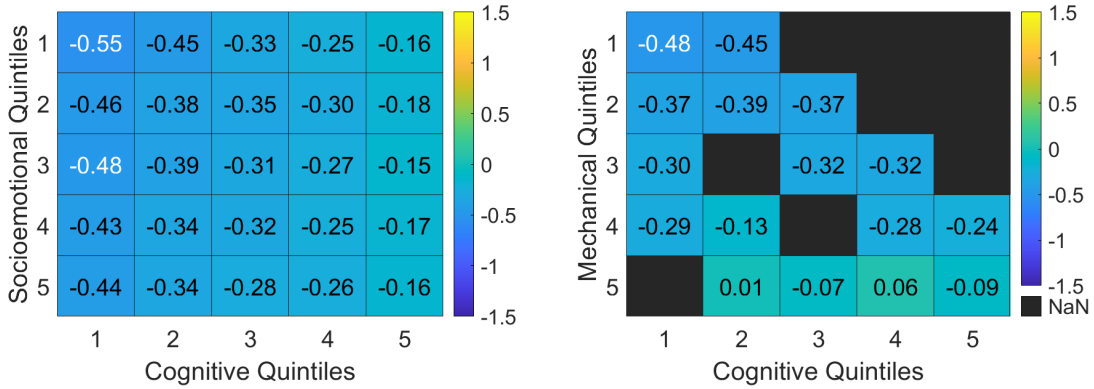
B) High School Relative to Two-year College



A) High School Relative to Four-year College



B) High School Relative to Two-year College



Note: The simulated data contains 1,000 replications of the sample. We compute the average treatment effect relative to the next-best alternative, normalized by the mean of the next-best alternative at each grid point

Figure 3.34: Treatment on the Treated for High School Graduates - Women

Table 3.1: Summary Statistics

	Men				Women			
	All	HS	2y	4y	All	HS	2y	4y
Black	0.12	0.15	0.08	0.06	0.16	0.19	0.09	0.12
Hispanic	0.11	0.14	0.08	0.07	0.12	0.16	0.13	0.06
Living in the South in 1997	0.31	0.32	0.32	0.27	0.33	0.35	0.31	0.31
Living in an urban area in 1997	0.70	0.70	0.60	0.71	0.70	0.72	0.58	0.71
Single-parent home in 1997	0.40	0.51	0.36	0.21	0.44	0.57	0.42	0.28
Family income 1997 ($1,000s)	56.72	47.07	52.40	75.92	54.72	41.80	51.36	72.18
No. siblings[a]	2.19	2.38	2.05	1.85	2.34	2.64	2.29	1.96
Mother's years of schooling in 1997	13.30	12.66	13.15	14.54	13.19	12.33	12.93	14.36
Cohort 1981	0.21	0.22	0.20	0.20	0.23	0.22	0.22	0.23
Cohort 1982	0.19	0.20	0.16	0.20	0.21	0.19	0.27	0.23
Cohort 1983	0.23	0.22	0.26	0.23	0.20	0.21	0.12	0.20
Cohort 1984	0.19	0.17	0.23	0.20	0.17	0.17	0.13	0.19
Earnings ($1,000s)[b]	39.30	31.78	42.10	52.70	26.36	16.21	26.66	39.47
Living in an urban area	0.79	0.75	0.77	0.85	0.77	0.76	0.58	0.81
Region of current residency: South	0.33	0.35	0.32	0.30	0.38	0.38	0.36	0.37
Region of current residency: North Central	0.28	0.26	0.30	0.31	0.25	0.24	0.29	0.26
Region of current residency: West	0.23	0.22	0.22	0.24	0.22	0.23	0.20	0.21
No. Children	0.46	0.55	0.56	0.27	0.96	1.34	1.05	0.46
Married	0.37	0.34	0.45	0.41	0.45	0.42	0.52	0.47
Observations	1,181	707	97	377	1,204	624	99	481

Note: [a]2011 is the most recent year in which sibling information is available in the NLSY97. [b]Annual earnings are measured in real 2010 USD, at ages 28-30. Cohort 1980 is the baseline category for cohort dummies. East is the baseline category for region dummies. HS = High school graduates, 2y = two-year graduates, and 4y = four-year graduates. If a person enrolled but did not graduate, she is classified as a high school graduate.

Table 3.2: Model Specification

	Schooling	Earnings	TIPI tests	ASVAB tests
Cohort dummies	✓	✓	✓	✓
Race dummy (being Black)	✓	✓	✓	✓
Ethnicity dummy (being Hispanic)	✓	✓	✓	✓
Living in the South in 1997	✓		✓	✓
Living in an urban area in 1997	✓		✓	✓
Single-parent home in 1997	✓		✓	✓
Family income in 1997	✓		✓	✓
Number of siblings[a]	✓		✓	✓
Mother's years of schooling in 1997	✓		✓	✓
Regional variables at age 17[b]	✓			
Years of schooling when TIPI was taken			✓	
Years of schooling when ASVAB was taken				✓
Living in an urban area		✓		
Region of current residency (dummies)		✓		
Number of biological children in the household		✓		
Dummy variable for being married		✓		

Note: [a]2011 is the most recent year in which sibling information is available in the NLSY97. [b]Regional variables include average public tuition, unemployment relative to HS graduates, and wage rate relative to HS graduates. Regional variables are specific to each sector (2YC and 4YC). TIPI is the Ten-Item Personality Inventory Scale, which provides the socioemotional measures. ASVAB is the Armed Services Vocational Aptitude Battery test, which provides information for the cognitive and mechanical measures.

Table 3.3: Reduced-form Results: OLS Results

	Earnings ($10,000s)					
	All	All	Men	Men	Women	Women
Dummy for being a 2y grad.	0.865***	0.727***	0.697***	0.584**	0.940***	0.786***
	(0.180)	(0.181)	(0.267)	(0.267)	(0.230)	(0.227)
Dummy for being a 4y grad.	1.761***	1.487***	1.592***	1.328***	1.733***	1.450***
	(0.135)	(0.137)	(0.225)	(0.231)	(0.145)	(0.149)
Cognitive		0.279***		0.224**		0.488***
		(0.072)		(0.102)		(0.089)
Socioemotional		0.141***		0.108		0.168***
		(0.052)		(0.089)		(0.052)
Mechanical		0.215***		0.293***		-0.148
		(0.076)		(0.098)		(0.102)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reduced-form estimates come from OLS specifications. Annual earnings are measured in $10,000s and in real 2010 USD, at ages 28-30. Abilities are measured as the standardized average of the same measures used in the measurement system. Staying as a high school graduate is the baseline category. Individuals who enrolled at some point in college but did not graduate are classified as high school graduates.

Table 3.4: Reduced-form vs. Structural Estimates

	Men					Women				
	School Choice		Earnings			School Choice		Earnings		
	2y	4y	HS	2y	4y	2y	4y	HS	2y	4y
Panel A: Reduced-Form Estimates:										
Cognitive	0.22**	0.76***	-0.00	-0.14	0.59**	0.32***	0.71***	0.27***	0.59	0.75***
	(0.09)	(08)	(0.11)	(0.37)	(0.24)	(0.12)	(0.10)	(0.09)	(0.40)	(0.17)
Socioemotional	0.09	0.14**	0.15*	-0.17	0.03	0.07	0.20***	0.22***	0.37*	0.06
	(0.07)	(0.07)	(0.09)	(0.33)	(0.19)	(0.08)	(0.06)	(0.06)	(0.21)	(0.10)
Mechanical	0.09	0.08	0.37***	0.08	0.29	0.25*	0.21*	0.03	-0.85**	-0.27
	(0.09)	(0.07)	(0.11)	(0.25)	(0.25)	(0.14)	(0.11)	(0.11)	(0.38)	(0.20)
Panel B: Structural Estimates:										
Cognitive	0.27***	0.95***	0.09	-0.71*	0.69**	0.13	0.79***	0.42***	0.66	0.74**
	(0.08)	(0.09)	(0.13)	(0.38)	(0.29)	(0.15)	(0.15)	(0.15)	(0.48)	(0.33)
Socioemotional	-0.02	0.03	0.04	-0.49	0.04	0.02	0.02	0.28***	0.34	0.03
	(0.09)	(0.08)	(0.13)	(0.39)	(0.25)	(0.08)	(0.08)	(0.09)	(0.30)	(0.16)
Mechanical	-0.07	-0.35***	0.30**	0.72**	-0.04	0.22	-0.24*	-0.22	-0.89**	-0.49
	(0.08)	(0.08)	(0.13)	(0.32)	(0.28)	(0.15)	(0.14)	(0.16)	(0.43)	(0.33)

Note: Standard errors are presented in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients are standardized. Reduced-form estimates come from OLS specifications in the case of earnings and from a multinomial probit estimation in the case of schooling choices. Annual earnings are measured in real 2010 USD, at ages 28-30. HS = High school graduates, 2y = two-year graduates, and 4y = four-year graduates. If a person enrolled but did not graduate, she is classified as a high school graduate.

Table 3.5: Point Estimates - Men, Utility

	HS → 2y Grad.	HS → 4y Grad.
Constant	-0.47	0.23
	(0.93)	(0.60)
Black	-0.30	-0.25
	(0.21)	(0.18)
Hispanic	-0.30	-0.25
	(0.20)	(0.18)
Living in the South in 1997	0.03	0.03
	(0.15)	(0.13)
Living in an urban area in 1997	-0.20*	0.06
	(0.12)	(0.12)
Single-parent home in 1997	-0.36***	-0.77***
	(0.13)	(0.12)
Family income 1997	-0.01	0.21***
	(0.07)	(0.05)
No. siblings	-0.07	-0.03
	(0.07)	(0.06)
Mother's years of schooling in 1997	0.11	0.43***
	(0.07)	(0.06)
Cohort 1981	0.09	-0.15
	(0.19)	(0.18)
Cohort 1982	-0.07	-0.14
	(0.23)	(0.20)
Cohort 1983	0.12	-0.07
	(0.18)	(0.18)
Cohort 1984	0.24	0.17
	(0.19)	(0.18)
Tuition	-0.16	0.14
	(0.46)	(0.10)
Unemployment Difference (relative to HS)	1.46	3.52
	(3.80)	(4.39)
Wage Ratio (relative to HS)	-0.13	-0.34
	(0.50)	(0.23)
Cognitive factor	0.27***	0.95***
	(0.08)	(0.09)
Socioemotional factor	-0.02	0.03
	(0.08)	(0.09)
Mechanical factor	-0.07	-0.35***
	(0.08)	(0.08)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, and mother's years of schooling are standardized. Tuition is in \$10,000s. Loadings are also standardized.

Table 3.6: Point Estimates - Men, Earnings.

	HS	2y Grad.	4y Grad.
Constant	2.37***	4.72***	5.08***
	(0.35)	(0.86)	(0.74)
Black	-1.06***	-0.41	-0.54
	(0.27)	(0.95)	(0.73)
Hispanic	-0.22	0.89	-0.59
	(0.27)	(0.85)	(0.69)
Living in an urban area	0.25	-0.76	0.28
	(0.22)	(0.59)	(0.50)
Region of current residency: South	0.27	-0.85	0.00
	(0.27)	(0.69)	(0.55)
Region of current residency: North Central	-0.14	-0.07	-0.59
	(0.29)	(0.71)	(0.55)
Region of current residency: West	0.36	-0.83	-0.31
	(0.30)	(0.76)	(0.57)
Cohort 1981	0.19	-0.50	-1.11*
	(0.29)	(0.79)	(0.58)
Cohort 1982	-0.02	0.10	-1.21**
	(0.30)	(0.82)	(0.58)
Cohort 1983	-0.04	-1.23*	-0.88
	(0.29)	(0.73)	(0.56)
Cohort 1984	0.41	-0.30	-0.07
	(0.31)	(0.76)	(0.59)
Children in the Household	0.19	-0.18	0.53*
	(0.12)	(0.31)	(0.29)
Married	1.48***	2.19***	1.13***
	(0.22)	(0.56)	(0.40)
Cognitive factor	0.09	-0.71*	0.69**
	(0.13)	(0.38)	(0.29)
Socioemotional factor	0.04	-0.49	0.04
	(0.13)	(0.39)	(0.25)
Mechanical factor	0.30**	0.72**	-0.04
	(0.13)	(0.32)	(0.28)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Earnings are measured in \$10,000s. Loadings are also standardized.

Table 3.7: Point Estimates - Men, Cognitive System.

	Math	Word	Para	Num	Cod	Arith
Constant	0.07	0.30***	0.09	-0.17*	-0.26***	0.15*
	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)	(0.09)
Black	-0.64***	-0.71***	-0.62***	-0.29***	-0.38***	-0.92***
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)
Hispanic	-0.30***	-0.43***	-0.33***	-0.35***	-0.15*	-0.43***
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)
Living in the South in 1997	0.05	-0.03	-0.05	0.10	0.12**	0.04
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
Living in an urban area in 1997	0.07	0.06	0.02	0.10*	0.12**	0.09*
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
Single-parent home in 1997	-0.12**	-0.05	-0.10*	-0.03	-0.12**	-0.11**
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)
Family income 1997	0.06**	0.06**	0.05*	0.06**	0.04	0.05**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
No. siblings	-0.00	-0.04*	-0.03	-0.07**	-0.07**	0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Mother's years of schooling in 1997	0.23***	0.22***	0.19***	0.12***	0.16***	0.20***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Cohort 1981	0.13	0.01	0.09	0.16*	0.15	0.13
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)
Cohort 1982	0.08	-0.09	-0.08	0.23**	0.09	0.10
	(0.09)	(0.09)	(0.10)	(0.11)	(0.10)	(0.10)
Cohort 1983	-0.02	-0.21*	-0.05	0.18	0.15	0.08
	(0.11)	(0.11)	(0.12)	(0.13)	(0.12)	(0.11)
Cohort 1984	-0.24**	-0.37***	-0.11	0.04	0.07	0.02
	(0.12)	(0.13)	(0.13)	(0.15)	(0.14)	(0.13)
Years of schooling when the ASVAB was taken	0.35***	0.22***	0.23***	0.35***	0.32***	0.26***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
Cognitive factor	1	0.87***	1.01***	0.80***	0.75***	1.09***
	-	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations.

Table 3.8: Point Estimates - Men, Socioemotional System.

	Extro	Agree	Consc	Stab	Open
Black	-0.11	-0.05	0.39***	0.16	0.34***
	(0.10)	(0.11)	(0.11)	(0.13)	(0.10)
Hispanic	0.00	0.10	0.16	0.05	0.10
	(0.10)	(0.11)	(0.11)	(0.13)	(0.10)
Living in the south in 1997	0.00	-0.09	0.09	-0.04	-0.01
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
Living in an urban area in 1997	-0.04	-0.06	-0.07	-0.26***	0.02
	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)
Single-parent home in 1997	-0.01	-0.09	-0.12*	-0.19**	0.07
	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)
Family income 1997	0.10***	-0.03	0.01	0.02	0.01
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
No. siblings	0.02	0.07**	0.02	0.01	0.00
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Mother's years of schooling in 1997	0.01	0.03	-0.04	0.05	0.06*
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Cohort 1981	0.04	-0.15	-0.10	-0.00	-0.11
	(0.10)	(0.11)	(0.10)	(0.12)	(0.10)
Cohort 1982	0.14	-0.22**	-0.02	-0.08	-0.12
	(0.10)	(0.11)	(0.10)	(0.13)	(0.10)
Cohort 1983	0.17*	-0.21**	-0.26***	0.04	-0.17*
	(0.10)	(0.10)	(0.10)	(0.12)	(0.10)
Cohort 1984	0.04	-0.06	-0.23**	-0.07	0.04
	(0.10)	(0.11)	(0.10)	(0.13)	(0.10)
Years of schooling when the TIPI was taken	-0.02	0.09**	0.02	0.20***	0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Socioemotional factor	1	2.46***	1.61***	3.99***	1.39***
	-	(0.60)	(0.39)	(1.14)	(0.32)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the TIPI test was taken are standardized. Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = conscientiousness.

Table 3.9: Point Estimates - Men, Mechanical System.

	Mech	Elect	Auto	Shop
Constant	0.55***	0.70***	0.93***	1.11***
	(0.09)	(0.10)	(0.09)	(0.10)
Black	-0.97***	-0.69***	-1.01***	-0.74***
	(0.08)	(0.09)	(0.08)	(0.09)
Hispanic	-0.47***	-0.55***	-0.65***	-0.45***
	(0.08)	(0.09)	(0.09)	(0.09)
Living in the South in 1997	0.00	-0.04	-0.07	0.07
	(0.05)	(0.06)	(0.06)	(0.06)
Living in an urban area in 1997	-0.13**	-0.05	-0.18***	-0.32***
	(0.06)	(0.06)	(0.06)	(0.06)
Single-parent home in 1997	-0.16***	-0.13**	0.01	-0.08
	(0.05)	(0.06)	(0.05)	(0.06)
Family income 1997	0.02	-0.00	-0.04	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)
No. siblings	-0.03	-0.00	-0.05*	-0.05*
	(0.03)	(0.03)	(0.03)	(0.03)
Mother's years of schooling in 1997	0.16***	0.13***	0.05*	0.06**
	(0.03)	(0.03)	(0.03)	(0.03)
Cohort 1981	0.18**	-0.05	0.04	-0.14
	(0.08)	(0.09)	(0.09)	(0.09)
Cohort 1982	-0.04	-0.16	-0.16	-0.49***
	(0.10)	(0.11)	(0.10)	(0.11)
Cohort 1983	-0.03	-0.36***	-0.40***	-0.70***
	(0.12)	(0.13)	(0.12)	(0.12)
Cohort 1984	-0.16	-0.41***	-0.61***	-0.81***
	(0.14)	(0.15)	(0.14)	(0.15)
Years of schooling when the ASVAB was taken	0.21***	0.22***	0.04	0.15***
	(0.04)	(0.05)	(0.05)	(0.05)
Mechanical factor	1	1.29***	1.63***	1.64***
	-	(0.09)	(0.11)	(0.12)
Cognitive factor	0.60***	0.50***	0.02	0
	(0.04)	(0.04)	(0.05)	-

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Mech = mechanical comprehension, Auto = auto information, Elect = electronics information.

Table 3.10: Point Estimates - Women, Utility

	HS → 2y Grad.	HS → 4y Grad.
Constant	-0.49	-0.23
	(0.61)	(0.55)
Black	-0.24	0.03
	(0.19)	(0.15)
Hispanic	-0.03	-0.19
	(0.18)	(0.16)
Living in the South in 1997	-0.14	0.05
	(0.18)	(0.12)
Living in an urban area in 1997	-0.28**	-0.00
	(0.13)	(0.11)
Single-parent home in 1997	-0.26**	-0.65***
	(0.12)	(0.10)
Family income 1997	0.11	0.31***
	(0.07)	(0.06)
No.siblings	-0.03	-0.06
	(0.06)	(0.05)
Mother's years of schooling in 1997	0.17***	0.48***
	(0.07)	(0.05)
Cohort 1981	-0.09	0.26*
	(0.23)	(0.16)
Cohort 1982	0.19	0.50***
	(0.21)	(0.16)
Cohort 1983	-0.37	0.22
	(0.23)	(0.17)
Cohort 1984	-0.13	0.34**
	(0.19)	(0.16)
Tuition	-0.51	0.11
	(0.41)	(0.08)
Unemployment Difference (relative to HS)	-3.30	-0.35
	(4.39)	(4.22)
Wage Ratio (relative to HS)	0.06	-0.09
	(0.27)	(0.16)
Cognitive factor	0.13	0.79***
	(0.15)	(0.15)
Socioemotional factor	0.02	0.02
	(0.08)	(0.08)
Mechanical factor	0.22	-0.24*
	(0.15)	(0.14)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, and mother's years of schooling are standardized. Tuition is in \$10,000s. Loadings are also standardized.

Table 3.11: Point Estimates - Women, Earnings.

	HS	2y Grad.	4y Grad.
Constant	2.37***	3.25***	3.49***
	(0.24)	(0.79)	(0.48)
Black	-0.09	0.40	-0.23
	(0.17)	(0.81)	(0.37)
Hispanic	0.16	0.21	-0.28
	(0.17)	(0.66)	(0.47)
Living in an urban area (currently)	0.20	-0.50	0.48
	(0.15)	(0.45)	(0.30)
Region of current residency: South	-0.29	0.40	0.16
	(0.19)	(0.68)	(0.34)
Region of current residency: North Central	-0.21	0.35	-0.15
	(0.20)	(0.71)	(0.36)
Region of current residency: West	-0.36*	0.54	0.47
	(0.20)	(0.78)	(0.37)
Cohort 1981	-0.31*	0.38	0.15
	(0.18)	(0.65)	(0.37)
Cohort 1982	-0.30	0.39	-0.28
	(0.19)	(0.60)	(0.37)
Cohort 1983	-0.18	-0.63	0.01
	(0.19)	(0.78)	(0.38)
Cohort 1984	0.02	-1.14	0.61
	(0.20)	(0.73)	(0.39)
Children in the Household	-0.36***	-0.33	-0.69***
	(0.05)	(0.21)	(0.15)
Married	0.14	-0.34	0.16
	(0.13)	(0.48)	(0.25)
Cognitive factor	0.42***	0.65	0.74**
	(0.15)	(0.48)	(0.33)
Socioemotional factor	0.28***	0.34	0.03
	(0.09)	(0.30)	(0.16)
Mechanical factor	-0.22	-0.89**	-0.49
	(0.16)	(0.43)	(0.33)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Earnings are measured in \$10,000s. Loadings are also standardized.

Table 3.12: Point Estimates - Women, Cognitive System.

	Math	Word	Para	Num	Cod	Arith
Constant	0.22***	0.17**	0.34***	-0.01	0.33***	0.07
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)
Black	-0.56***	-0.56***	-0.55***	-0.15**	-0.30***	-0.69***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
Hispanic	-0.13*	-0.30***	-0.14*	-0.13*	0.02	-0.19**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Living in the South in 1997	0.08	0.01	-0.02	0.07	0.09*	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Living in an urban area in 1997	0.04	0.02	-0.06	0.08	0.02	0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Single-parent home in 1997	-0.25***	-0.18***	-0.16***	-0.22***	-0.15***	-0.22***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Family income 1997	0.10***	0.08***	0.07**	0.09***	0.08***	0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
No. siblings	-0.03	-0.05*	-0.02	-0.01	-0.07***	0.01
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Mother's years of schooling in 1997	0.17***	0.24***	0.22***	0.09***	0.09***	0.20***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Cohort 1981	0.09	0.08	0.07	0.14*	-0.01	0.09
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Cohort 1982	0.11	-0.02	0.03	0.16*	-0.07	0.07
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)
Cohort 1983	-0.05	-0.11	-0.08	0.18*	-0.17	0.09
	(0.09)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)
Cohort 1984	-0.30***	-0.14	-0.19	-0.01	-0.30**	0.05
	(0.11)	(0.11)	(0.12)	(0.12)	(0.13)	(0.11)
Years of schooling when the ASVAB was taken	0.30***	0.26***	0.18***	0.29***	0.19***	0.23***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Cognitive factor	1	0.97***	1.06***	0.76***	0.71***	1.05***
	-	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Arith = arithmetic reasoning, Math = math knowledge, Word = word knowledge, Para = paragraph comprehension, Cod = coding speed, Num = numerical operations.

Table 3.13: Point Estimates - Women, Socioemotional System.

	Extro	Agree	Consc	Stab	Open
Black	-0.05	-0.08	0.11	0.22*	0.25***
	(0.09)	(0.10)	(0.10)	(0.12)	(0.09)
Hispanic	0.04	-0.07	-0.02	0.37***	0.05
	(0.10)	(0.11)	(0.10)	(0.13)	(0.10)
Living in the south in 1997	-0.02	0.06	-0.06	0.03	-0.03
	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)
Living in an urban area in 1997	0.07	0.07	0.08	0.06	0.13*
	(0.07)	(0.08)	(0.07)	(0.09)	(0.07)
Single-parent home in 1997	-0.06	-0.03	0.01	-0.14	-0.06
	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)
Family income 1997	0.04	-0.04	-0.01	-0.00	0.03
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
No. siblings	0.02	-0.04	-0.03	-0.01	-0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Mother's years of schooling in 1997	0.06*	0.06	-0.06	0.05	0.07*
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Cohort 1981	-0.06	-0.04	-0.01	-0.25**	-0.00
	(0.09)	(0.10)	(0.10)	(0.12)	(0.10)
Cohort 1982	0.00	-0.13	-0.06	-0.14	0.01
	(0.10)	(0.11)	(0.10)	(0.12)	(0.10)
Cohort 1983	0.02	-0.29***	-0.07	-0.13	0.04
	(0.10)	(0.11)	(0.10)	(0.12)	(0.10)
Cohort 1984	0.09	0.07	-0.12	-0.05	0.12
	(0.10)	(0.11)	(0.10)	(0.13)	(0.10)
Age when the TIPI was taken	0.03	0.10**	0.10***	0.17***	0.01
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Socioemotional factor	1	2.24***	1.37***	3.53***	1.21***
	-	(0.49)	(0.30)	(0.76)	(0.25)

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the TIPI test was taken are standardized. Extro = extroversion, Stab = emotional stability, Open = openness to experience, Agree = agreeableness, Consc = conscientiousness.

Table 3.14: Point Estimates - Women, Mechanical System.

	Mech	Elect	Auto	Shop
Constant	0.08	0.10	0.02	0.14*
	(0.08)	(0.07)	(0.07)	(0.07)
Black	-0.79***	-0.37***	-0.63***	-0.56***
	(0.07)	(0.06)	(0.06)	(0.06)
Hispanic	-0.27***	-0.26***	-0.31***	-0.23***
	(0.07)	(0.07)	(0.07)	(0.07)
Living in the South in 1997	-0.09*	0.02	-0.10**	0.02
	(0.05)	(0.05)	(0.05)	(0.04)
Living in an urban area in 1997	-0.09*	-0.15***	-0.20***	-0.12***
	(0.05)	(0.05)	(0.05)	(0.05)
Single-parent home in 1997	-0.11**	-0.11**	-0.05	-0.05
	(0.05)	(0.04)	(0.05)	(0.04)
Family income 1997	0.05*	0.01	0.01	0.03
	(0.03)	(0.02)	(0.02)	(0.02)
No. siblings	-0.01	-0.03	0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Mother's years of schooling in 1997	0.12***	0.13***	0.12***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)
Cohort 1981	-0.02	-0.06	-0.03	-0.19***
	(0.07)	(0.07)	(0.07)	(0.07)
Cohort 1982	0.10	-0.03	0.01	-0.20***
	(0.08)	(0.08)	(0.08)	(0.07)
Cohort 1983	0.04	-0.18**	-0.04	-0.34***
	(0.09)	(0.09)	(0.09)	(0.09)
Cohort 1984	-0.08	-0.33***	-0.19*	-0.36***
	(0.11)	(0.10)	(0.10)	(0.10)
Years of schooling when the ASVAB was taken	0.17***	0.17***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
Mechanical factor	1	1.24***	2.12***	1.30***
	-	(0.28)	(0.45)	(0.35)
Cognitive factor	0.42***	0.20**	-0.36**	0
	(0.12)	(0.10)	(0.15)	-

Note: Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Family income in 1997, siblings, mother's years of schooling, and the years of schooling when the ASVAB test was taken are standardized. Mech = mechanical comprehension, Auto = auto information, Elect = electronics information.

Table 3.15: Goodness of Fit: Schooling Choices and Earnings

	Schooling Choices		Earnings (in 10,000s)			
	Fraction of individuals		Mean		Variance	
	Simulated	Observed	Simulated	Observed	Simulated	Observed
Panel A. Men						
HS grad.	0.616	0.599	3.226	3.178	6.795	6.845
2y grad.	0.082	0.082	4.066	4.210	6.816	6.641
4y grad.	0.302	0.319	5.322	5.270	12.367	12.262
Panel B. Women						
HS grad.	0.553	0.518	1.728	1.565	2.476	2.528
2y grad.	0.084	0.082	2.594	2.649	4.944	4.936
4y grad.	0.363	0.400	3.719	3.973	6.581	6.502

Note: The simulated data contains 1,000 replications of the sample.

Table 3.16: Estimated loading parameters by socio-emotional measure: Ordered vs. Continuous Systems

	Men				Women			
	Number of Mixtures				Number of Mixtures			
	1	2	3	4	1	2	3	4
Panel A: Ordered System								
Extroversion	1	1	1	1	1	1	1	1
Agreeableness	2.32	2.36	2.39	2.41	2.18	2.23	2.23	2.24
Conscientiousness	1.65	1.53	1.58	1.68	1.38	1.42	1.33	1.33
Stability	3.71	3.43	3.48	3.91	4.06	4.03	3.89	3.90
Openness	1.31	1.33	1.37	1.38	1.16	1.15	1.24	1.24
Panel B: Continuous System								
Extroversion	1	1	1	1	1	1	1	1
Agreeableness	1.98	2.71	2.96	2.95	1.95	2.03	2.05	2.05
Conscientiousness	1.59	2.34	2.48	2.46	1.37	1.49	1.48	1.48
Stability	2.86	8.46	9.88	9.88	3.30	5.94	6.45	6.44
Openness	1.21	1.01	1.08	1.07	1.19	1.05	1.02	1.02

Note: Comparison of socioemotional system loadings under two assumptions: ordered (with 13 distinct levels) and continuous. We consider a multi-start algorithm for each specification.

Table 3.17: Ranking of Preferences by Group

Ranking		Group Percentage	
First Option	Second Option	Men	Women
HS degree	2y degree	30.2%	22.1%
HS degree	4y degree	31.4%	33.2%
2y degree	HS degree	5.4%	4.9%
2y degree	4y degree	2.8%	3.4%
4y degree	HS degree	22.0%	25.5%
4y degree	2y degree	8.3%	10.9%

Note: Each column shows the percentage of simulated individuals the indicated preference ranking by group. Columns sum up to 100%.

Table 3.18: Sector Preferences by Group

	Men			Women		
	First Option	Second Option	Third Option	First Option	Second Option	Third Option
HS degree	61.6%	27.3%	11.1%	55.3%	30.4%	14.3%
2y degree	8.2%	38.5%	53.3%	8.4%	33.0%	58.7%
4y degree	30.2%	34.2%	30.2%	36.3%	36.6%	22.1%

Note: Each column displays the percentage of simulated individuals in each group ranking each alternative in the place indicated by the headline, unconditionally of other alternative's places.

3.10 Additional Figures and Tables

Table 3.19: Wald Tests for Differences on the Effect of Decisions on Earnings between Women and Men in the Reduced Form Estimation

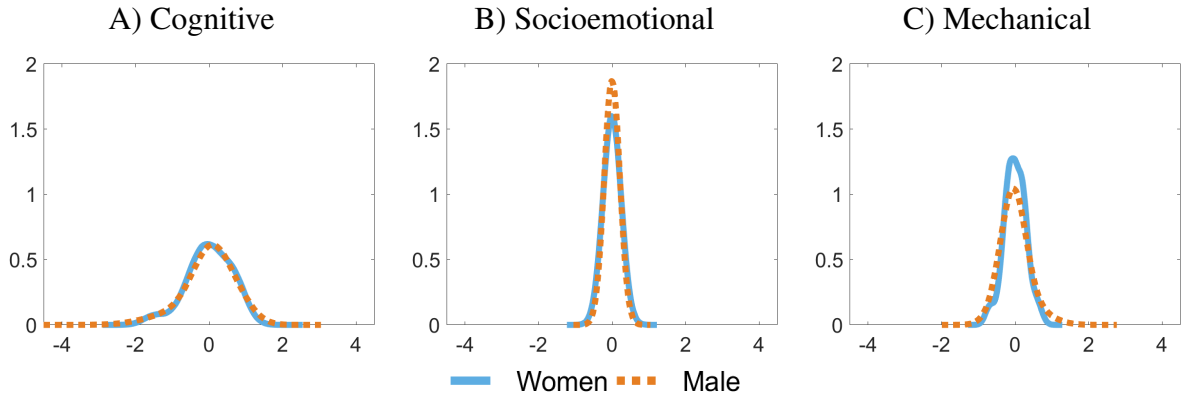
	F-statistic	P-value
Dummy for being a 2y grad.	0.33	0.565
Dummy for being a 4y grad.	0.20	0.655

Note: Wald tests are conducted on a fully-interacted model to pool estimates from Columns 4 and 6 in Table 3.3.

Table 3.20: T-tests for Differences on Loadings between Women and Men in the Structural Estimation

	Utility		Earnings		
	2y	4y	HS	2y	4y
Cognitive	0.829	0.942	-1.669	**-2.215**	-0.098
Socioemotional	-0.311	0.052	-1.528	-1.673	0.022
Mechanical	-1.719	-0.663	**2.454**	**2.979**	1.049

Note: The t-statistic is calculated as follows: $\hat{t} = \frac{\hat{\alpha}_M - \hat{\alpha}_W}{\sqrt{\hat{SE_{\alpha_M}}^2 + \hat{SE_{\alpha_W}}^2}}$.



Note: Comparison between the densities of men's abilities (orange, dashed line) and women's abilities (blue, solid line). The simulated data contains 1,000 replications of the sample. The number of mixtures for each factor is based on Likelihood-Ratio Tests comparing the fit in the measurement system. Cognitive factors have three mixtures, socioemotional factors have one mixture, and the uncorrelated components of the mechanical factors have two mixtures.

Figure 3.35: Factors - Densities, Comparisons between Women and Men.

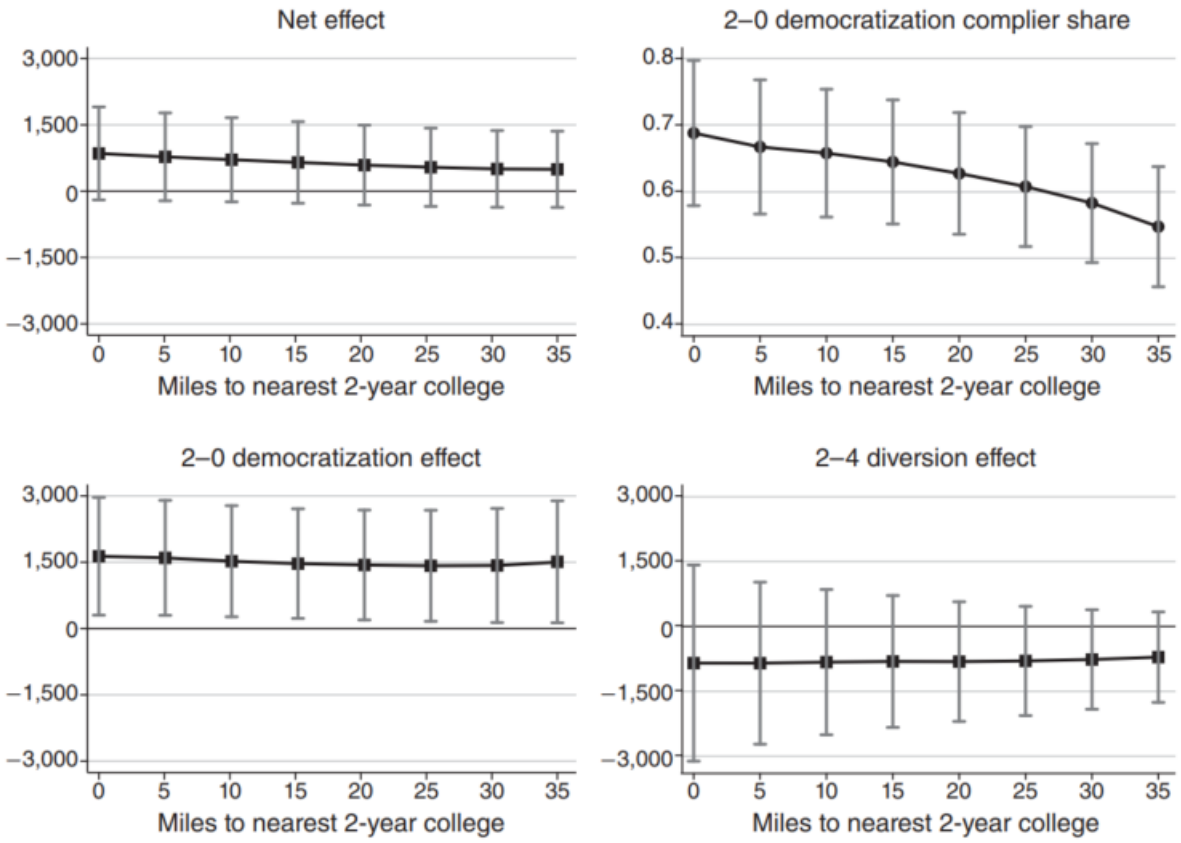
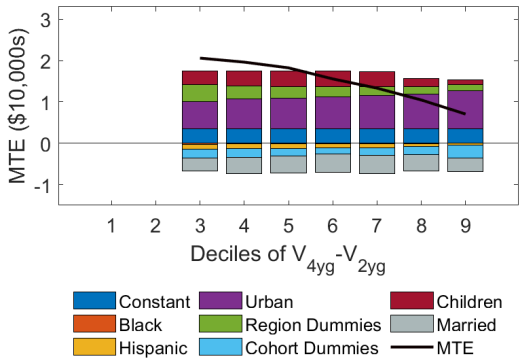


FIGURE 7. SELECTION PATTERNS AND EXTERNAL VALIDITY

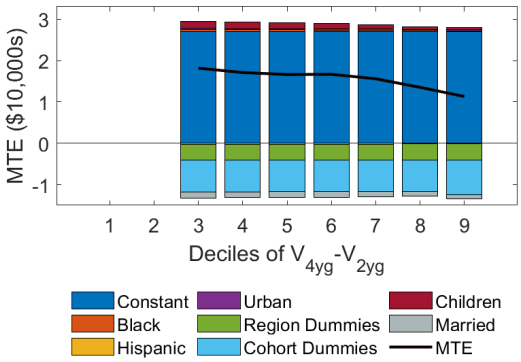
Notes: Each estimate is evaluated at a given two-year distance value holding four-year distance fixed at its mean. Quarterly earnings are measured in real 2010 US dollars and averaged within person over ages 28–30. Ninety-five percent confidence intervals are estimated via block bootstrap at the high school campus by cohort level.

Figure 3.36: Mountjoy (2022)'s Results.

A) Four-year College ← Two-year College

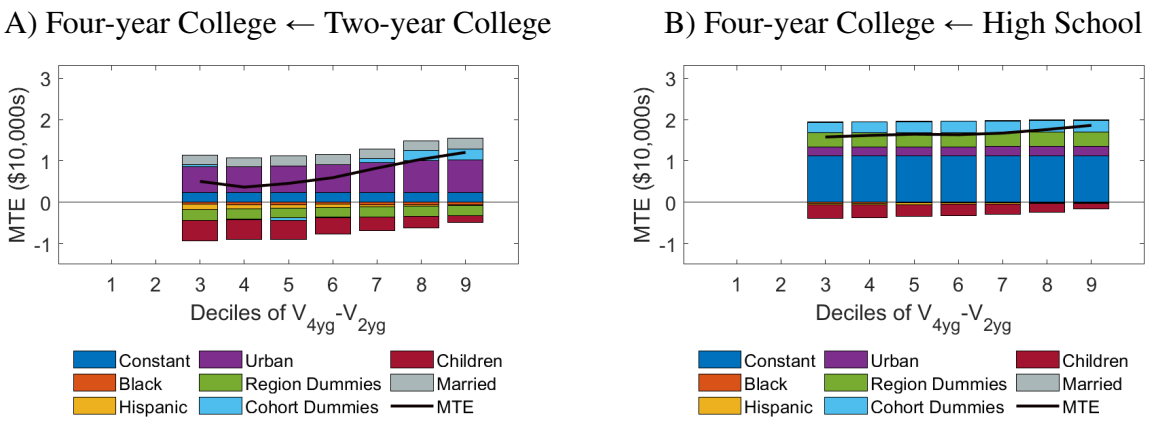


B) Four-year College ← High School



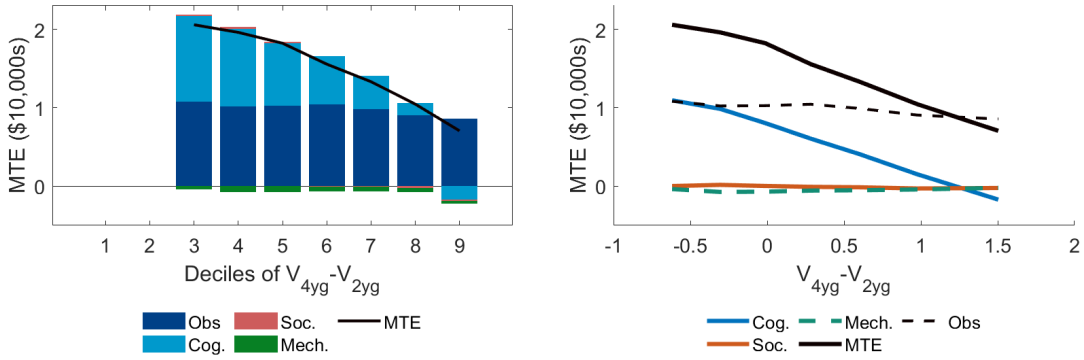
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.37: MTE Decomposition of Observables for Four-year College - Men



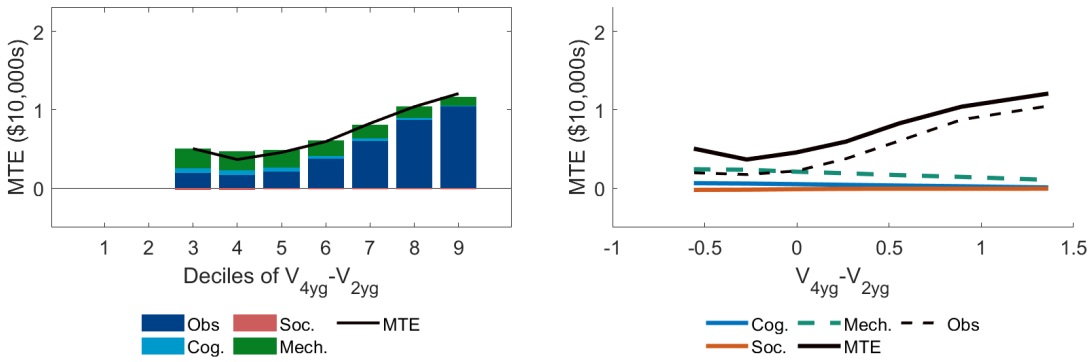
Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.38: MTE Decomposition of Observables for Four-year College - Women



Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.39: MTE Decomposition: 4y ← 2y - Men



Note: The simulated data contains 1,000 replications of the sample. We use $|C_j - C_k| < \epsilon$ to determine indifference, where $\epsilon = 0.25$. Results are similar but noisier considering $\epsilon = 0.1$. Calculations are displayed for points with at least 0.25% of the simulated sample. This threshold does not change the calculations for populated-enough grids, but prevent outlier-driven evaluations. Even without this restrictions, we have some grid points without any simulated individual in the indifference margin.

Figure 3.40: MTE Decomposition: 4y ← 2y - Women.

Chapter 4: Beyond the Bennett Hypothesis: Financial Aid, College Quality, and Education Expansion

With Sebastian Montaño

4.1 Introduction

Financial aid programs are widely used to promote access to college education, especially among low-income students who are underrepresented at the postsecondary level (Ferreyra et al., 2017; Hoxby and Avery, 2016). However, aid programs often raise concerns about their effectiveness and overall impact on education markets (Dynarski, 2003; Kane, 1995). In particular, policymakers have long expressed concerns about the potential impact that financial assistance can have on tuition prices (Bennett, 1987). While several studies have explored the effect on tuition (e.g. Espinoza, 2017; Kelchen, 2019, 2020; Lucca, Nadauld and Shen, 2019), a gap remains in the literature regarding how other outcomes might respond to financial aid policy. An impact on tuition, and therefore on profits, can introduce incentives for colleges to attract more loan recipients, likely motivating them to expand their educational offerings or adjust quality standards. Understanding changes in other dimensions is important because it can ultimately impact students' welfare. Any reduction in the consumer surplus that students experience after tuition increases can be offset or exacerbated by improvements or declines in service quality.

Our main contribution is studying the effect of financial aid on outcomes beyond tuition

prices. In particular, we examine whether the program changed hiring decisions, student-to-faculty ratios, and educational offerings. We pursue this question in the context of a comprehensive aid program in Colombia. Between 2014 and 2018, the program *Ser Pilo Paga* provided public loans to almost 40,000 students. Several reasons make the Colombian setting appealing. First, beneficiaries of the program were only allowed to enroll at high-quality colleges, which represent 15 percent of all higher education institutions in the country, and must undergo a standardized peer-reviewed process to obtain this distinction. Second, most loan recipients enrolled at private colleges, where tuition prices are commonly the same for all the enrollees in the same program or major (i.e., there is no price discrimination). Third, the higher education market is highly segmented. In the case of bachelor's programs, high-income students mainly attend high-quality private institutions, while high-ability low-income individuals attend high-quality public universities (Ferreyra et al., 2017).[1] Finally, the program was generous and large in scale, seeking to fund tuition and stipends for one-third of new enrollees at high-quality colleges (Londoño, Rodríguez and Sánchez, 2020).[2]

This program enables the possibility to study the effect of financial aid on tuition for a specific type of institution—high-quality universities—that may have their particular ways of reacting to external stimuli as they compete for reputation (Azuero and Zarruk, 2017; Blair and Smetters, 2021; Bulman, 2022). We focus mainly on analyzing high-quality private institutions, as they receive most of the beneficiaries, although beneficiaries could also enroll in high-quality public institutions. We find that high-quality private colleges increased tuition prices by about

[1]Moreover, low-ability students attend low-quality private universities, while low-ability, low-income students attend low-quality public universities (Ferreyra et al., 2017).

[2]We calculate that from 2014 to 2021, the government spent over $1 billion dollars in tuition fees and stipends for the program. This amount is equivalent to 5.6 percent of the 2019 national education budget. The program covered students' full tuition fees at any high-quality college and provided a small stipend. While students received a stipend to cover living expenses, the government directly transferred tuition fees to each college.

6.9 percent after the government introduced the program in 2014. Additionally, we find evidence consistent with high-quality colleges having inelastic supply, as they do not expand the number of admissions as much as the number of applications increases. However, high-quality colleges were able to accommodate additional students, partly due to lower dropout rates (Londoño et al., 2023; Londoño, Rodríguez and Sánchez, 2020).

Our findings also suggest that, as a response to the increase in enrollment and tuition, high-quality private colleges hired new instructors, and, in particular, they hired a larger fraction of part-time instructors as an immediate response. As such, we observe a null effect in the student-instructor ratio over time. These trends suggest that high-quality institutions care about their reputation and the quality of the education they provide. A final piece of evidence shows that high-quality private colleges launched about two new undergraduate programs in the medium run, which aligns with the evidence of additional hires of full-time staff and serves as a mechanism to meet the excess demand without drastically increasing their number of seats that could compromise their reputation. All these findings suggest that colleges may utilize the extra revenue generated from the program to enhance their faculty and offerings. Our results align with a story in which high-quality private colleges may prefer a gradual expansion to preserve quality despite experiencing a surge in demand and revenue increases.

We make contributions to multiple branches of the existing literature. First, we contribute to the literature on the Bennett hypothesis, which investigates the relationship between financial aid and tuition increases. The hypothesis posits that increased financial aid leads to higher tuition rates, thereby examining the incidence of financial aid in higher education. Prior studies conducted in the United States have yielded mixed findings regarding the validity of this hypothesis, often dependent on the type of institution analyzed or the specific variation explored (e.g.

Cellini and Goldin, 2014; Kelchen, 2019, 2020; Singell Jr and Stone, 2007; Turner, 2017). Recent studies by Lucca, Nadauld and Shen (2019) and Black, Turner and Denning (2023) exploit variations in policy changes, recognizing that certain institutions have higher exposure to these policy shifts. They provide noteworthy evidence supporting the Bennett hypothesis in the United States, focusing on undergraduate and graduate programs, respectively. We contribute to the literature studying the Bennett Hypothesis when a program targets only high-quality universities. The question of whether the Bennett hypothesis holds in the Latin American context has also been explored in some studies. For example, de Mello and Duarte (2020) and Dobbin, Barahona and Otero (2022) use data from Brazil and, respectively, find positive effects of 4.6 and 1.6 percent in tuition prices. On the other hand, Espinoza (2017) identifies a 6 percent increase for the Chilean context. Our results using data from Colombia are similar in magnitude to the estimates documented in these latter studies.

We also contribute to the existing literature investigating the potential spillover effects of financial aid programs on non-beneficiaries. Prior research by Turner (2012), Turner (2017), Black, Turner and Denning (2023) shows that universities change internal grants allocation due to the availability of financial aid. While Lucca, Nadauld and Shen (2019) and Black, Turner and Denning (2023) identify increases in sticker prices–which affect all enrolled students–in programs that were more exposed to the expansion of federal student loan caps. However, these findings are unlikely to apply to Colombia, where price discrimination and internal grants are uncommon in the private higher education institutions.[3] The Bennett hypothesis in a context where price discrimination is an uncommon practice will affect non-beneficiaries too (e.g., Azuero and Zarruk,

[3] According to Londoño, Rodríguez and Sánchez (2020), few private colleges offer aid to low-income high achievers, and only 11 percent of incoming students had access to student loans before SPP.

2017; Espinoza, 2017). In contrast, this chapter examines whether non-beneficiaries might be affected in other dimensions as universities change margins of choice beyond pricing. Furthermore, we also explore whether spillover effects extend to different market segments. For instance, Bound and Simon (2021) shows funding targeting public higher education institutions affects tuition, composition, and wages of students attending private institutions in the U.S. Contributing to this strand of the literature, we investigate whether non-eligible universities, belonging to the low-quality segment of the market, also have an incentive to increase tuition fees.[4] In Section 4.3, we provide a discussion on the rationale behind exploring this question. In essence, if there is a significant expansion in demand and high-quality universities exhibit an inelastic supply, students may be displaced from the eligible segment. Nonetheless, our findings suggest that there is no significant observed increase in tuition fees within the untargeted segment of the market.

If the program had spillover effects, finding a valid control group is challenging, as all institutions in the higher education market could have been affected. We define two-year low-quality colleges as the control group. We discuss in Section 4.2.1 the institutional reasons supporting why this group is the market segment with the lowest probability of being affected by the program. In summary, the lack of formal paths from two-year to four-year colleges, market segmentation, and stigma make students much less willing to substitute a four-year college education for the education provided in these institutions. In fact, although beneficiaries were allowed to enroll in two-year high-quality colleges, they rarely did so. In Section 4.5, we also present empirical evidence using raw data supporting that if the program affected these institutions, they could still provide lower bound estimates for our primary outcomes. As part of our main arguments, we

[4] Azuero and Zarruk (2017) also analyze the Bennett hypothesis, differentiating how high-quality and low-quality universities react to a student loan program. However, in their case, students can use the loans to enroll in any institution. Therefore, all institutions are directly affected by the policy.

show that the average number of applicants these institutions receive remains virtually unchanged in all years in our sample.

Furthermore, the existing literature predominantly focuses on examining the effects of increased financial aid generosity (Turner, 2012 and Frederick, Schmidt and Davis, 2012) and student loan programs (Espinoza, 2017, Kelchen, 2019, Lucca, Nadauld and Shen, 2019, Kelchen, 2020, Black, Turner and Denning, 2023).[5] This chapter, however, specifically investigates the introduction of a financial aid program primarily consisting of government loans that were forgivable upon graduation and were advertised as scholarships. This distinction carries noteworthy implications. As discussed by Dobbin, Barahona and Otero (2022), comprehending the price elasticity of demand among financial aid recipients is crucial for understanding the overall impact on tuition fees. Notably, students with loans tend to exhibit reduced price elasticity as they are not directly burdened with the full cost of tuition, leading to tuition increases. Conversely, loan programs often target low-income students, thereby increasing their market share. Since low-income students generally have higher price elasticity, the average price elasticity of the market increases, resulting in reduced prices. However, in the case of a scholarship-based program, low-income recipients are likely to have very inelastic demand. Consequently, universities may have a stronger incentive to increase prices in such a context.

Extensive evidence has documented positive impacts on the recipients of the financial aid program studied in this chapter. Previous studies find significant increases in high-quality private college enrollment for this group (Londoño, Rodríguez and Sánchez, 2020), as well as positive effects on earnings, graduation, and learning, seven years after the implementation of the pro-

[5]Some exceptions are Cellini and Goldin (2014) and Singell Jr and Stone (2007) who do not have pre-subsidy data and Turner (2017) who uses a regression discontinuity approach.

gram (Londoño et al., 2023). Furthermore, there have been several studies examining the impact of the program on non-recipients, although most of them concentrate on potentially eligible individuals based on their socioeconomic status (SES) since the program targeted low-income, high-achieving students. The evidence shows that the program increased middle- and high-school students' test scores (Laajaj, Moya and Sánchez, 2022), reduced fertility rates among female teenagers (Bloem and Villero, 2021), and reduced the high school dropout rate (Basto Aguirre et al., 2019).

Londoño et al. (2023) also explore effects on enrollment in the private sector to analyze the impact on non-beneficiaries. They consider an event study approach and find that high-quality private colleges expanded their enrollment by 50% during the program's first year. We propose a framework that offers a more global perspective of the market as we consider all first-year students entering private colleges, not only those who took the high school exit exam on time. We also exploit variation not only across time but also across treatment and control groups, demonstrating null effects over four pre-treatment periods. To the best of our knowledge, we are the first to estimate the causal effect of the program on tuition prices.

In the next section, we describe the institutional setting. In particular, we describe important features of the Colombian higher educational system and *Ser Pilo Paga*, the financial aid program providing the variation we exploit in this study. Then, in Section 4.3, we introduce our conceptual framework. This section explains why we postulate this program might have had spillover effects on untargeted sectors. Section 4.4 describes our data and primary sources of information. In Section 4.5, we explain our empirical strategy, discussing the threats to identification and providing empirical evidence supporting our control group selection. Section 4.6 presents our main results, first focusing on the outcomes directly related to the Bennett Hypothesis and then on the

outcomes associated with other colleges' choices. Finally, 4.7 concludes.

4.2 Institutional Setting

4.2.1 The Colombian Higher Education System

In Colombia, higher education institutions offer different types of programs to meet the diverse academic needs of students. Undergraduate programs can be either vocational or professional. Vocational programs are short-cycle and typically last between two and three years. Individuals graduating from a vocational program obtain either a technical or a technological degree, similar to an associate's degree in the United States. Most technical programs provide instruction for two years, while technological programs do it for three years. Professional programs, on the other hand, are designed to be completed in four to six years, as their length can vary depending on the field of study and the institution where the program is offered. Graduates from professional programs are granted a diploma equivalent to a bachelor's degree. In this chapter, we refer to vocational programs as *two-year* and to professional programs as *four-year*.

Two-year programs are considered terminal, and students rarely transfer to four-year ones due to a lack of formal pathways to make such transitions (Dinarte et al., 2023). In fact, only about 6 percent of the students in two-year programs eventually graduate from a four-year program (Ferreyra, Galindo and Urzúa, 2022).[6] Although colleges are allowed to offer two-year programs where students earn credits transferable to four-year programs in the same field, these kinds of

[6]Using data from the college exit exam, which is mandatory for all students in their last year, we find that for the 2009-2014 high school cohorts, between 4.6 percent of seniors in four-year programs have also been enrolled in a two-year program from 2009 to 2020. Conversely, among seniors in two-year programs, 16.2 percent have taken the exam specifically designed for students in four-year programs.

programs are uncommon.[7] The absence of a system that facilitates transfers between different types of programs segments the market and influences students' decisions regarding which type of program to apply for and enroll in.

Higher education institutions are classified into four types: technical institutes, technological institutes, university institutes, and universities. Throughout the chapter, we refer to any of these types generically as *colleges*. Depending on their classification, colleges can offer two-year programs, four-year programs, or both. Technical and technological institutes exclusively offer two-year programs, while university institutes and universities have the flexibility to offer two-year and four-year programs alike.[8] Based on their primary funding source, colleges can also be categorized as private or public. Private colleges represent 65 percent of all institutions, offer 64 percent of the undergraduate programs, and enroll approximately 60 percent of all students.

Colleges and programs are highly heterogeneous in terms of quality, selectivity, tuition fees, and reputation (MacLeod et al., 2017). To provide educational services, colleges and programs are required to obtain a *quality registry*, which must be renewed every seven years to continue operating. This policy helps ensure minimum educational standards are maintained. Colleges and programs can voluntarily undergo a rigorous process to obtain *high-quality accreditation*. The accreditation process consists of several evaluation stages that culminate in a final statement by the National Accreditation Council.[9] Colleges are eligible for accreditation if they have operated

[7]Two-year programs with transferable credits are regulated in Decrees 749 of 2002 and 1188 of 2008, through which the Ministry of Education authorized colleges to offer programs known in Colombia as *propaedeutic-cycle* programs. (Ministry of Education, 2024)

[8]To clarify why colleges are classified into four types, it is worth mentioning that technical institutes can only offer technical programs, while technological institutes are allowed to offer both technical and technological degree programs. Universities can offer graduate degree programs, such as master's or doctoral degrees, while university institutes cannot.

[9]The National Accreditation Council is supervised by the Ministry of Education, but its members belong to the academic and scientific community. Therefore, accreditation is considered a peer-reviewed process.

for at least five years and if one-quarter of their programs have already been granted accreditation. In this chapter, we refer to colleges with accreditation as *high-quality colleges*, as this certificate is correlated with quality measures such as test scores and labor market earnings (Camacho, Messina and Uribe, 2017). For simplicity, we refer to colleges without accreditation as *low-quality colleges*. By 2014, only 12 percent of the approximately 300 colleges operating in the country had been awarded accreditation.[10]

Tuition varies substantially across colleges and programs. At public colleges, tuition fees are determined based on the student's financial capacity.[11] This allows public colleges to allocate a higher share of governmental subsidies toward low-income students. Tuition represents, on average, about 10 percent of public college revenues, while governmental transfers account for around 55 percent (Bayona, Rueda and Ome, 2023). For students with the same ability to pay, public colleges can be less costly compared to private colleges.

Tuition at private colleges can be expensive or even exceed income parity standards in more developed economies (OECD and World Bank, 2012). The Ministry of Education regulates the annual increase in tuition that private colleges can implement. According to Decree 110 of 1994, tuition increases must be capped by the year's inflation rate. However, the same regulation also allows colleges to raise tuition above the inflation ceiling if they justify that additional revenues are being invested to improve education quality. In practice, most private colleges increase prices above the inflation rate every year (Ministerio de Educación Nacional, 2006).[12] Consequently, market dynamics seem to influence tuition prices, as programs in fields with higher demand –such

[10]The number of private and public colleges that have been granted accreditation has increased over time, as illustrated in Appendix Figure 4.11.

[11]At enrollment, colleges determine a student's ability to pay through various measures such as family income, high school tuition fees, and the household's socioeconomic stratum.

[12]In Appendix Figure 4.13, we show evidence that a large number of private colleges increase their tuition prices above the inflation ceiling suggested by the government.

as law or business– have lower tuition rates than programs in other areas.[13] Other factors, like quality, reputation, or even campus amenities, can also influence tuition across private colleges. Students in private schools are typically charged the same tuition price, and their tuition payments account for 70 to 80 percent of the school's revenues.

In Colombia, the college application process is decentralized, with students applying directly to individual colleges instead of through a centralized system. At the time of application, students must declare their major (or program), as these can have different admission requirements across and within colleges. A common factor that determines students' admission outcomes is their performance on the high school exit exam, known as *Saber 11*. Similar to the SAT in the United States, the exam evaluates knowledge in various subjects, including mathematics, natural sciences, social sciences, reading comprehension, and English proficiency. The exam is a mandatory requirement to enroll in college, but most students take the test regardless of whether they intend to apply for college or not. Colleges open admissions twice a year, to accommodate the different academic calendars in which high schools operate. This is necessary as most seniors graduate during the fall semester, but a significant share graduate in spring. Student characteristics differ widely based on the semester of graduation, as most seniors graduating in spring attend elite private schools.

4.2.2 Merit-based Financial Aid Program: *Ser Pilo Paga*

Access to college education has increased dramatically in Colombia over the last few decades. In the early 2000s, the enrollment rate of individuals aged 17 to 21 was approximately 23 percent, a lower rate than in other countries in Latin America. By 2014, enrollment reached 48

[13] See Appendix Figure 4.12.

percent, a remarkable 25 percentage point rise in just fifteen years. However, access has remained unequal across income groups. Indeed, while 54 percent of high school graduates from middle- and upper-income households enroll in college, only 25 percent from low-income ones pursue higher education. Although various factors contribute to these access disparities, the absence of a well-functioning financial aid system is commonly cited as one of the most significant reasons (de Wit et al., 2005; Holm et al., 2003; OECD and World Bank, 2012).

In an effort to improve access for low-income students at high-quality colleges, the Colombian government launched the financial aid program *Ser Pilo Paga* in October 2014. The program was advertised as a scholarship, although student aid consisted of a publicly funded loan to cover all tuition charges at any college with high-quality accreditation, whether public or private.[14] The government directly transferred tuition payments to colleges, so students had no access to such funds. The program also provided a modest stipend twice a year to help loan recipients cover some living and educational expenses.[15] The amount of a student's loan included both tuition fees and stipends, comprising a debt forgivable only upon graduation. This condition implied that students must repay their accumulated loans if they dropped out of college.[16]

Eligibility was determined by merit and need criteria. The merit condition was based on the student's scores in the *Saber 11* exam. The minimum score for eligibility increased over the years, moving from 310 out of 500 in 2014 (or the 91st percentile) to 318 in 2015 (92nd percentile), 342 in 2016 (96th percentile), and 348 in 2017 (97th percentile).[17] Students were

[14] See Appendix Figure 4.14.

[15] The stipend amounts ranged from one to four times the minimum wage, depending on whether the student had to relocate and the city's living costs.

[16] By June 2022, approximately 11 percent of all loan recipients had begun to repay their debt after dropping out (Espectador, 2022; Ministerio de Educación Nacional, 2022).

[17] Various reasons explain the increase in eligibility thresholds over time, including a tight budget, the high take-up rate of the program, and the motivational effect of the program that encouraged high school seniors to get higher scores (Laajaj, Moya and Sánchez, 2022; Londoño, Rodríguez and Sánchez, 2020).

informed of their eligibility for financial aid alongside their *Saber 11* exam scores, which many universities use as one component in their admission decisions, and hence, contributed to a high program's take-up rate. The need condition relied on a poverty index, known as SISBEN, to target students from disadvantaged households.[18] Eligibility varied depending on the student's residence location. Consequently, students living in the main metropolitan areas required an index below 57.21 points, while those in other urban and rural areas needed values below 56.32 and 40.75, respectively. These conditions allowed the government to identify high-achieving, low-income students who would benefit the most from financial assistance. Finally, for students to obtain the loan, they must have applied and been admitted to a high-quality college.

From 2015 to 2018, almost 40,000 students enrolled in high-quality institutions as program beneficiaries. Nearly 80 percent of them enrolled in private colleges (see Figure 4.15), with a high concentration observed among specific schools (see Figure 4.1a). In fact, in just ten private colleges, the number of loan recipients accounted for 54 percent of all beneficiaries. On the other hand, as Figure 4.1b shows, for a considerable number of private colleges, the number of loan recipients among first-year students was over 20 percent. This suggests that *Ser Pilo Paga* represented a significant shock for high-quality private colleges.[19]

[18]The Colombian government allocates most social welfare benefits through SISBEN (Sistema de Identificación de Beneficiarios de Programas Sociales in Spanish).

[19]The sorting of loan recipients into private colleges is challenging to explain. Appendix Table 4.4 and Appendix Figure 4.16 show that the share of beneficiaries across schools is uncorrelated with information that students might consider when they apply to college, such as graduation rates, employment rates, average earnings of recent graduates, and the geographic location of schools. Only two factors seem to influence the observed sorting: an indicator equal to one if the college is private and a measure of college reputation that we compute following MacLeod et al. (2017).

4.3 Conceptual Framework

Before conducting any empirical analysis, we introduce a conceptual framework to guide our discussion of the impacts of financial aid on higher education markets. This framework provides an economic rationale that allows us to focus on specific college outcomes. We start assuming an education market that is segmented into low-quality and high-quality sectors. Colleges can offer programs in only one sector, while students are allowed to apply to and enroll in colleges from either segment. However, some individuals do not participate in this market, including a group that faces credit constraints. We also assume that colleges in the low-quality sector provide education at a lower price than high-quality colleges. Finally, suppose that a market regulator—the government—introduces a financial aid policy that affects exclusively one side of the market, for instance, the high-quality sector. This simple setting allows us to understand the implications of the financial aid program *Ser Pilo Paga* broadly, described in Section 4.2.2. It also highlights the potential spillover effects that can emerge from a policy that targets a specific college type.

Figure 4.2 shows a graphical representation of our model. S_i and D_i represent the inverse supply and demand curves for sector $i = \{HQ, LQ\}$.[20] Tuition prices (P) are displayed on the vertical axis, while the horizontal axis depicts the seats supplied by colleges or the number of college applicants (Q). In both sectors of the model, demand is downward-sloping, and supply exhibits capacity constraints after a given level of seats. We introduce such constraints to capture the idea that, after receiving a given level of students, colleges can only provide (or prefer to offer) a limited number of seats, which is a reasonable assumption, at least in the short run. Therefore,

[20]The subscript HQ is used to denote the high-quality sector, while LQ is used for the low-quality sector.

the supply curve is upward-sloping, but it kinks when capacity constraints hold, which is visually represented by the perfectly inelastic section of the curve. However, a perfectly inelastic section is not a necessary condition. Colleges may still have a margin for small adjustments. This idea could be illustrated using alternative representations.[21]

Consider initially that in equilibrium, the demand for high-quality education intersects the supply curve at its perfectly inelastic section (see Figure 4.2). In such equilibrium, high-quality colleges provide seats at their maximum capacity, $\bar{Q}_{HQ}$. This assumption is plausible, as high-quality colleges are usually oversubscribed. The assumption can also hold if colleges maximize profits by considering their installed capacity, reputation, the resources available for enrolled and incoming students, and the quality of instruction they can provide. In fact, previous literature has focused on understanding why elite colleges have been reluctant to expand their supply over time (Blair and Smetters, 2021; Bulman, 2022). In reality, the validity of this assumption depends on the ability of colleges to adjust their resources and their objective to maintain particular education and reputation standards. Empirically, operating at capacity could be related to the process by which colleges monitor measures such as the student-to-faculty ratio, the student-to-staff ratio, and the ratio to other educational resources.

Now, assume that the regulator introduces a subsidy (or financial aid program) that can only be used to enroll in high-quality colleges. By relaxing students' financial constraints, the subsidy induces an upward shift in demand. The after-subsidy demand curve is represented by $D_{HQ} + Govt$, as seen in Figure 4.2. Given the inelastic supply, this upward shift in demand causes an increase in tuition prices at high-quality colleges. As the additional number of offered

[21] A supply curve such that $S_i' > 0$, $S_i'' >> 0$ would also capture the idea that colleges might face capacity constraints or difficulties in adjusting the number of seats that they offer after some $\bar{Q}$.

seats does not keep pace with the additional applicants—who probably have a higher willingness to pay due to the subsidy—some students who could have been offered admission before the introduction of the subsidy may no longer be admitted. This implies that the demand for low-quality colleges might shift upwards, as some students could be better off by enrolling in this sector rather than not pursuing any higher education. Graphically, the demand for low-quality colleges shifts from D_{LQ} to D'_{LQ}. Again, the increase in demand implies an increase in tuition prices, this time at low-quality colleges. These spillover effects on the demand and tuition at low-quality colleges will depend on different factors, such as the ability or willingness of high-quality colleges to respond to the surge in their specific demand, students' preferences, and the elasticity of demand and supply for low-quality education. To examine if the financial aid program studied in this chapter created a displacement effect, we estimate the causal impact of this policy on the number of first-year students enrolling in each market segment. This framework leads to the following prediction:

Prediction 1 *The enrollment of first-year students at high-quality colleges does not respond to the upward demand shift that resulted from the introduction of a financial aid program in this sector. Yet, tuition prices increase at high-quality colleges. This is,* $\Delta Q_{HQ} = 0 \Rightarrow \Delta P_{HQ} \geqslant 0$.

In Figure 4.2, we assume that the specific demand for low-quality colleges intersects the supply in the less elastic section of the curve, where capacity constraints are not binding. This assumption is not necessary to observe an increase in tuition at low-quality colleges, although the degree of the elasticity of supply certainly affects the magnitude of the rise. Yet, the assumption can be reasonable since low-quality colleges might focus more on enrolling a large number of students rather than investing in their quality. Therefore, low-quality institutions will likely

have greater flexibility to accommodate additional students than high-quality ones. A second prediction from our conceptual framework states that:

Prediction 2 *If first-year students' enrollment at low-quality colleges increases (stays unchanged), so will tuition prices. This is,* $\Delta Q_{LQ} \geqslant 0 \Rightarrow \Delta P_{LQ} \geqslant 0$.

Assuming that the above predictions are correct, the pink area in Figure 4.2 would represent the surplus lost by students who do not receive the subsidy. However, the program's overall impact on these students is not necessarily negative. Previous research has discussed that the net welfare effect on students depends on how colleges allocate additional tuition revenues (Black, Turner and Denning, 2023; Espinoza, 2017). For instance, if colleges invest these extra funds to improve education quality, the net effect on students without the subsidy could be smaller than the pink area or even positive. Yet, there is no evidence in the literature showing that colleges utilize the revenues from tuition hikes to enhance their quality. Our analysis aims to provide evidence to fill this gap.

Our conceptual framework makes several implicit assumptions about the demand for higher education. For instance, we assume that some students may not apply to either sector because they face substantial credit constraints. Financial aid programs relax these constraints, allowing them to apply to college. Observe that if all students could apply to both sectors, the subsidy may not affect the demand for either college type. On the other hand, if eligible students for financial aid (i.e., low-income students) would only apply to low-quality colleges in the absence of the program, then the demand for low-quality education could shift downward and not upward. In addition, although we do not stress the importance of the elasticity of demand in our framework, we recognize that it can explain the direction and magnitude in which tuition changes (e.g.

de Mello and Duarte, 2020; Dobbin, Barahona and Otero, 2022; Espinoza, 2017). Furthermore, since the financial aid program *Ser Pilo Paga* represented an important shock for the composition of first-year students in the high-quality sector, especially for the private colleges, it is likely that the elasticity of demand had also changed as a result of the policy. Especially if we consider that loan (or subsidy) recipients display an inelastic demand for higher education. We do not explore changes in demand elasticity due to the aggregated nature of our data, which makes it impossible for us to study compositional changes or differential effects across income groups.

4.4 Data

We use administrative data of all higher education institutions in Colombia spanning from 2009 to 2018. This data is collected by the Ministry of Education through SNIES (the National Information System for Higher Education) and is available upon request. All colleges in the country are required to report annually various types of information to this system, including the number of applicants to each program in the spring and fall semesters, the number of admissions offered, the number of first-year students who enroll, the total number of enrolled students, and the number of teaching and administrative staff hired by the institution.[22] Information on the type of college (i.e., private or public) and the level of all programs (i.e., two-year or four-year) are also recorded in the data. We also obtained information from the National Accreditation Council that allows us to determine which colleges received and renewed high-quality accreditation and in what year. This is particularly relevant for our study since loan recipients from the aid program *Ser Pilo Paga* could only enroll in colleges with accreditation. The data is organized into cross-

[22]The deadlines and details of the information that colleges must report can be found in Resolution 1780 of 2010, issued by the Ministry of Education.

sections that can be linked using unique college identifiers or program identifiers, depending on the level of granularity.

Tuition information is recorded in SNIES annually at the program (or major) level. In particular, colleges report the following year's tuition for each program, as mandated by the Ministry of Education's Resolutions 1780 of 2010 and 12161 of 2015. The information is submitted every year between November 1st and December 15th. We focus our analysis of tuition on private colleges since these schools typically charge a uniform price for all students without offering any discounts. On the contrary, public colleges charge differential tuition prices depending on the student's financial needs using rules that change across institutions.[23] As we do not observe sticker prices or tuition at the student level for public colleges, we can not study the effects of financial aid on tuition in the public market segment.

As mentioned in Section 4.2, colleges can offer two-year programs, four-year programs, or both, depending on their type. We define a "two-year college" as any college where more than 50 percent of the students are enrolled in two-year programs. According to this definition, all technical and technological institutes are classified as two-year colleges, as well as a subset of university institutes and universities. We refer to the remaining institutions as "four-year colleges."[24]

[23] As discussed earlier, public colleges in Colombia employ third-degree price discrimination, as students' tuition is determined through college-specific rules based on their socioeconomic backgrounds and family assets at enrollment.

[24] Table 4.3 describes the type of higher education institution in each sample group.

4.5 Empirical Strategy

We estimate the causal effect of financial aid on various college outcomes using a difference-in-differences design that compares four-year and two-year colleges. We further classify colleges according to whether or not they have high-quality accreditation. The latter division allows us to study the direct and spillover effects of the policy as students eligible for *Ser Pilo Paga* aid were only permitted to enroll in the colleges with high-quality distinction. We use low-quality two-year colleges as our control group. The identifying assumption of this approach is that, in the absence of financial aid, the observed outcomes for high-quality and low-quality four-year colleges would have followed similar trends to those of low-quality, two-year colleges. In other words, we assume that two-year, low-quality colleges serve as a valid counterfactual to estimate the effects of providing financial aid to enroll in high-quality schools.

If the program had spillover effects, as we postulated, then finding a control group proves challenging, as all institutions in the higher education market could have been affected. However, two-year programs in Latin America have a poor reputation and are often viewed as "second-class programs and an academic dead end," to cite Di Gropello and Ferreyra (2022). Given this stigma, market segmentation, and the lack of formal and common pathways from two-year to four-year college education, low-quality two-year colleges are the market segment with the lowest likelihood of being exposed to the program's effects. To define this group as our control group, we assume that students interested in and capable of attending high-quality colleges, which mainly offer four-year programs, are unlikely to substitute this type of education with that provided in a low-quality two-year college. Nevertheless, this control group still has production and cost functions similar to other colleges, meaning low-quality two-year colleges are still comparable

despite students' preferences and their substitution patterns.

Suppose this assumption does not hold, and a significant number of students still end up applying to two-year low-quality colleges. In that case, it is plausible to believe they would still react to the program in the same direction as the other sectors—either increasing or keeping constant tuition, seats, and other production inputs—hence, our control would generate lower bound estimates. If, on the other hand, these institutions did not receive additional students but lost them, our estimates could be upper bounds. This last situation is plausible if we believe that beneficiaries of the program would have enrolled in two-year colleges in the absence of the policy. We present evidence supporting the first hypothesis, validating that usage of these colleges as our control group.

Figure 4.3 presents the raw average of the number of freshmen and applicants for the control group in purple and our main group interest—private four-year high-quality colleges—in blue. We can observe that the control group remains relatively stable and does not show significant falls in terms of first-year students or applicants. This pattern is observed for the cohorts entering and applying in the Spring term—when program beneficiaries enter college—and in the Fall term. In addition, we also examine the evolution of college characteristics that the program should not have altered. The raw mean for these characteristics are shown in Figure 4.4. Panel (a) presents the share of female applicants, Panel (b) the share of females offered admission, Panel (c) the share of first-year female students, and Panel (d) the share of female students enrolled. In all these cases, we can see that the evolution of these groups is very similar and that they all remain relatively stable through time. Overall, the absence of significant changes in the trends observed for the low-quality two-year colleges provides confidence that this group is a valid control.

We use the following difference-in-differences strategy:

$$
\begin{aligned}
Y_{ct} =& \delta^{Private} \left(\text{Private HQ 4-Year}_c \times \text{Post}_t\right) + \beta^{Private} \left(\text{Private LQ 4-Year}_c \times \text{Post}_t\right) + \\
& \delta^{Public} \left(\text{Public HQ 4-Year}_c \times \text{Post}_t\right) + \beta^{Public} \left(\text{Public LQ 4-Year}_c \times \text{Post}_t\right) + \\
& \mu_c + \mu_t + X_{ct}'\gamma + \varepsilon_{ct},
\end{aligned}
\tag{4.1}
$$

and the equivalent event study representation to analyze dynamic responses:

$$
\begin{aligned}
Y_{ct} = & \sum_{\tau \neq 2013} \delta_{\tau}^{Private} \cdot \mathbb{1}\left[\tau = t\right] \cdot \text{Private HQ 4-Year}_c \; + \\
& \sum_{\tau \neq 2013} \beta_{\tau}^{Private} \cdot \mathbb{1}\left[\tau = t\right] \cdot \text{Private LQ 4-Year}_c \; + \\
& \sum_{\tau \neq 2013} \delta_{\tau}^{Public} \cdot \mathbb{1}\left[\tau = t\right] \cdot \text{Public HQ 4-Year}_c \; + \\
& \sum_{\tau \neq 2013} \beta_{\tau}^{Public} \cdot \mathbb{1}\left[\tau = t\right] \cdot \text{Public LQ 4-Year}_c \; + \mu_t + \mu_c + X_{ct}'\gamma + \varepsilon_{ct},
\end{aligned}
\tag{4.2}
$$

where Y_{ct} is the outcome of program i offered by college c in year t. Several outcomes are of interest in this chapter: tuition, applicants, admissions, freshmen, enrollment, student-to-faculty ratio, number of faculty members, and number of undergraduate programs. Private HQ 4-Year$_c$ is an indicator variable equal to one if college c is a private four-year institution and holds high-quality accreditation. Public HQ 4-Year$_c$ is the analogous variable for public high-quality colleges. Private LQ 4-Year$_c$ is an indicator equal to one if college c is a private four-year institution and does not have accreditation. Public LQ 4-Year$_c$ is the equivalent dummy for public four-year colleges without such distinction. To control for time-invariant heterogeneity across colleges and for structural changes that may affect all higher education institutions over time, we include college fixed effects, μ_c, and year fixed effects, μ_t. Our most saturated specification includes a

set of controls, X_{it}. Controls include department-specific time trends.[25] The time trends control for heterogeneity in geographic markets (departments), which likely evolve following different patterns. We estimate equation (4.1) by Ordinary Least Squares (OLS) and cluster the standard errors across all specifications at the college level.

It is important to remember that, as discussed in Section 4.4, the information colleges report by December 15th of each year corresponds to the tuition prices they will charge students in the next academic term. Given that the government announced *Ser Pilo Paga* on October 1st, it is possible that colleges responded to this policy in the same year of its announcement. Consequently, we consider the years before 2014 to be our analysis's "pre-treatment" period. This definition is particularly relevant to estimate the effect of financial aid on tuition, but to be coherent through the analysis, we also keep this definition to assess the impact on other outcomes.

The effects of financial aid over time are captured by the coefficients δ_τ^κ and β_τ^κ, $\tau \in \{2009, ..., 2012, 2014, ...2018\}$ and $\kappa \in \{Private,\ Public\}$. The parameters δ_τ^κ, associated with colleges where loan recipients enrolled, estimate the *direct effects* of introducing the financial aid program *Ser Pilo Paga*. On the other hand, the parameters β_τ^κ, associated with colleges where aid recipients could not enroll, capture the *spillover effects* of the program. However, the main parameters of interest are $\delta_\tau^{Private}$ since most beneficiaries decided to enroll in private colleges. The identifying assumptions for this empirical design cannot be directly tested. Although the estimates of δ_τ^κ and β_τ^κ for "pre-treatment" years (i.e., years when the program was not yet introduced) provide a natural test of validity, the absence of effects in the pre-treatment period is, however, not sufficient. As we described earlier in this section, if our control group was still subject to changes because of the program, their trends could have also varied after the program's

[25] Cities (or municipalities) in Colombia are grouped into 32 administrative regions known as departments.

launch. In that case, our estimates would be biased, and we previously presented some evidence supporting that our estimates would likely be downward biased.

4.6 Results

4.6.1 Testing the Bennett Hypothesis

Effects of Financial Aid on Tuition **–** We begin by examining the Bennett hypothesis in the Colombian context, where the government implemented a comprehensive financial aid program in 2014, aiming to improve the enrollment of low-income students in high-quality colleges. We investigate whether colleges raised their tuition above previous observed trends due to the introduction of this financial aid program.

Figure 4.5 presents the estimates of our event-study strategy, using the logarithm of the average tuition at private colleges as the outcome variable. Various observations are worth highlighting from these results. First, between 2009 and 2013 (the pre-treatment period), mean tuition at four-year high-quality colleges (the treatment group) and at two-year low-quality colleges (the control group) followed similar trends (see Figure 4.5a). As such, during the pre-treatment period, the normalized tuition gap between these two groups cannot be statistically distinguished from zero.[26] If we consider low-quality four-year colleges, which could be affected indirectly by the program, the same conclusion holds (see Figure 4.5b). These results provide empirical evidence supporting the validity of our identification strategy.

Second, from 2014 to 2018 (the post-treatment period), there was a change in the tuition trends among high-quality colleges (see Figure 4.5a). In fact, real prices increased by about 4

[26]The tuition gap is expressed in logs and normalized with respect to the observed gap in 2013.

percent a few months after the government had announced the financial aid program *Ser Pilo Paga*. Average tuition continued rising throughout 2017, reaching a 7 percent average increase compared to the evolution of prices during the pre-treatment period, a further increase observed just after the number of beneficiaries enrolling in private colleges peaked in 2016 (see Figure 4.15). In 2018, the tuition gap between the treatment and control groups ceased widening as high-quality colleges reverted to their previous trend of annual price adjustments. These findings provide direct empirical evidence supporting the Bennett hypothesis. They are also consistent with anecdotal evidence indicating a general dissatisfaction among students concerning the tuition increases in high-quality private colleges.[27] Third, the average tuition trends of low-quality four-year colleges are not statistically different from zero, supporting the absence of spillover effects. However, this result must be taken with a grain of salt as most of the point estimates are positive after the program's launch (see Figure 4.17b). This pattern could suggest that there could have been spillover effects on the tuition of untargeted colleges, but we do not have enough power to disentangle them.

Fourth, these results are robust to various specifications and sample restrictions. In particular, compared to the baseline benchmark that controls for college and year fixed effects, our conclusions hold after we control for specific tuition trends in different education markets (i.e., departments). In addition, we run our analysis at the program level, as programs could have different tuition within a given college. For this sample, we consider additional specifications where we exclude colleges that received high-quality accreditation after 2014 and exclude each college and field of study at a time.[28] Our conclusions remain unchanged to these restrictions.

[27] Students from various elite colleges protested against substantial tuition hikes in 2016 and 2017 (Vargas, 2017). Staff from some of these colleges provided details on the increases in tuition after student discontent gained media attention (Rojas, 2017).

[28] Appendix Figure 4.17 presents the results excluding colleges granted high-quality status after 2014. Figures

Table 4.1 presents standard difference-in-differences estimates, summarizing the results of our event-study specification. On average, the *direct effect* of financial aid on average tuition at high-quality colleges ranges between 6.7 to 6.9 percent. These estimates are similar in magnitude to the impact of subsidized loans on tuition prices found in Brazil and Chile (de Mello and Duarte, 2020; Dobbin, Barahona and Otero, 2022; Espinoza, 2017). Moreover, as the programs could have different tuition within a given college, we also examine the effects on different tuition quartiles in Panels 4-6. The results indicate that tuition increases the most (least) for programs that had the lowest (highest) pre-program tuition. High-quality colleges increased tuition at the lowest quartile by 9.6 percent, in the median by 6 percent, and in the highest quartile by 5.5 percent. We do not observe *spillover effects* on average nor quartile tuition at colleges where financial aid recipients were not allowed to enroll. The coefficients associated with low-quality colleges are not significant but also small in magnitude, ranging from -0.2 to 2.7 percent.

Why does tuition increase? – As we highlight in our conceptual framework, financial aid programs can induce an increase in the demand for higher education. The increase can be more pronounced if the target population of these programs is low-income, high-achieving students; especially if they receive direct and clear communication about the aid package (Dynarski et al., 2021). Now, if colleges have difficulties to expand their supply in the short run or preferences for not doing so, a simple economic model predicts an increase in tuition prices. Guided by this framework, we explore whether high-quality colleges in Colombia might exhibit binding capacity constraints that could help to rationalize the observed increase in tuition.

We begin by analyzing if the admission rates at high-quality colleges changed after the introduction of *Ser Pilo Paga*. Figure 4.6 presents the results of estimating equation (4.2) on the

4.18 and 4.19 exclude one college and one field of study at a time.

ratio of the number of students who are offered admission to the number of applicants during the Fall and the Spring semesters. We run separate regressions for each semester, considering that the number and characteristics of the students who apply to college in both terms vary substantially. Although post-treatment coefficients suggest a reduction of the admission rate of around 5 percentage points, only the coefficient for 2016 is marginally significant (see Figure 4.6a). This pattern is observed not only during the Spring semester—when loan recipients enroll—but also in the Fall. In Figures 4.6b and 4.6c we present estimates for the number of applicants and admissions separately. The effect on the number of applicants exhibits a similar pattern to that of the number of loans intended to be granted by the government each year.[29] The effect on the number of admissions appears to follow a similar trend but with much smaller magnitudes and, in some cases, not statistically significant from zero.

This evidence suggests that although there was a slight decline in the admissions rate of high-quality colleges—indicating that their supply is somewhat inelastic—these colleges are still willing to expand their admissions amidst the application hike. To understand this response, it is worth recalling some program features. First, the median ratio of beneficiaries to entering private institutions' cohorts is more than 15 percent. Second, private, high-quality colleges rely heavily on tuition as a source of revenue. Last, the government was willing to pay for any tuition level at these institutions as long as they had high-quality accreditation. Therefore, it seems plausible that high-quality colleges were still willing to expand their admissions as this stimulus represented an opportunity to increase revenue—and probably the average ability of their student body. We will see later that this result is still compatible with a story where high-quality colleges care about the

[29] From 2015 to 2018, the annual number of loan recipients was, respectively: 10,142 (in 2015), 12,751 (in 2016), 9,086 (in 2017), and 7,384 (in 2018). Appendix Figure 4.15 presents the number of recipients who enrolled in private and public colleges each year.

quality of their education.

In Figure 4.7, we show that the number of first-year students (the flow) enrolling in high-quality colleges remained unchanged during the post-treatment period (see Figure 4.7a). In other words, the policy does not seem to have a significant effect in increasing the average size of the entering cohorts.[30] This contrasts with the effect on the number of enrollees (the stock), which increased after the aid program was put in place (see Figure 4.7b). By 2018, the number of students enrolled in a high-quality college had increased by 14 percent compared to the average number of enrollees in 2013. There are three possible explanations for these seemingly contradictory results. First, during the post-treatment period, students may take longer to graduate from high-quality colleges compared to previous cohorts. This would translate into an increase in the stock of enrollees over time. We rule out this explanation by estimating the effect of financial aid on the number of graduates.[31] The second explanation has to do with the effect that financial aid can have on the dropout rates among the cohorts that enrolled after 2014. Unfortunately, information on the number of dropouts is unavailable. Yet, we know from the literature that dropout rates among loan recipients are lower than among their peers in high-quality colleges, even when their academic performance can be lower.[32] This effect on dropout rates is likely explained by the strong incentives of the program to deter loan recipients from dropping out. Notably, program beneficiaries who do not enroll during two consecutive semesters must repay their education

[30] Although the post-treatment coefficients are not statistically significant from zero, they are positive. However, we see that this trend is not different from that of the pre-treatment period. Moreover, the cumulative effect of the effect on the number of freshmen can only explain 43% of the increase observed in the stock of students based on DiD coefficients.

[31] See Appendix Figure 4.25.

[32] Meisel and Granger (2022) use data from the private college that enrolled that largest share of loan recipients and find that the dropout rate of aid recipients is 15 percentage points lower than that of their peers. On the other hand, Londoño et al. (2023) exploit the discontinuity in aid eligibility to estimate that loan recipients are 66 percent (or 27 percentage points) more likely to take the college exit exam within seven years of enrolling in college.

debt.[33] The final explanation might be that, as we explained in the previous section, our control groups could have also increased their entering cohort because of the program. Figure 4.3 shows that the average number of applicants in those institutions remains virtually unchanged. However, our estimates could still be a lower bound if the ability and preferences of the pool of applicants changed and, as a response, two-year colleges accepted more students. In that case, the variation we are exploiting could not be enough to identify an increase in the flow of students.

Table 4.2 presents static difference-in-differences estimates summarizing the effects of financial aid on admission rates, applicants, admissions, and freshmen at all four-year college segments, including private and public sectors.[34] For the low-quality private sector, we do not see significant effects in any of the outcomes, except for an increase in enrollment for some years at the beginning of the program. Consistent with a story where there is not an important displacement, the number of applicants does not increase nearly as much as in the case of the high-quality universities, despite the private low-quality system having significantly more students. All these patterns are consistent with the observation that there is no significant effect on real tuition for this sector.

For the public sector, we observe a significant increase of 1,050 additional applicants for high-quality colleges in the Spring semester, representing a 16 percent increase relative to the level observed in the pre-treatment period. However, the number of admissions does not keep pace with the number of additional applicants, and although the effect is positive, it is not statistically significant. This result is also supported by a negative admission rate, which becomes

[33] Dropouts are identified by the Colombian Ministry of Education using this definition of failing to enroll during two consecutive terms.

[34] In Appendix Figures 4.20 and 4.21, we show the estimates of the effect of financial aid on admission rates, freshmen, and enrollment at low-quality private colleges. The equivalent results for four-year public colleges are shown in Appendix Figures 4.22, 4.23, and 4.24.

statistically significant for the final periods of the program. For low-quality public colleges, we observe a negative admission rate mainly driven by a noisy but positive rise in the number of applicants amidst a small and insignificant effect in the number of additional admissions. For both sectors, the number of freshmen exhibits a null effect while the number of enrollees increases. However, enrollment in public high-quality colleges increased only by 5 percent in 2018 relative to the mean level observed in 2013. These patterns in the number of freshmen and enrollees are consistent with those observed for the private sector.

Our estimates of the impact on the number of first-year students across all types of colleges could suggest that *Ser Pilo Paga* did not have a general equilibrium effect on college access for the cohorts entering college between 2015 and 2018. However, the positive effect observed in the number of enrollees at low-quality public colleges could suggest that the program increased overall persistence in the four-year college system. This explanation would be possible if students were more motivated and prepared for college because of the program. Previous research documents spillover effects on middle-school students' test scores and fertility rates among young women, aligning with such hypothesis (Bloem and Villero, 2021; Laajaj, Moya and Sánchez, 2022). Moreover, although we observe increases in the applications and, in some cases, admissions, this does not necessarily mean that more students are entering the market. Several applications and admissions can be associated with only one student. Therefore, the results could also suggest that the program introduced more incentives for competing for high-quality seats—in in part, by removing credit constraints affecting high-ability students.

These findings suggest that high-quality private colleges are willing to increase their number of admissions, but they do not increase their seats as much as the demand expands. While the supply curve may be inelastic, colleges do have the ability to accommodate more students

as the number of enrollees increases. Therefore, the empirical evidence supports a story where capacity constraints are not binding and although inelastic supply might still play a role in the tuition increase, it could also result from higher markups since loan recipients in our context are completely price-inelastic (Dobbin, Barahona and Otero, 2022).

4.6.2 Beyond the Bennett Hypothesis

Effect of Financial Aid on College Resources – To complement our analysis of how colleges respond to financial aid, we investigate if other outcomes, such as the resources that students find in schools, can also be affected after the implementation of an aid program.

We begin by checking if colleges hired additional faculty members as a result of *Ser Pilo Paga*. Figure 4.8 displays the estimates of this analysis by type of contract and education of the faculty working in high-quality colleges. Positive effects are observed for all types of faculty: faculty working full-time and part-time, and faculty with and without a PhD degree. Larger effects are concentrated among part-time faculty and faculty without a PhD. One potential explanation for these effects is the concern of colleges for the resources available to students. We previously showed how high-quality colleges experienced an increase in the stock of students due to the effect that *Ser Pilo Paga* had on dropout rates. The increase in enrollment can imply that fewer resources are available to students, which may lead colleges to hire additional teaching personnel. Our estimates show that by the end of 2018, high-quality colleges had, on average, an additional 160 part-time faculty (or a 33% increase compared to the mean for 2013), 65 full-time faculty (or 32%), 76 PhD faculty (or 135%), and 155 Non-PhD faculty (or 25%). These findings align with the trend followed by higher education institutions in the US, where the share

of part-time and adjunct professors increased dramatically since the late 1980s in response to the growing demand for college education and to reduce educational expenses (Bettinger and Long, 2010; Figlio, Schapiro and Soter, 2015).

To determine if colleges are concerned about the teaching resources available to students, we investigate the effect on the student-to-faculty ratio. Figure 4.9 displays the estimates of our event-study strategy. Remarkably, we observed a null impact on both the pre-treatment and post-treatment periods (see Figure 4.9a). This finding suggests that high-quality colleges closely monitor the resources available to their students. Consequently, in response to an increase in enrollment (see Figure 4.9b), colleges hire additional faculty (see Figure 4.9c) to maintain a constant student-to-faculty ratio over time. This is important for students since teaching resources can have a direct impact on degree attainment (Bound, Lovenheim and Turner, 2010), as well as other future outcomes.

Given that colleges provide other services such as academic advice and career counseling, we also examine the impact of financial aid on hiring decisions regarding staff personnel. The Ministry of Education classifies college staff in Colombia into: *i)* heads or directors, *ii)* professionals, and *iii)* auxiliary staff. Our results suggest that high-quality colleges did not hire additional personnel for any of these job types. Consequently, the student-to-staff ratio increased during the post-treatment period.[35]

Effect of Financial Aid on the Supply of College Programs – Colleges may also hire additional faculty to introduce new undergraduate programs. Launching new programs can result from education expansion plans to attract financial aid recipients interested in fields where colleges don't currently offer a major. Figure 4.10 shows the estimated impact of equation (4.2)

[35] See Appendix Figures 4.26 and 4.27.

on the number of available programs at high-quality colleges over time. By 2018, when the last cohort of the program beneficiaries entered college, high-quality colleges had introduced an average of two additional programs. The significant impact observed only after several years is reasonable, considering the extensive planning and bureaucratic efforts needed to launch a new program in Colombia. Note that the increase in full-time instructors, alongside this trend, implies that financial aid policies may prompt colleges to expand their education supply in the medium term. Therefore, while high-quality colleges do not significantly expand the size of entering cohorts while preserving quality—as measured by a stable student-to-faculty ratio—they could be interested in absorbing excess demand by launching new programs.

4.7 Conclusion

This chapter examines the impact of college financial aid on tuition, leveraging Colombian data and the exogenous variation from a large-scale government financial aid program's introduction. To identify the effect of the policy, we use a difference-in-differences strategy, in which our control group is the set of two-year colleges where loan recipients do not enroll. Our findings suggest that tuition at high-quality colleges increased by about 6.9 percent as a result of the introduction of the program. We do not find evidence of spillover effects on tuition at non-eligible four-year colleges (i.e., colleges offering similar programs as schools with high-quality accreditation). Additionally, we provide suggestive evidence showing that high-quality colleges—which increased tuition—are willing to expand to receive more students as they increase the number of admissions. Still, these institutions seem to have an inelastic supply since the increase in admissions does not increase at the same pace as applications.

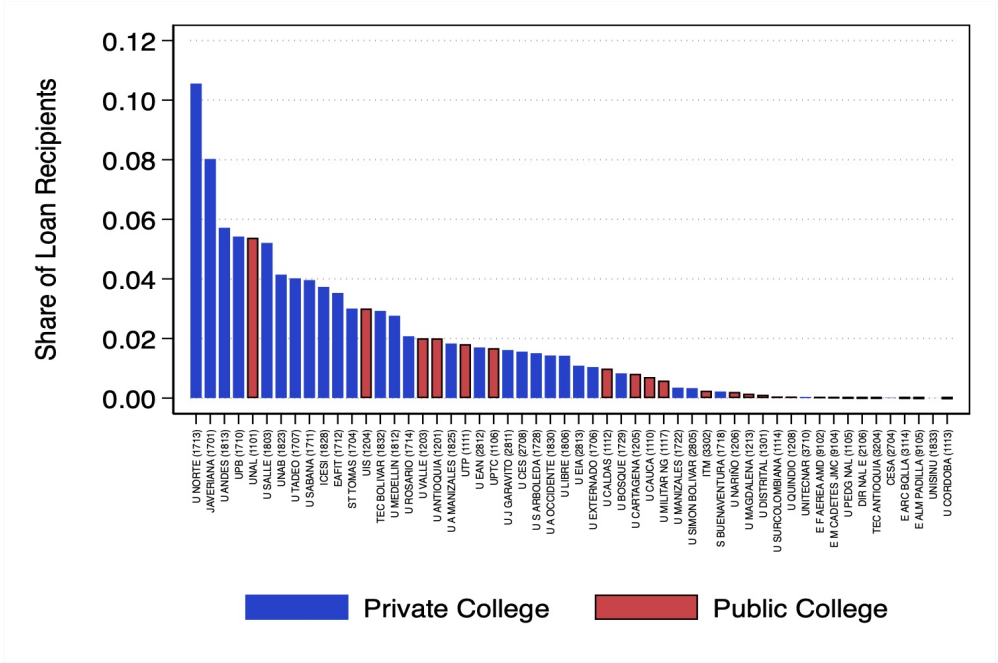
We find total enrollment in all four-year college colleges increases in response to the program. In response to this increase, high-quality private colleges—our main focus of interest, as they received most program beneficiaries—hire more part-time and full-time instructors to accommodate the higher student population. This effort ensures that the student-to-faculty ratio remains unchanged despite the fact that the stock of students in a program increased by 14 percent. Furthermore, all types of faculty, including those with and without PhD degrees, experience an increase in hiring. Finally, we provide evidence that financial aid may lead high-quality colleges to open new undergraduate programs. These trends suggest that high-quality colleges use the additional revenues obtained from the rise in tuition to expand their educational offerings while maintaining the quality of education they provide. This evidence supports a narrative where high-quality private colleges prioritize their reputation, opting for gradual expansion without compromising quality.

Finally, we close our discussion, emphasizing that financial aid might have indirectly affected our control group, although that scenario has a low probability—at least relative to other market segments. This chapter presents evidence supporting that our control group does not receive fewer applications nor enroll fewer students after the program. These patterns might indicate that if our estimates are biased, they would be downward biased. Consequently, our results, especially those with small or no effects, need to be interpreted cautiously.

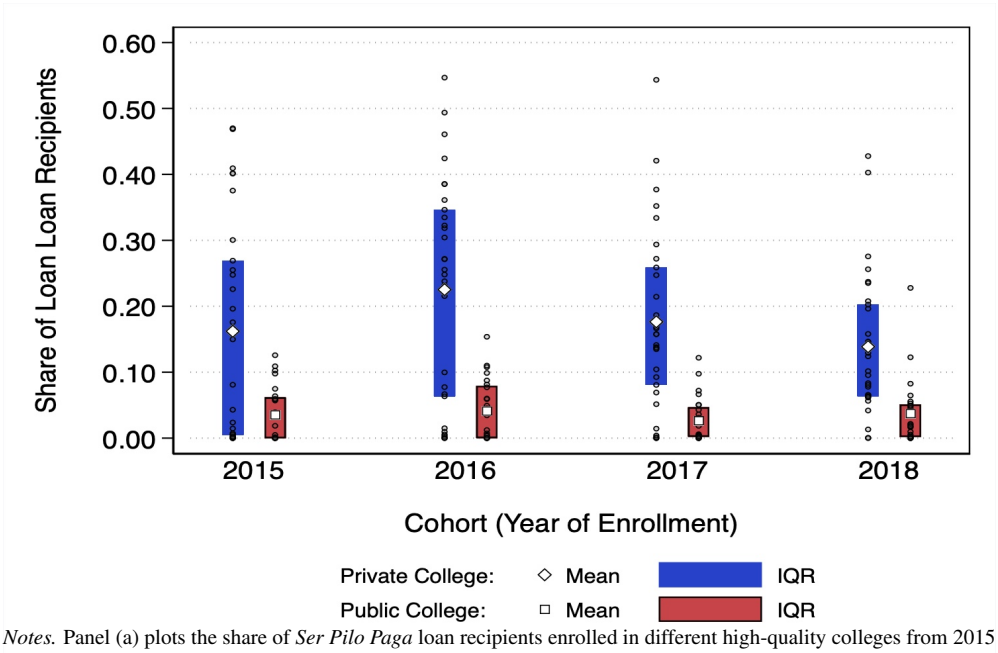
4.8 Figures and Tables

Figure 4.1: Financial Aid Recipients Across and Within Colleges, 2015-2018

(a) Share of Recipients Across Colleges

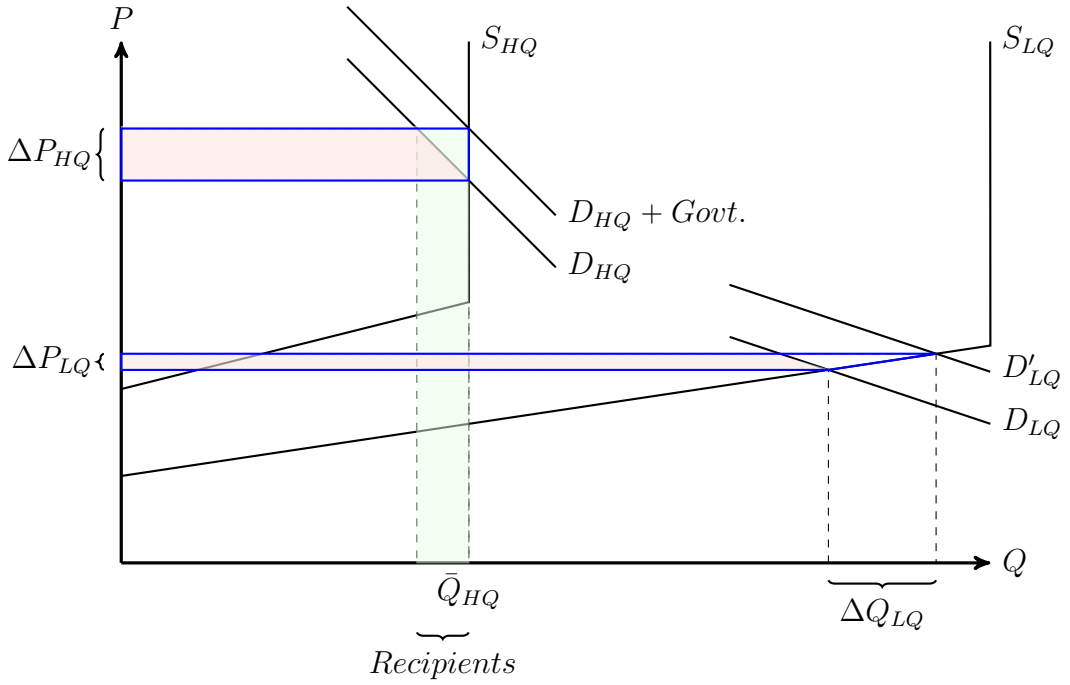


(b) Share of Recipients Among Freshmen



Notes. Panel (a) plots the share of *Ser Pilo Paga* loan recipients enrolled in different high-quality colleges from 2015 to 2018. Panel (b) plots the share of loan recipients within cohorts of first-year students. Each plotted dot represents the share of newly enrolled students in college who are loan recipients. Boxes represent the interquartile range (1st and 3rd quartiles) across college-cohorts. Rhombus and square markers correspond to the average share of recipients across college-cohorts.

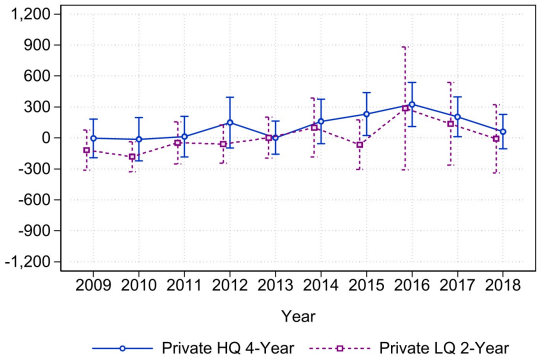
Figure 4.2: Conceptual Framework Relating College Financial Aid and Tuition Prices



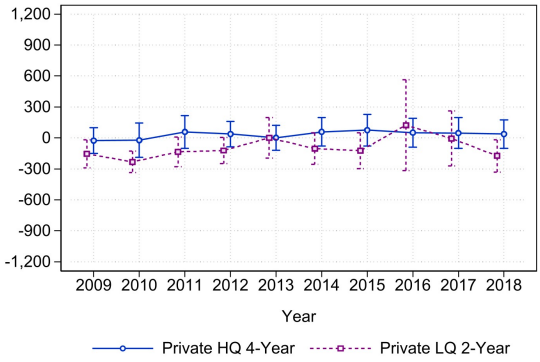
Notes. This graph serves as a visual representation of the conceptual framework employed to support the main hypotheses investigated in this study. It depicts the bachelor's degree market in Colombia, distinguishing between two segments: universities with high-quality accreditation (represented as HQ) and universities lacking such accreditation (represented as LQ). It is important to note that this graph assumes a constant price elasticity of demand for the purpose of simplification. However, in section 2.2, we elaborate on the reasons why the price elasticity of demand may have undergone changes as well.

Figure 4.3: Average Freshmen and Applicants Across Type of Colleges

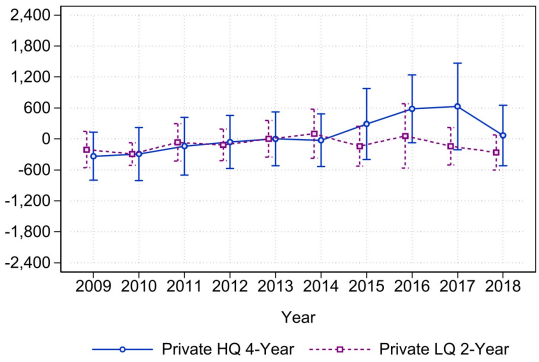
(a) Number of Freshmen, Spring



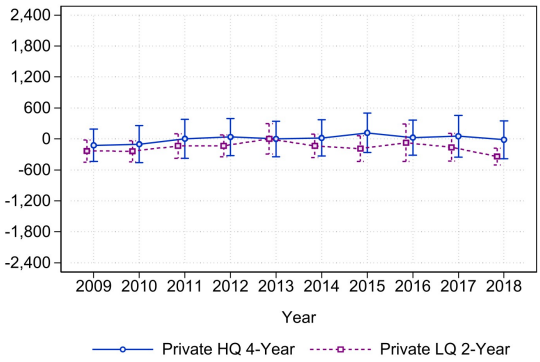
(b) Number of Freshmen, Fall



(c) Number of Applicants, Spring



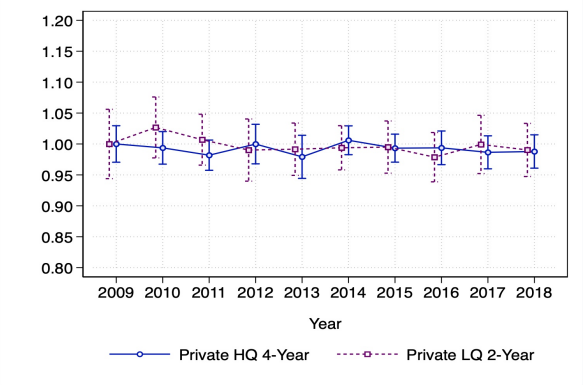
(d) Number of Applicants, Fall



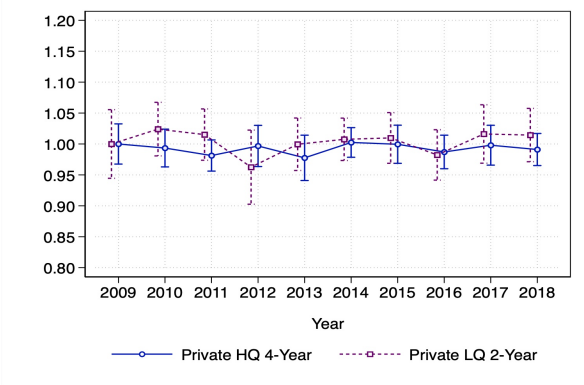
Notes. These figures display the average of the number of freshmen and applicants across college types (i.e., high-quality four-year and low-quality two-year colleges). Means are normalized to the base value of 2013. 95% confidence intervals are displayed around sample means.

Figure 4.4: Average Student Characteristics Across Type of Colleges

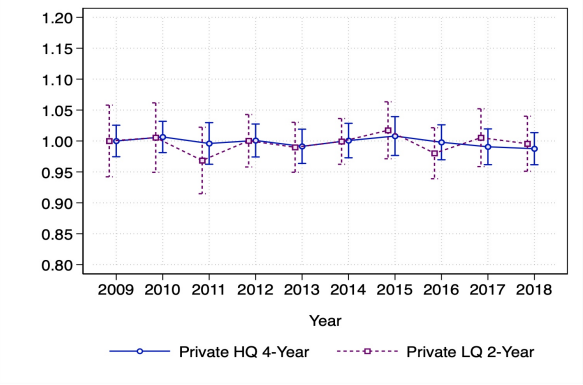
(a) Share of Female Applicants



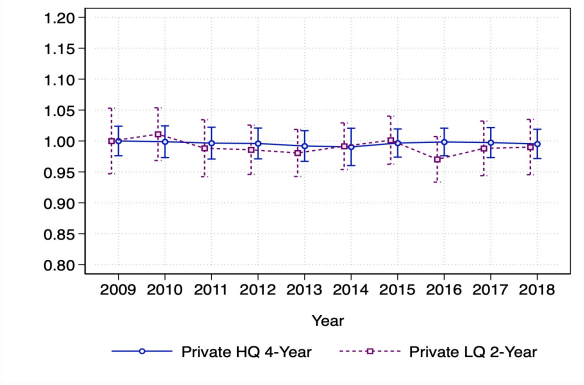
(b) Share of Females Offered Admission



(c) Share of First-Year Female Students



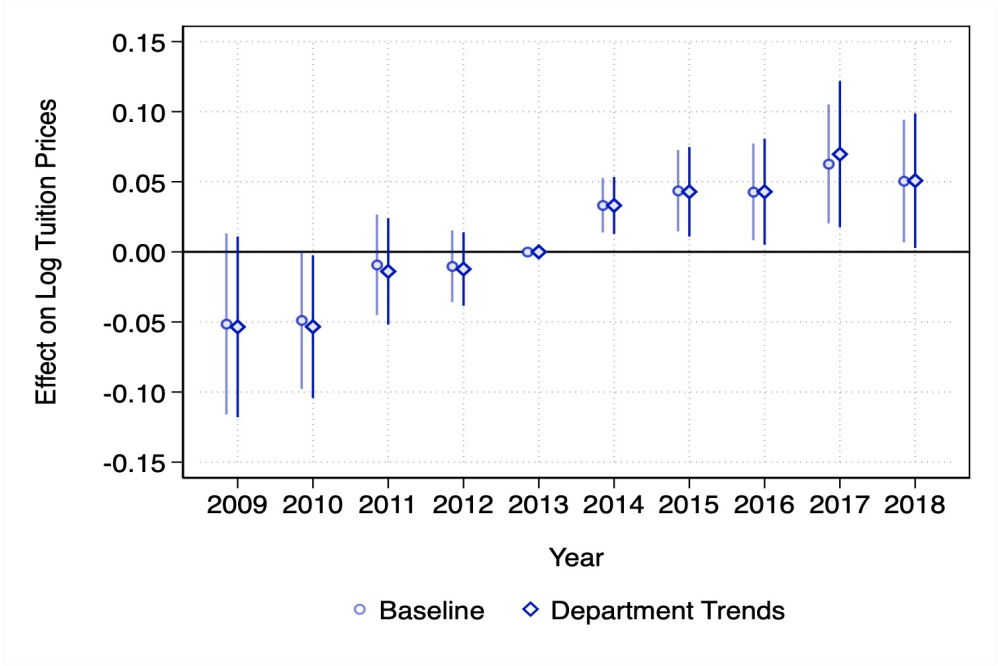
(d) Share of Female Students Enrolled



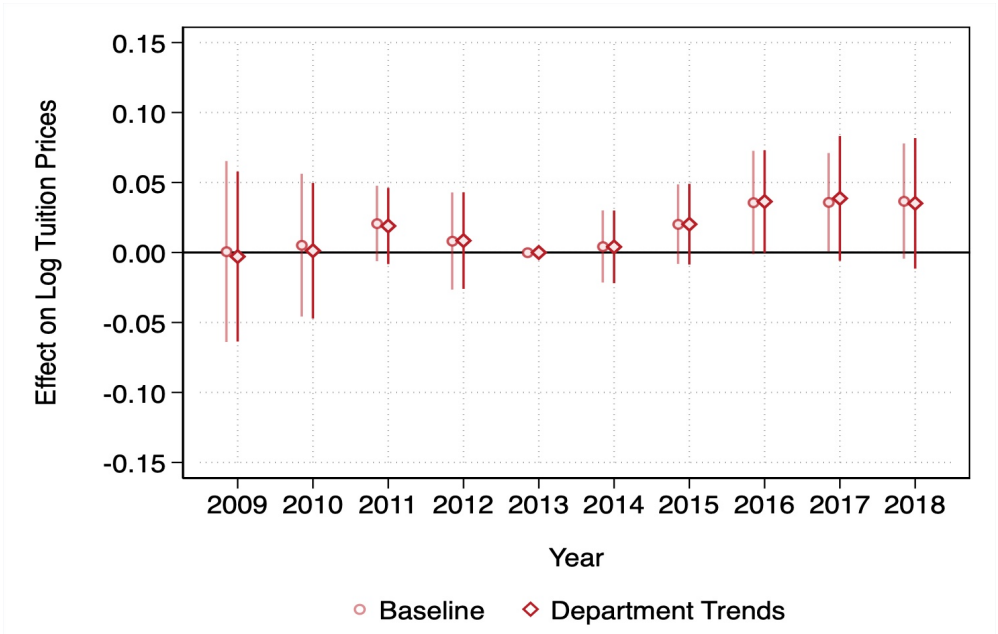
Notes. These figures display the average of the share of females across college types (i.e., high-quality four-year and low-quality two-year colleges) for different outcomes. Means are normalized to the base value of 2009. 95% confidence intervals are displayed around sample means.

Figure 4.5: Effect of Financial Aid on Private College Tuition Prices

(a) *Direct Effect*: High-Quality Four-Year Colleges



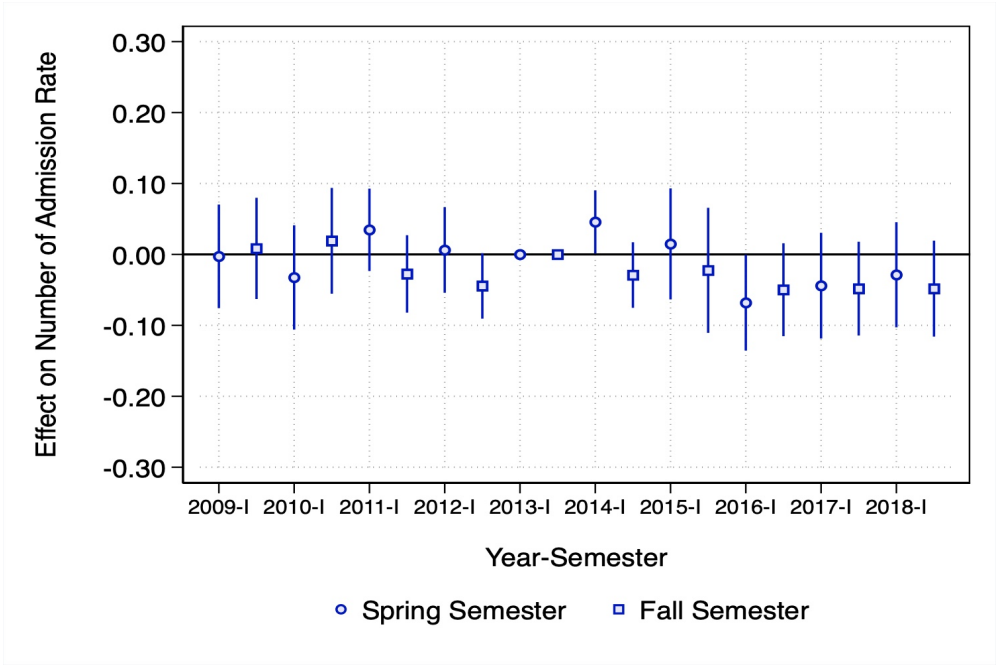
(b) *Spillover Effect*: Low-Quality Four-Year Colleges



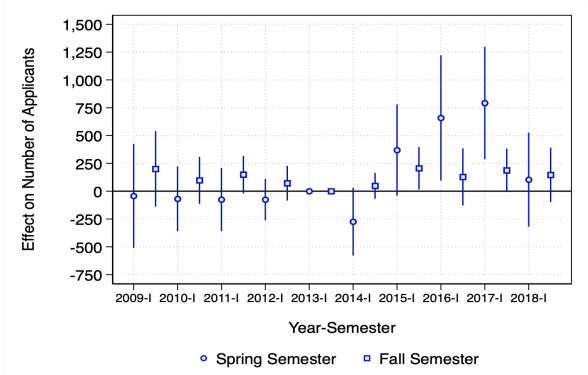
Notes. Ordinary least squares (OLS) estimates of Equation (4.2). Tuition for all college programs is expressed in prices of 2009 to account for inflation. The outcome variable is the logarithm of mean tuition in each college. Panel (a) displays the estimates of $\delta_{\tau}^{Private}$, with $\tau \in \{2009, ..., 2018\}$, representing the (*direct*) effect on tuition at high-quality four-year colleges after the government introduced the financial aid program *Ser Pilo Paga*. Panel (b) displays the estimates of $\beta_{\tau}^{Private}$, corresponding to the (*spillover*) effect on tuition at low-quality four-year colleges. Circle markers represent the estimates from a baseline specification that controls for college and year fixed effects. Rhombus markers represent the full specification, including linear and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.6: Direct Effect of Financial Aid on Private College Admission Rates

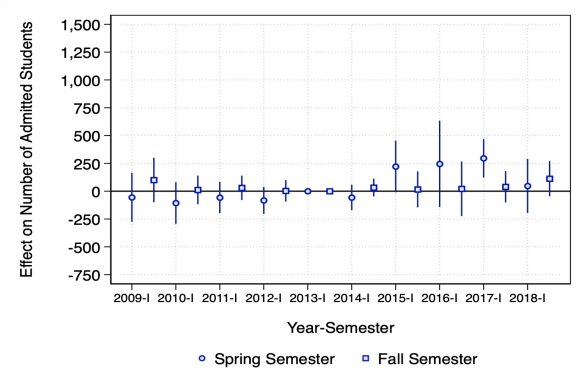
(a) Admission Rate



(b) Number of Applicants



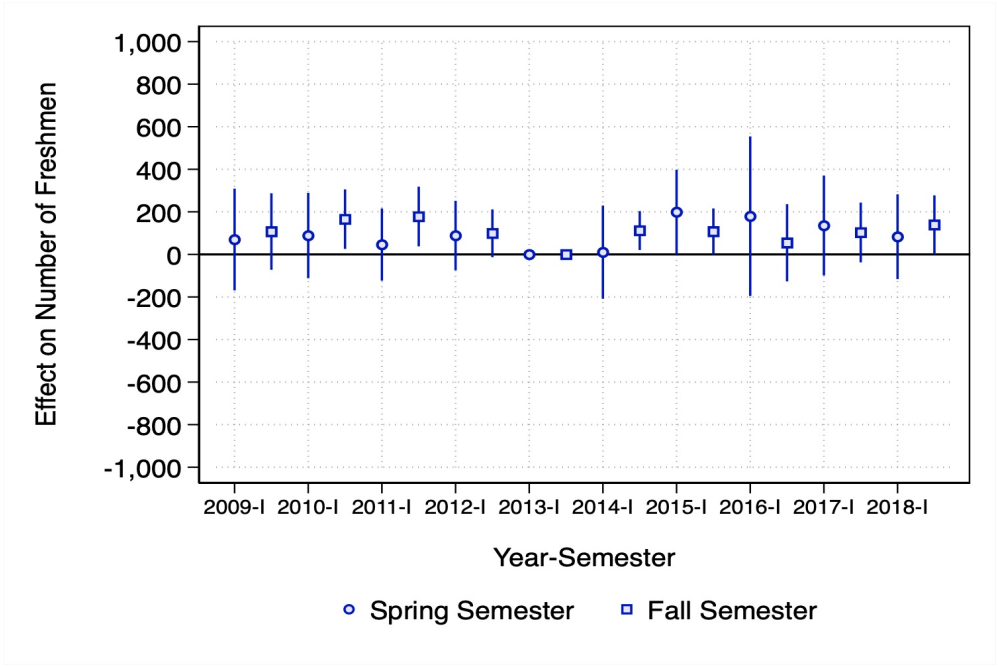
(c) Number of Admissions



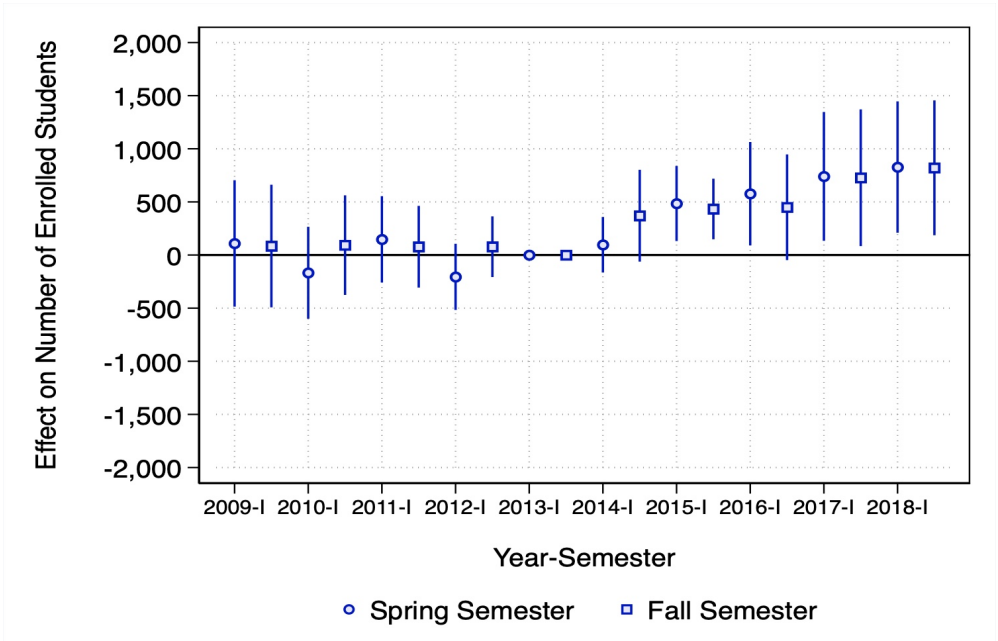
Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable in Panel (a) is the admission rate of college programs, computed as the fraction of students offered admission among the total number of applicants to a program. In panels (b) and (c), the outcome variables are the number of applicants and the number of admissions offered, respectively. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.7: Direct Effect of Financial Aid on Private College Enrollment

(a) Number of Freshmen (Flow)



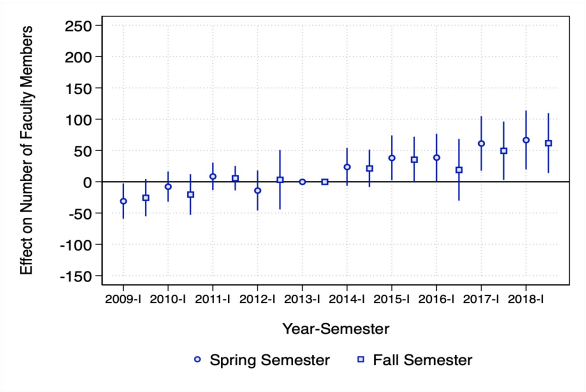
(b) Number of Enrolled Students (Stock)



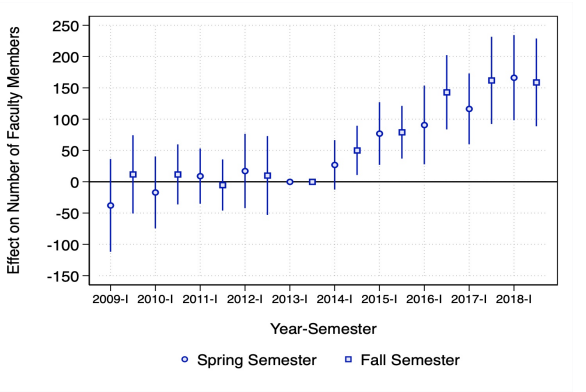
Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. In panels (a) and (b), the outcome variables are the number of first-year students (freshmen) in a college program and the number of all enrolled students, respectively. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester.All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.8: Direct Effects of Financial Aid on Faculty Hiring - Private Colleges

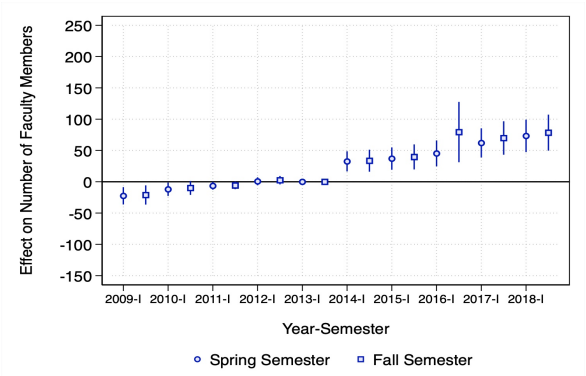
(a) Full-Time Faculty



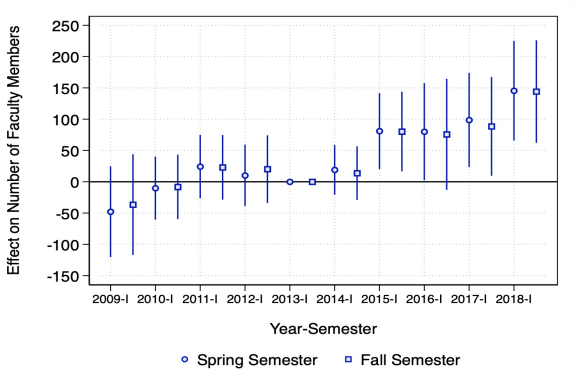
(b) Part-Time Faculty



(c) PhD Faculty



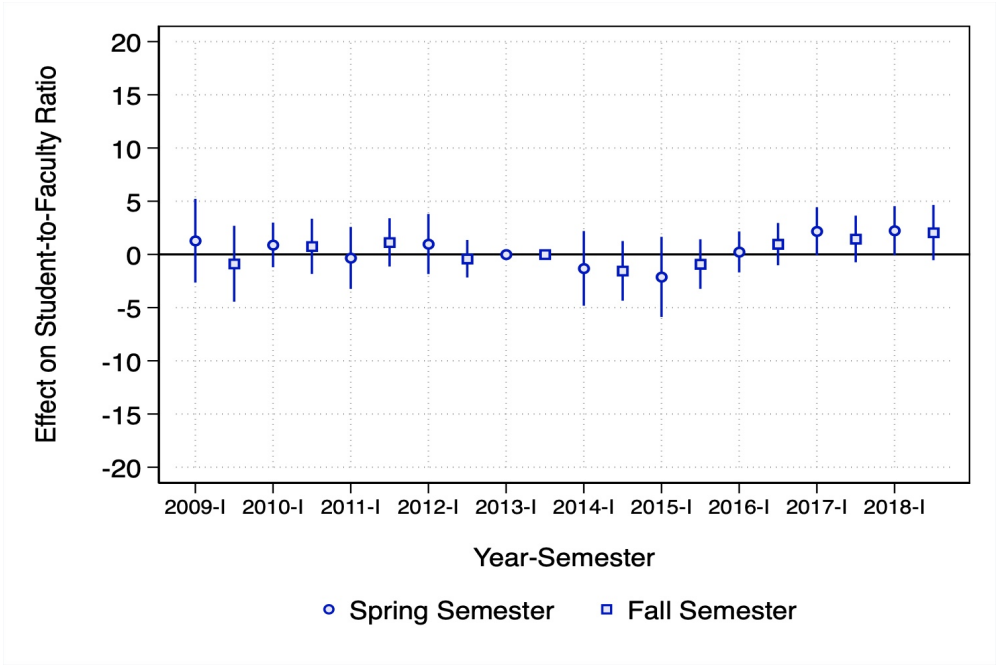
(d) Non-PhD Faculty



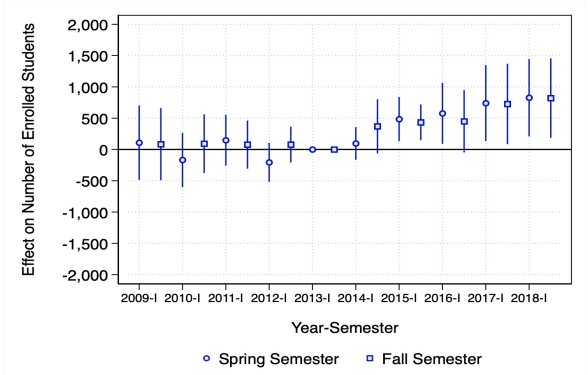
Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. In panels (a) and (b), the outcome variables are the number of faculty members working under a full-time contract in a college and the number working part-time. In panels (b) and (c), the outcome variables are, respectively, the number of faculty members in a college who hold a PhD degree and the number holding a Master's or a Bachelor's degree. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.9: Direct Effect of Financial Aid on the Student-to-Faculty Ratio - Private Colleges

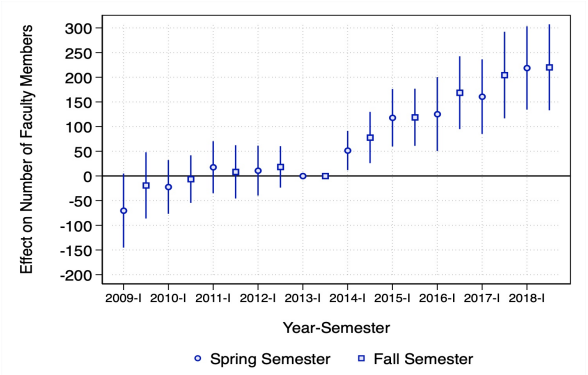
(a) Student-to-Faculty Ratio



(b) Number of Enrolled Students

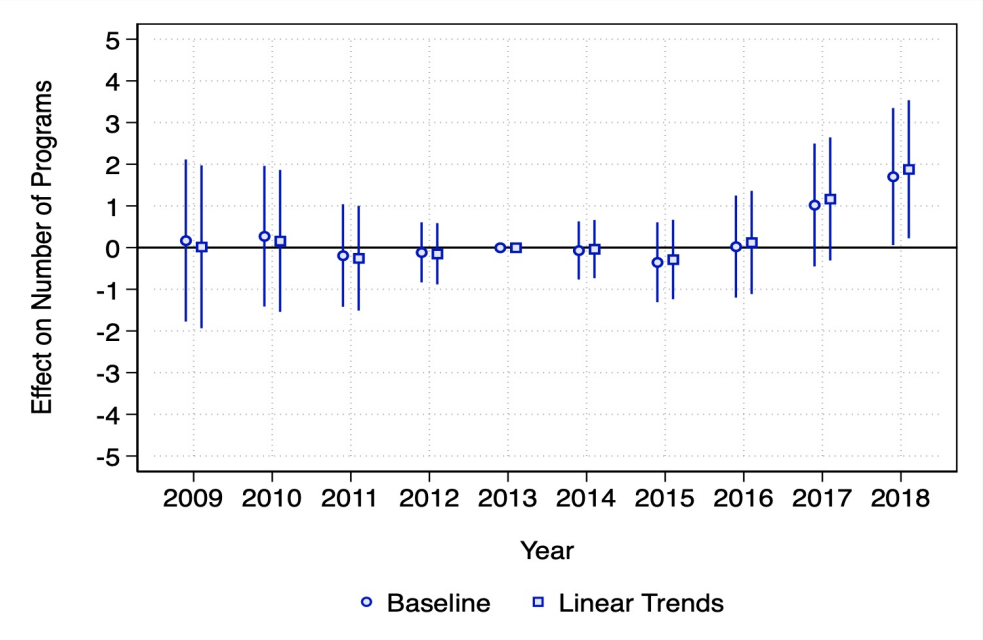


(c) Number of Faculty Members



Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable in Panel (a) is the student-to-faculty ratio in each college. In panels (b) and (c), the outcome variables are the number of students enrolled in a college and the total number of faculty members, respectively. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.10: Direct Effect of Financial Aid on the Number of Private Undergraduate Programs



Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable is the number of undergraduate programs offered in each college. Circle markers represent the estimates from a baseline specification that controls for college and year fixed effects. Square markers additionally control for department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Table 4.1: Effect of Financial Aid on College Tuition Prices

	Dependent Variable : log(Tuition)					
	Average Tuition			1st Quartile	Median	3rd Quartile
	(1)	(2)	(3)	(4)	(5)	(6)
Private HQ 4-Y × Post	0.068***	0.067***	0.069***	0.096***	0.060**	0.055***
	[0.017]	[0.017]	[0.019]	[0.025]	[0.028]	[0.020]
Private LQ 4-Y × Post	0.020	0.017	0.018	–0.002	0.009	0.027
	[0.017]	[0.017]	[0.017]	[0.021]	[0.024]	[0.017]
Observations	1,190	1,190	1,190	1,190	1,190	1,190
R-squared	0.975	0.979	0.980	0.949	0.968	0.973
College FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes
Department Trends			Yes	Yes	Yes	Yes

Notes. Ordinary-least-squares estimates of the effect of a financial aid policy on college tuition prices, based on equation 4.1. HQ 4-Year$_c$ is an indicator equal to 1 if c is a four-year college holding high-quality accreditation. LQ 4-Year$_c$ is an indicator equal to 1 if c is an non-accredited four-year college. Post is an indicator equal to 1 for the post-treatment period 2014-2018. μ_c and μ_t represent college and year fixed effects. X_{it} is a set of controls that include field of study fixed effects, study area time-trends, and department time-trends. The outcome variable is the log of tuition prices charged at private colleges to students enrolled in each undergraduate program. Colombia is divided into 32 administrative regions known as departments. Standard errors in square brackets are clustered at the college level. * p<0.10, ** p<0.05, *** p<0.01.

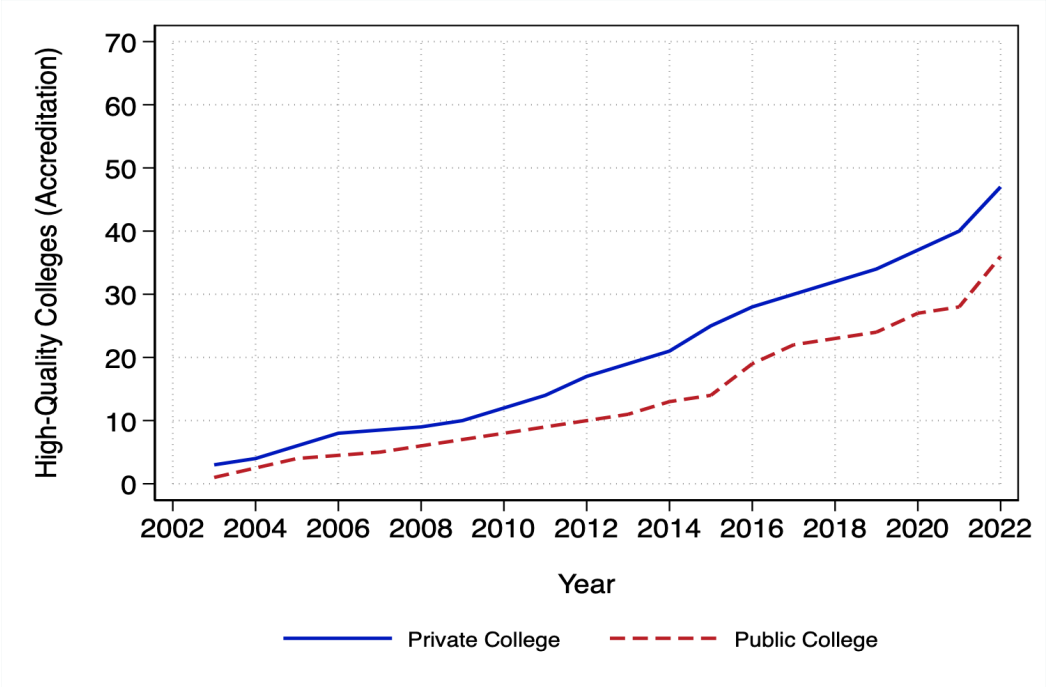
Table 4.2: Effect of Financial Aid on College Admission Rates

	Dependent Variable :							
	Admission Rate		Applicants		Admissions		Freshmen	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Spring								
Private HQ 4-Y × Post	–0.025	–0.013	443.726***	338.390	195.753**	205.774**	51.109	60.686
	[0.027]	[0.027]	[162.867]	[210.841]	[92.226]	[91.872]	[75.176]	[74.854]
Private LQ 4-Y × Post	–0.039	–0.043	162.388	89.243	74.546	70.168	6.476	6.246
	[0.025]	[0.026]	[114.509]	[156.967]	[92.531]	[95.728]	[75.819]	[78.727]
Public HQ 4-Y × Post	–0.049	–0.039	1,142.479**	1,050.873***	115.435	156.492	22.562	38.760
	[0.031]	[0.035]	[502.715]	[370.415]	[104.215]	[109.841]	[84.224]	[87.267]
Public LQ 4-Y × Post	–0.080***	–0.056*	1,041.251	1,170.908	23.846	45.311	4.345	21.999
	[0.028]	[0.029]	[681.137]	[857.099]	[93.430]	[87.758]	[89.503]	[85.103]
R-squared	0.786	0.791	0.916	0.923	0.897	0.899	0.859	0.863
Panel B: Fall								
Private HQ 4-Y × Post	–0.034	–0.028	135.592*	36.702	24.993	17.707	5.472	–1.544
	[0.027]	[0.028]	[74.760]	[98.045]	[61.057]	[63.801]	[50.399]	[51.508]
Private LQ 4-Y × Post	–0.061**	–0.068**	155.292**	99.399	57.654	47.815	–3.477	–1.449
	[0.028]	[0.028]	[63.708]	[80.595]	[61.318]	[64.617]	[46.016]	[47.832]
Public HQ 4-Y × Post	–0.048	–0.051	223.199	89.037	–37.825	–50.295	37.866	36.609
	[0.035]	[0.038]	[323.874]	[264.609]	[65.899]	[70.588]	[64.321]	[66.615]
Public LQ 4-Y × Post	–0.106***	–0.080**	529.344**	468.989*	37.277	22.323	66.815	45.861
	[0.034]	[0.033]	[242.613]	[262.155]	[62.477]	[61.400]	[60.486]	[55.983]
R-squared	0.757	0.765	0.937	0.942	0.905	0.906	0.876	0.878
Observations	2,134	2,134	2,134	2,134	2,134	2,134	2,134	2,134
College FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department Trends		Yes		Yes		Yes		Yes

Notes. Ordinary-least-squares estimates of the effect of a financial aid policy on college tuition prices, based on equation 4.1. HQ 4-Year$_c$ is an indicator equal to 1 if c is a four-year college holding high-quality accreditation. LQ 4-Year$_c$ is an indicator equal to 1 if c is an non-accredited four-year college. Post is an indicator equal to 1 for the post-treatment period 2014-2018. μ_c and μ_t represent college and year fixed effects. In columns (1) to (3) the outcome variable is the admission rate at each college program, computed as the fraction of students offered admission among the total number of applicants to a program (or major). The outcome variable in columns (4) to (6) is the number of applicants to a program, whereas the outcome in columns (4) to (6) is the number of students who are offered admission. Colombia is divided into 32 administrative regions known as departments. Standard errors in square brackets are clustered at the college level. * p<0.10, ** p<0.05, *** p<0.01.

4.9 Additional Figures and Tables

Figure 4.11: Number of Colleges with High-Quality Accreditation.



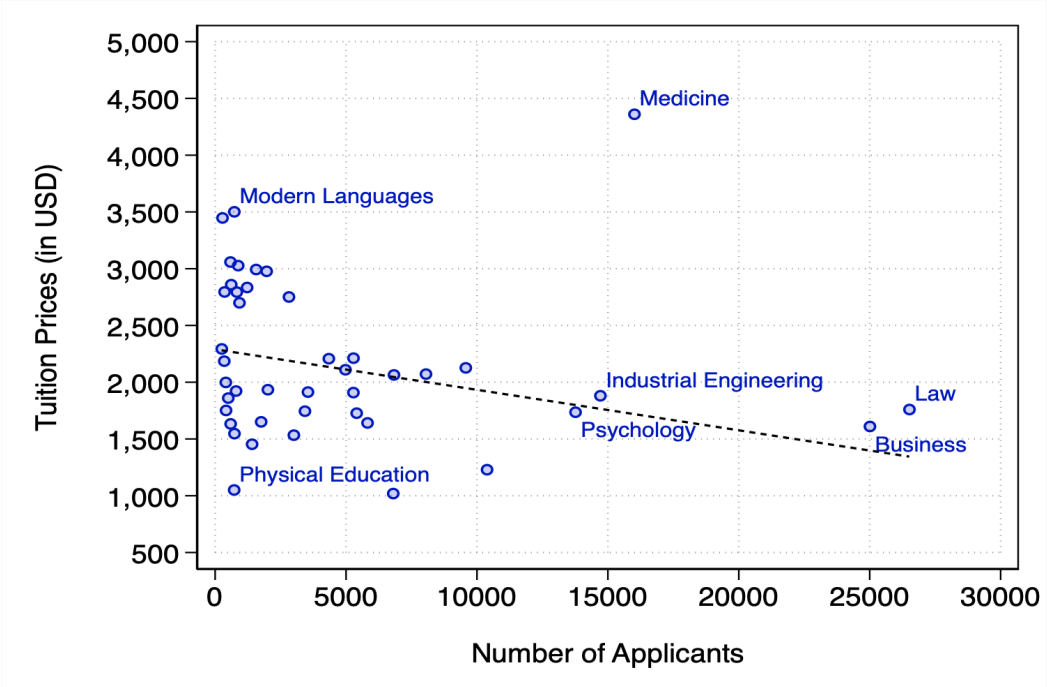
Notes. This figure displays the number of colleges with high-quality accreditation over time. The solid blue line represents private colleges, while the red dashed line represents public colleges.

Table 4.3: Number of Colleges and Programs, 2009-2018 (Pool)

	Four-Year		Two-Year	
	High-Quality	Low-Quality	High-Quality	Low-Quality
	Panel A: Private Colleges			
Colleges by Type				
Technical Institute	-	-	-	14
Technological Institute	-	-	1	26
University	44	32	-	1
University Institute	2	60	-	18
Total	46	92	1	59
Programs by Study Area				
Agronomy	4	33	-	4
Arts	47	80	-	102
Economics & Business	171	344	8	277
Education	44	72	-	5
Engineering	229	333	11	172
Health	63	149	1	13
Math & Natural Sc.	31	13	-	-
Social Sciences	177	207	2	38
Total	766	1231	22	611
	Panel B: Public Colleges			
Colleges by Type				
Technical Institute	-	-	-	7
Technological Institute	-	-	2	8
University	29	17	-	-
University Institute	1	12	3	9
Total	30	29	5	24
Programs by Study Area				
Agronomy	22	19	1	5
Arts	39	16	2	12
Economics & Business	106	81	12	68
Education	163	72	5	3
Engineering	217	133	25	97
Health	53	27	3	1
Math & Natural Sc.	79	24	1	1
Social Sciences	126	44	6	14
Total	805	416	55	201

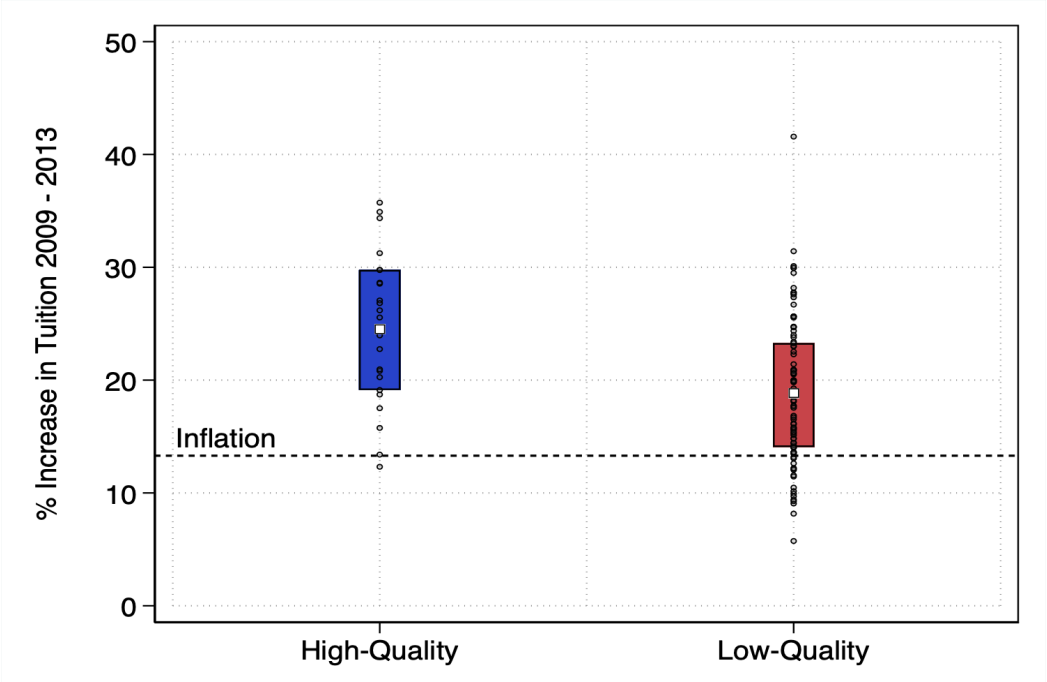
Notes. This table presents the number of colleges by type and the number of in-person undergraduate programs by area of study. Counts for private colleges are displayed in Panel A, while counts for public are displayed in Panel B. Two-year colleges are defined as colleges where more than 50 percent of students are enrolled in two-year programs.

Figure 4.12: Tuition Prices and College Applicants by Field of Study



Notes. This figure shows the relationship between college tuition prices and the number of applicants to programs in different fields of study. The Ministry of Education classifies college programs into 56 fields. Only tuition prices from four-year programs at private colleges are considered. Fields where less than two colleges offer undergraduate programs are omitted.

Figure 4.13: Increase in Tuition Prices by College Quality, 2009-2013



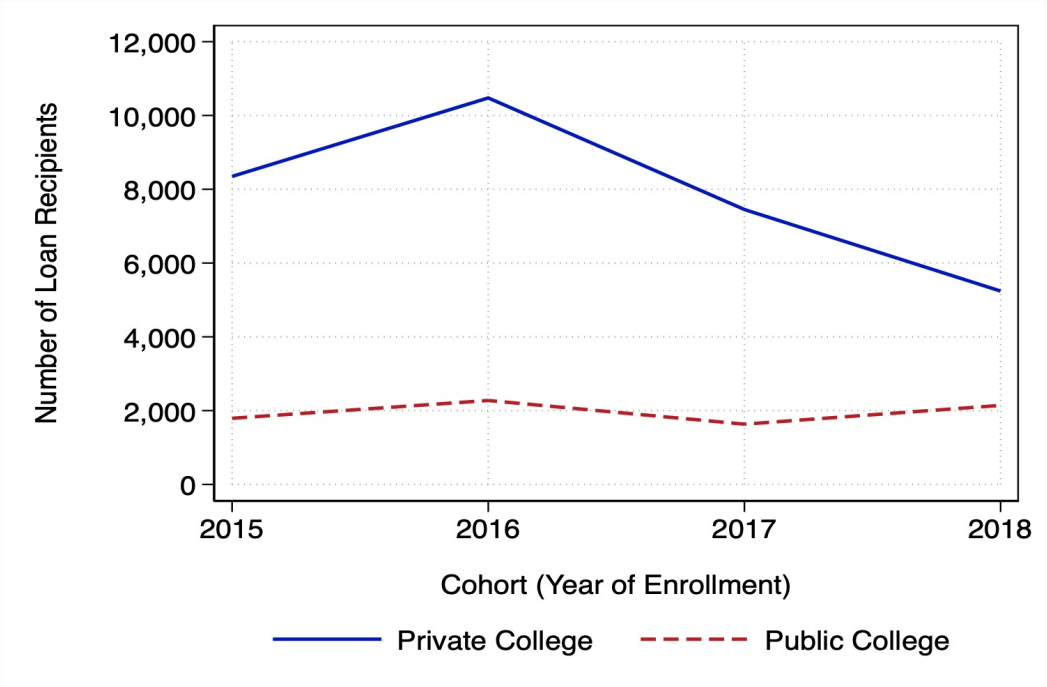
Notes. This figure displays the relationship between inflation and tuition increase across private colleges. Plotted dots represent the average tuition increase of private colleges' programs, measured between 2009 and 2013. Square markers represent the mean of tuition increases across schools. The horizontal dashed line represents the 2009-2013 inflation rate.

Figure 4.14: Eligibility Announcement for the Financial Aid Program *Ser Pilo Paga*



Notes. This figure displays the message that high school seniors received after logging in to check their performance in the *Saber 11* exit exam. In English, it reads: "Your score is equal to or above 310. You may be eligible for one of 10,000 scholarships to pursue higher education."

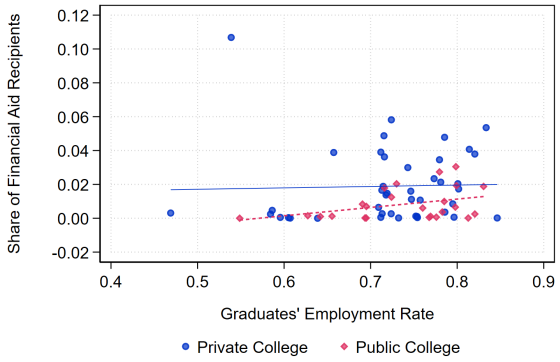
Figure 4.15: Financial Aid Recipients by Cohort of Enrollment



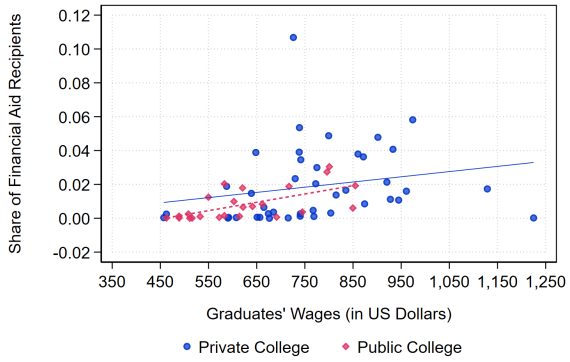
Notes. This figure displays the number of loan recipients of the financial aid program *Ser Pilo Paga* by year of enrollment. The solid blue line represents the number of recipients who enrolled in any private college, whereas the red dashed line represents the number who enrolled in public colleges.

Figure 4.16: Relation between College Characteristics and Loan Recipients' Sorting

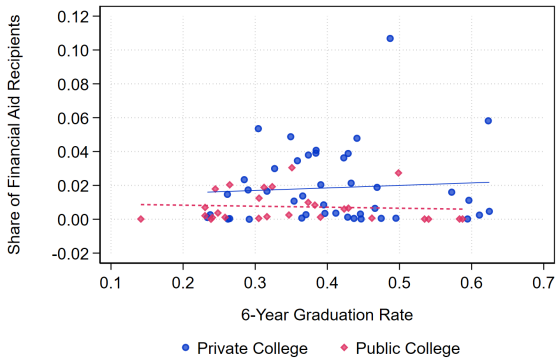
(a) Employment Rate



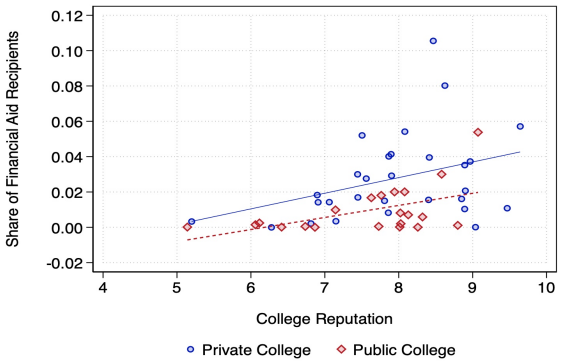
(b) Graduates' Earnings



(c) Six-Year Graduation Rates



(d) College Reputation



Notes. This Figure plots the relationship between the fraction of *Ser Pilo Paga* beneficiaries across colleges and different college outcomes measured by 2014. College reputation is computed as the average percentile in the high school exit exam (*Saber 11*) of each college's graduates between 2006 and 2014. For details about the college reputation measure see MacLeod et al. (2017). Six-year graduation rates are computed using the data of students who enrolled in bachelor's degree programs between 2000 and 2007. Employment rates correspond to the fraction of graduates employed in the formal sector one year after getting a college degree. Employment rates are computed by pooling all graduates between 2007 and 2013. Monthly earnings correspond to the average monthly earnings of graduates working in the formal sector one year after getting a college degree.

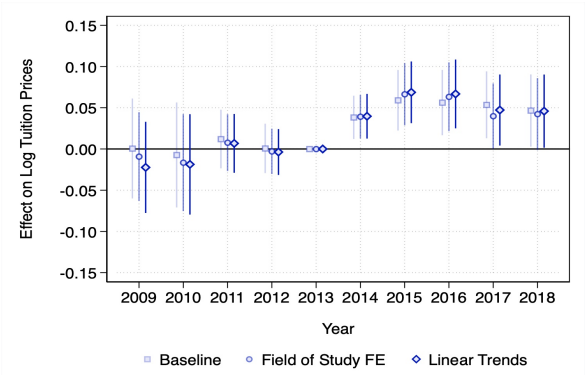
Table 4.4: Relation between College Characteristics and Loan Recipients' Sorting

	Dependent Variable : Share of Loan Recipients						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Private	0.017***	0.016***	0.017***	0.015*	0.014***	0.023***	0.025***
	[0.006]	[0.006]	[0.006]	[0.008]	[0.005]	[0.007]	[0.009]
Graduation Rate		0.015				0.007	0.002
		[0.031]				[0.031]	[0.048]
Employment Rate			0.016			0.007	0.140**
			[0.039]			[0.039]	[0.067]
Graduates' Earnings				0.000		–0.000*	–0.000*
				[0.000]		[0.000]	[0.000]
College Reputation					0.008***	0.012***	0.014**
					[0.003]	[0.004]	[0.006]
Observations	48	48	48	48	48	48	48
R-squared	0.142	0.147	0.148	0.147	0.275	0.325	0.556
Department FE							Yes

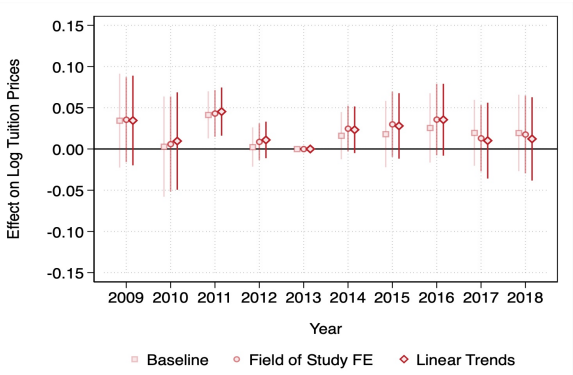
Notes. Ordinary-least-squares estimates. The dependent variable is the share of all loan recipients that enroll in each college between 2015 and 2018. College reputation is computed as the average percentile in the high school exit exam (*Saber 11*) of each college's graduates between 2006 and 2014. For details about the college reputation measure see MacLeod et al. (2017). Six-year graduation rates are computed using the data of students who enrolled in bachelor's degree programs between 2000 and 2007. Employment rates correspond to the fraction of graduates employed in the formal sector one year after getting a college degree. Employment rates are computed by pooling all graduates between 2007 and 2013. Monthly earnings correspond to the average monthly earnings of graduates working in the formal sector one year after getting a college degree. Robust standard errors are displayed in square brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 4.17: Robustness of the Effect of Financial Aid on Tuition at Program Level

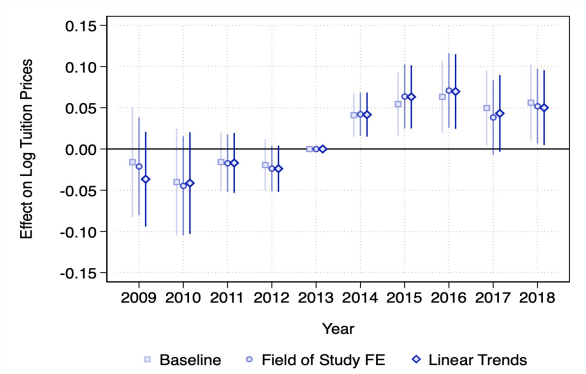
(a) High-Quality Four-Year Colleges



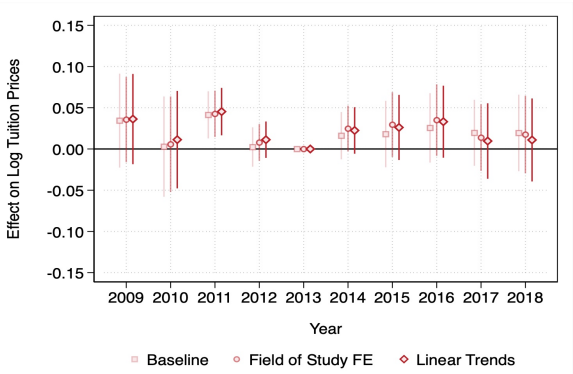
(b) Low-Quality Four-Year Colleges



(c) High-Quality Four-Year Colleges, Restricted



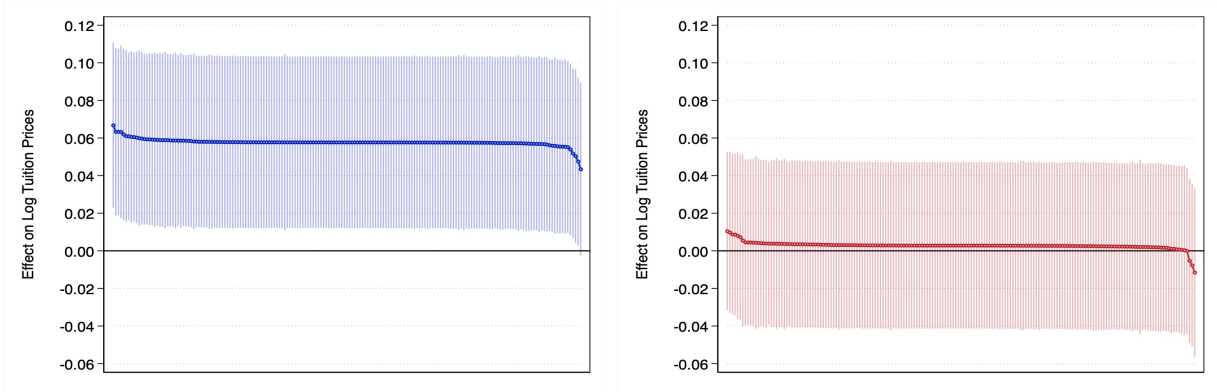
(d) Low-Quality Four-Year Colleges, Restricted



Notes. Ordinary least squares (OLS) estimates of Equation (4.2). The outcome variable is the logarithm of tuition prices. Tuition for all college programs is expressed in prices of 2009 to account for inflation. Panels (a) and (c) display the estimates of δ_τ, with $\tau \in \{2009, ..., 2018\}$, representing the (*direct*) effect on tuition at high-quality four-year colleges after the government introduced the financial aid program *Ser Pilo Paga*. Panels (b) and (d) display the estimates of β_τ, corresponding to the (*spillover*) effect on tuition at low-quality four-year colleges. Square markers represent the estimates from a baseline specification that controls for college and year fixed effects. Circle markers additionally control for field of study fixed effects. Rhombus markers represent the full specification, which includes study area linear trends and department linear trends. College programs are classified by the Ministry of Education into 56 fields of study and 8 study areas (Agronomy, Arts, Business and Economics, Education, Engineering, Health, Math and Natural Sciences, and Social Sciences). Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients. Panels (a) and (b) use the unrestricted sample, where all colleges that received high-quality accreditation during the sample are classified as high-quality. Panels (c) and (d) exclude from the sample colleges that obtained high-quality accreditation post-treatment.

Figure 4.18: Robustness of the Effect of Financial Aid on Tuition - Excluding Colleges

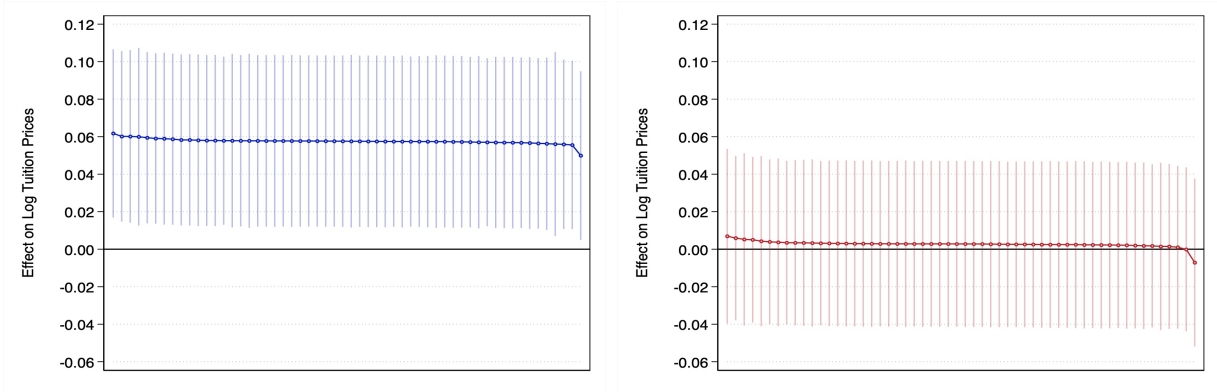
(a) *Direct Effect*: HQ Four-Year Colleges (b) *Spillover Effect*: LQ Four-Year Colleges



Notes. Each plotted dot represents the estimated effect of financial aid on tuition prices dropping from the sample one college at a time. Estimates are based on equation 4.1. The outcome variable is the log of tuition prices charged at private colleges to students enrolled in each undergraduate program. College programs are classified by the Ministry of Education into 56 fields of study and 8 study areas (Agronomy, Arts, Business and Economics, Education, Engineering, Health, Math and Natural Sciences, and Social Sciences). Colombia is divided into 32 administrative regions known as departments. Standard errors in square brackets are clustered at the college level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 4.19: Robustness of the Effect of Financial Aid on Tuition - Excluding Fields

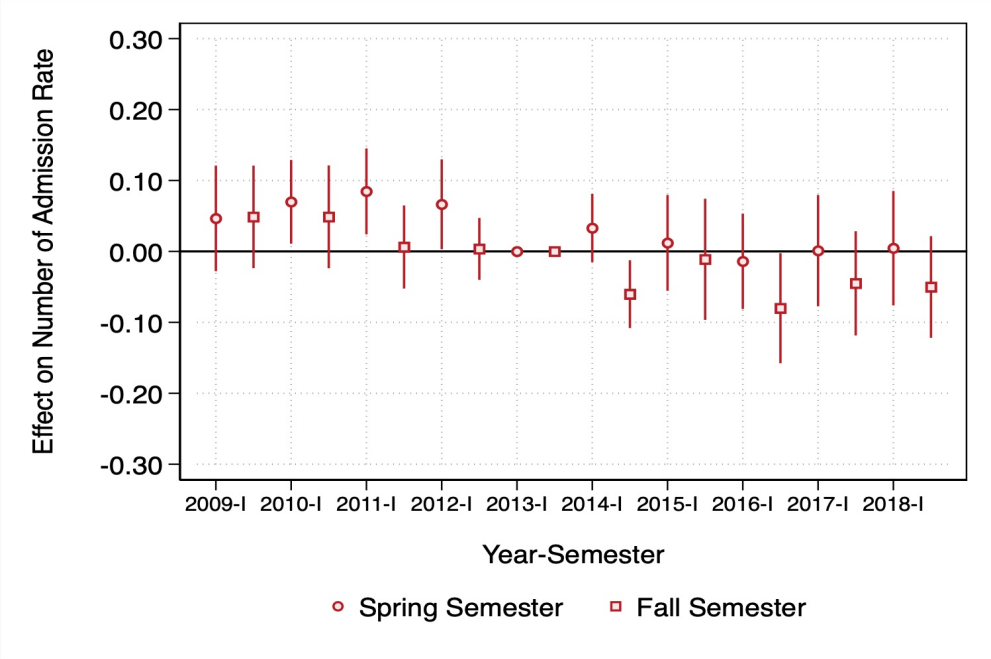
(a) *Direct Effect*: HQ Four-Year Colleges (b) *Spillover Effect*: LQ Four-Year Colleges



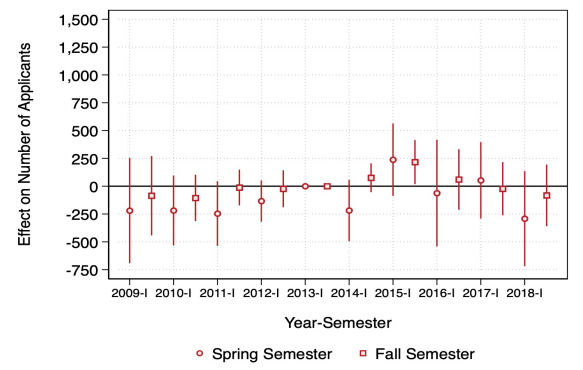
Notes. Each plotted dot represents the estimated effect of financial aid on tuition prices, with all programs in a field of study being dropped at a time. Estimates are based on equation 4.1. The outcome variable is the log of tuition prices charged at private colleges to students enrolled in each undergraduate program. College programs are classified by the Ministry of Education into 56 fields of study and 8 study areas (Agronomy, Arts, Business and Economics, Education, Engineering, Health, Math and Natural Sciences, and Social Sciences). Colombia is divided into 32 administrative regions known as departments. Standard errors in square brackets are clustered at the college level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 4.20: Spillover Effect of Financial Aid on Private College Admission Rates

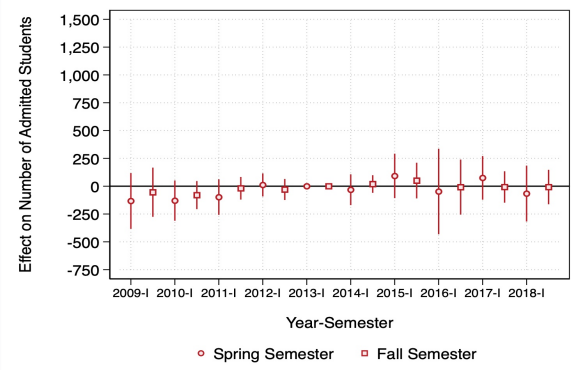
(a) Admission Rate



(b) Number of Applicants



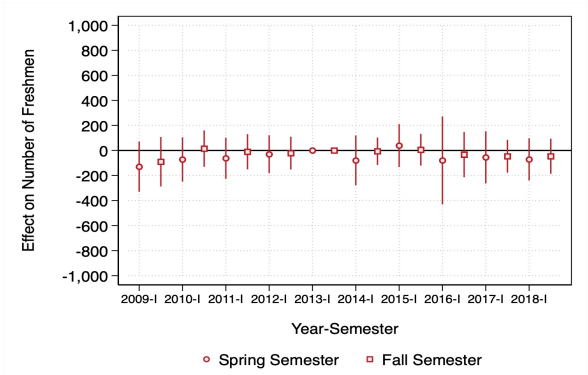
(c) Number of Admissions



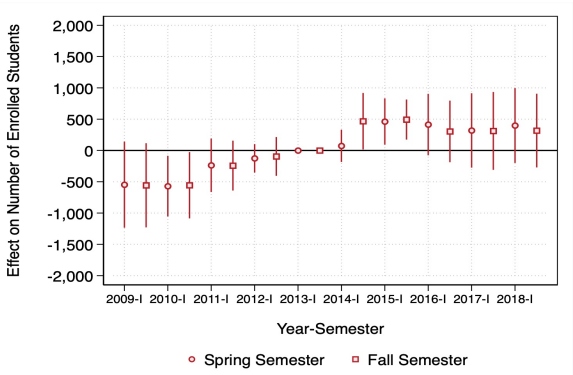
Notes. Ordinary least squares (OLS) estimates of the β_τ coefficients in Equation (4.2), corresponding to the (*spillover*) effect on low-quality private four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable in Panel (a) is the admission rate of college programs, computed as the fraction of students offered admission among the total number of applicants to a program. In panels (b) and (c), the outcome variables are the number of applicants and the number of admissions offered, respectively. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.21: Spillover Effect of Financial Aid on Private College Enrollment

(a) Number of Freshmen



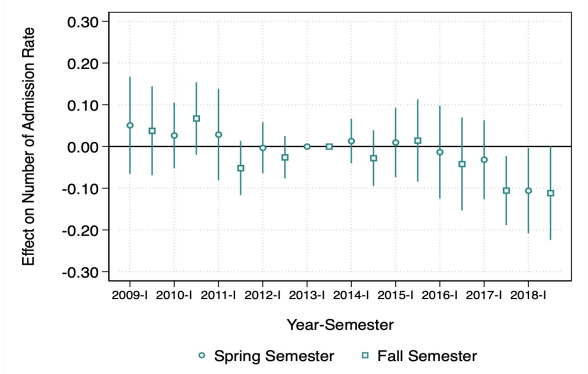
(b) Number of Enrollees



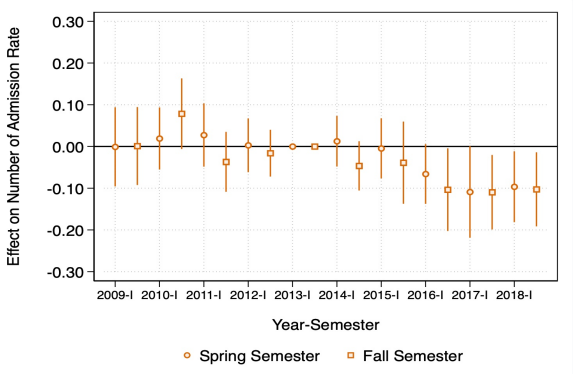
Notes. Ordinary least squares (OLS) estimates of the β_τ coefficients in Equation (4.2), corresponding to the (*spillover*) effect on low-quality private four-year colleges after introducing the financial aid program *Ser Pilo Paga*. In panels (a) and (b), the outcome variables are the number of first-year students (freshmen) in a college program and the number of all enrolled students, respectively. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.22: Effect of Financial Aid on Admission Rates at Public Colleges

(a) High-Quality 4-Year Public Colleges



(b) Low-Quality 4-Year Public Colleges

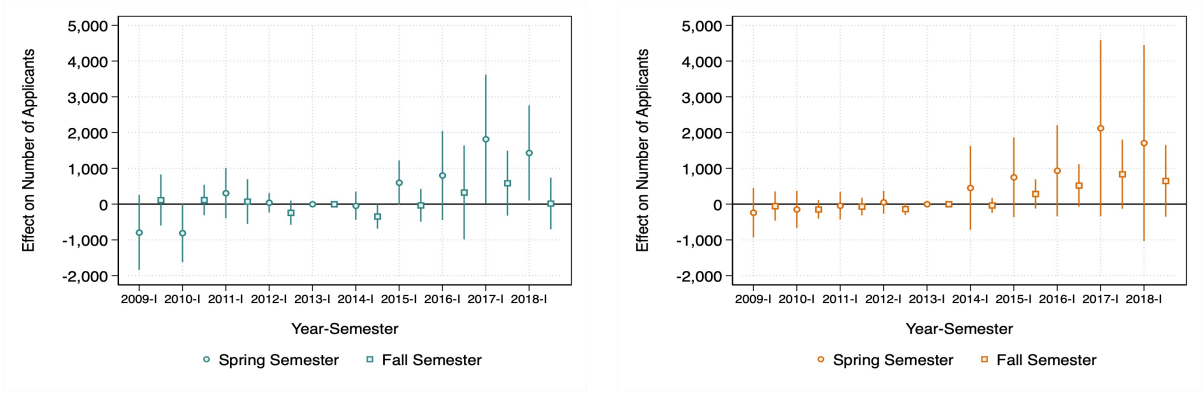


Notes. Ordinary least squares (OLS) estimates of Equation (4.2). Panel (a) displays the estimates of coefficients δ_τ^{Public}, corresponding to the effect on high-quality four-year public colleges. Panel (b) displays the estimates of coefficients β_τ^{Public}, corresponding to the effect on low-quality four-year public colleges. The control group is low-quality two-year private colleges. The outcome variable is the admission rate of college programs, computed as the fraction of students who are offered admission among the total number of applicants to a program. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.23: Effect of Financial Aid on Applicants and Admissions at Public Colleges

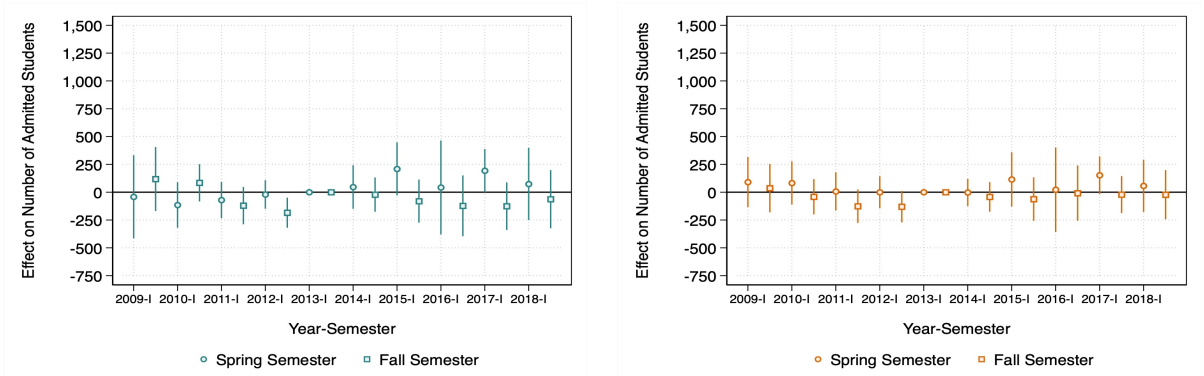
(a) High-Quality 4-Year: Applicants

(b) Low-Quality 4-Year: Applicants



(c) High-Quality 4-Year: Admissions

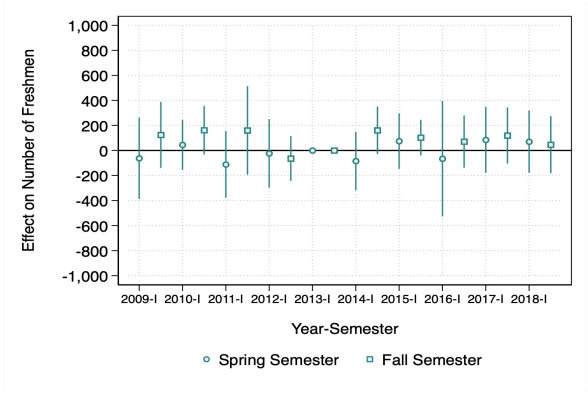
(d) Low-Quality 4-Year: Admissions



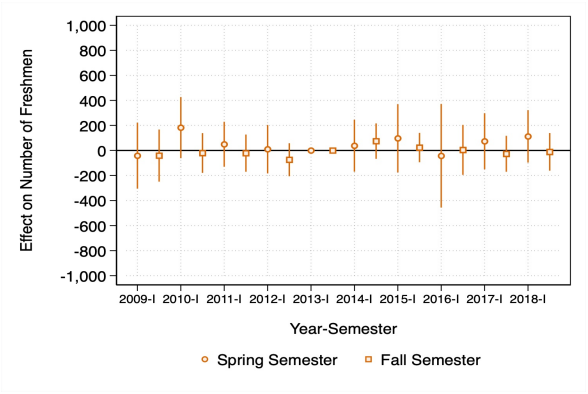
Notes. Ordinary least squares (OLS) estimates of Equation (4.2). Panels (a) and (c) display the estimates of coefficients δ_{τ}^{Public}, corresponding to the effect on high-quality four-year public colleges. Panels (b) and (d) display the estimates of coefficients β_{τ}^{Public}, corresponding to the effect on low-quality four-year public colleges. The control group is low-quality two-year private colleges. In Panels (a) and (b) the outcome variable is the number of applicants in the Spring and Fall semesters. In Panels (c) and (d) the outcome variable is the number of students who are offered admission in the Spring and Fall semesters. Separate regressions are run for outcomes measured in each semester. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.24: Effect of Financial Aid on Freshmen and Enrollment at Public Colleges

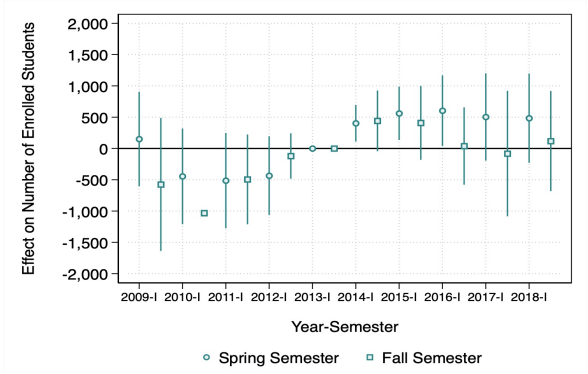
(a) High-Quality 4-Year: Freshmen



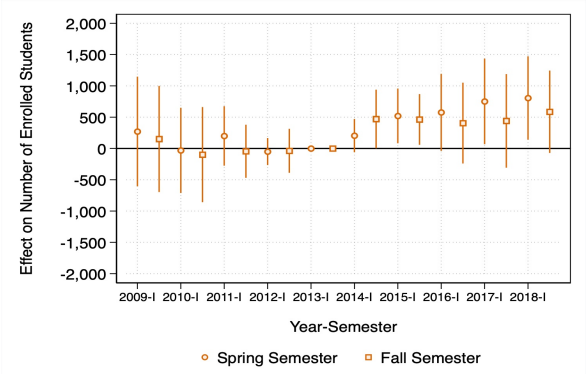
(b) Low-Quality 4-Year: Freshmen



(c) High-Quality 4-Year: Enrollees

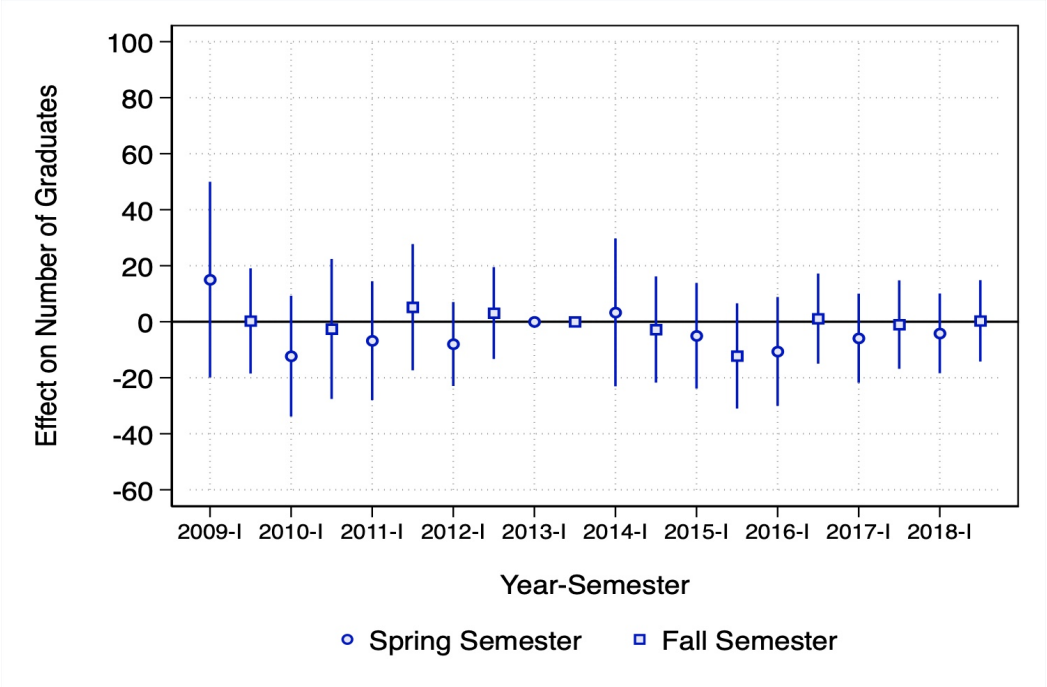


(d) Low-Quality 4-Year: Enrollees



Notes. Ordinary least squares (OLS) estimates of Equation (4.2). Panels (a) and (c) display the estimates of coefficients δ_{τ}^{Public}, corresponding to the effect on high-quality four-year public colleges. Panels (b) and (d) display the estimates of coefficients β_{τ}^{Public}, corresponding to the effect on low-quality four-year public colleges. The control group is low-quality two-year private colleges. In Panels (a) and (b) the outcome variable is the number of first-year students (freshmen) in the Spring and Fall semesters. In Panels (c) and (d) the outcome variable is the number of all the students enrolled in a program each semester. Separate regressions are run for outcomes measured in both semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

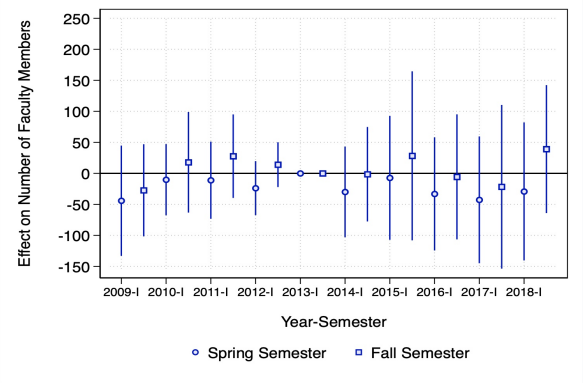
Figure 4.25: Direct Effect of Financial Aid on College Graduates



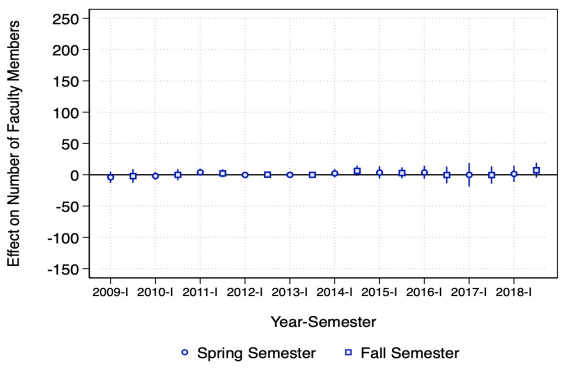
Notes. Ordinary least squares (OLS) estimates of the δ_τ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable is the number of students who graduate from any program at a private college. Separate regressions are run for the number of graduates in the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, field of study fixed effects, study area linear trends, and department linear trends. College programs are classified by the Ministry of Education into 56 fields of study and 8 study areas (Agronomy, Arts, Business and Economics, Education, Engineering, Health, Math and Natural Sciences, and Social Sciences). Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.26: Direct Effects of Financial Aid on Staff Hiring

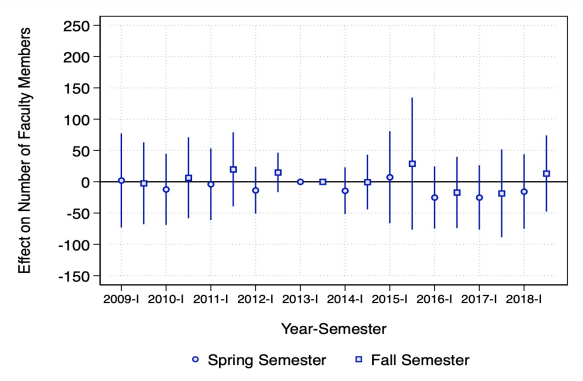
(a) All Staff



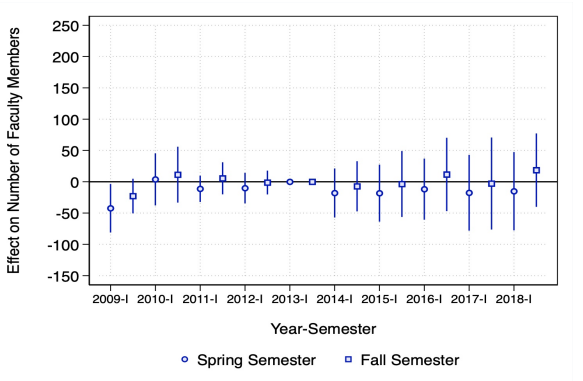
(b) Heads and Directors



(c) Professional Services

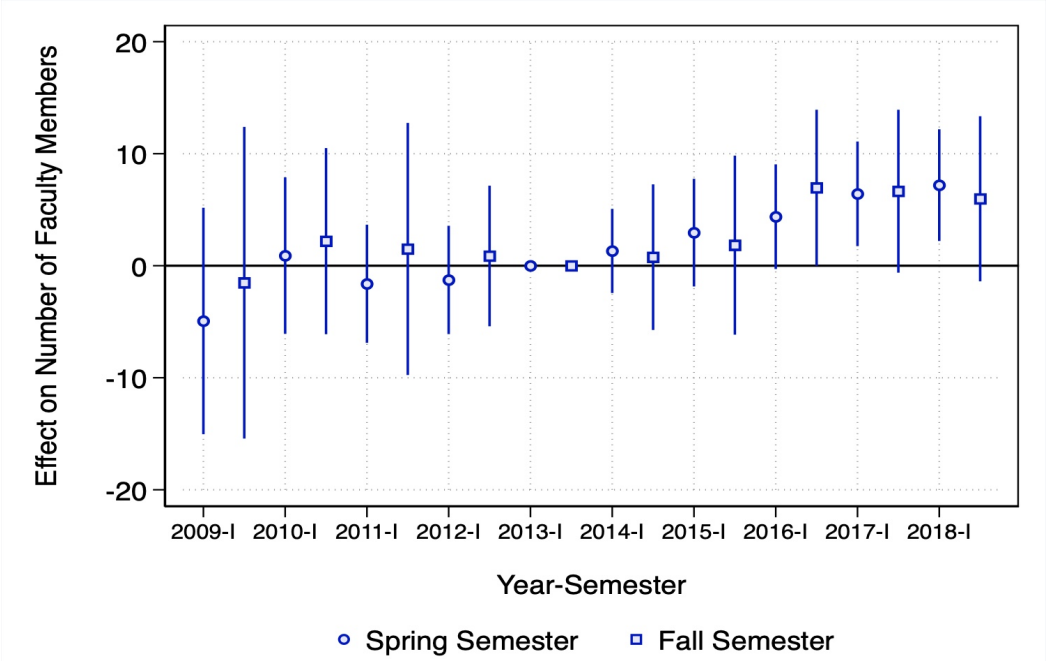


(d) Auxiliary Services



Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable in panel (a) is the number of all administrative staff working in a private college. In panels (b), (c), and (d) the outcome variables are, respectively, the number of staff members who are heads or directors, the staff who provide professional services, and the staff who provide general services. Separate regressions are run for outcomes measured during the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

Figure 4.27: Direct Effect of Financial Aid on the Student-to-Staff Ratio



Notes. Ordinary least squares (OLS) estimates of the $\delta_{\tau}^{Private}$ coefficients in Equation (4.2), corresponding to the (*direct*) effect on high-quality four-year colleges after introducing the financial aid program *Ser Pilo Paga*. The outcome variable is the student-to-faculty ratio in each college. Separate regressions are run for the Spring and Fall semesters. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. Estimates for the Spring semester are displayed using circle markers, while square markers are used for estimates corresponding to the Fall semester. All regressions control for college fixed effects, year fixed effects, and department linear trends. Colombia is divided into 32 administrative regions known as departments. 95% confidence intervals, based on standard errors clustered at the college level, are displayed around plotted coefficients.

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