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Student Employment and Persistence: Evidence of Effect Heterogeneity of Student Employment on College Dropout

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Abstract This study explores how student employment affects college persistence and how these effects differ by individual likelihood of participating in student employment. I analyze data from the National Longitudinal Survey of Youth 1997 using propensity score matching and stratification-multilevel analysis. This study finds that engaging in intense work has deleterious effects on college persistence. However, these negative effects vary significantly according to likelihood of participation in intense work. The results indicate that employment has less negative impacts on completion for those most likely to participate in intense work, who are typically those from the most disadvantaged social backgrounds. This finding suggests that efforts to reduce the deleterious effects of intense work on persistence should be practiced with careful consideration for sub-populations that may have different reasons for and effects of student employment.

Keywords Student employment · Dropout · Effect heterogeneity · National Longitudinal Survey of Youth 1997

Introduction

Prior research has identified the majority of college dropouts as those students who are socially and economically disadvantaged (Bean 1985; Braxton 1988, 2000; Pascarella and Chapman 1983; Spady 1970; Stage 1988; Stage and Hossler 1989); this has significant implications for educational stratification. Even though the opportunity to attend college has been expanded to include those who have historically not had access to higher education (National Center for Education Statistics 2010) and the importance of a college

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degree in the labor market has increased (Hebel 2000; Hout 2012), college completion has remained a challenging goal for disadvantaged students. Thus, a better understanding of the mechanism of college dropout is crucial to any thorough analysis of inequality in postsecondary education.

There are many factors that can contribute to an individual's decision to drop out; this study focuses on the effects of college student employment on dropout. Student employment is in many ways one of the most important activities that affects students' academic performance and decisions while in school (Bozick 2007; Iwai and Churchill 1982; Metzner and Bean 1987; Perna 2010; Riggert et al. 2006; Roksa and Velez 2010; Tinto 1975, 1993). With rising college costs and student debt, employment while in college has become a common option—sometimes the only option—for many less affluent students to meet educational costs. Even for affluent students, job experience during postsecondary education is considered to be an important factor in making a successful transition to the labor market after graduation. Therefore, as Riggert et al. (2006), p. 64 noted, "Student employment… is an educational fact of life." Given the prevalence of student employment and the significant use of time and energy that employment often entails, it is important to understand how such activities affect educational persistence.

Although the increasing rate of college student employment has garnered some media attention in recent years (e.g., Rampell 2011) the effects of college student employment on dropout have received far less scholarly attention than have the effects of high school student employment on high school dropout (Bozick 2007; Riggert et al. 2006). This is important because the findings gained from studies on high school student employment are not easily applicable to the college context, and postsecondary student employment differs from that of high school student employment in several significant ways. First, college students have much more flexibility than high school students in managing their time for work and study. They are required to spend less time in the classroom and have a variety of options by which to adjust their academic schedule. That is, unlike high school students, college students have more agency around their schedules, due to the way in which postsecondary education is structured (Bozick 2007, p. 263). Second, while high school is compulsory in the United States, college is not. Therefore, college students are already self-selected individuals in terms of academic motivation and achievement. Third, organizational and life-course conditions such as school tuition and living arrangements differ greatly from those of high school (Bozick 2007). Along these lines, the effects of student employment during postsecondary education may show somewhat different patterns from those of high school student employment.

In this study, I aim to examine how college student employment affects dropout and how this trend influences educational stratification in the United States. I build on prior studies of student employment on educational persistence, both in high school and college, by addressing several analytical issues.

First, I examine the relationship between college student employment and dropout using propensity score matching to address concerns over pretreatment heterogeneity. Many prior studies have pointed out that those who engage in student employment differ from those who do not in terms of social and educational background (Entwisle et al. 2000; National Research Council 1998; Schoenhals et al. 1998). If this pretreatment heterogeneity affects both selection into college employment and the decision to drop out, the estimated effects of student employment may be biased. Therefore, careful consideration should be given to students' preexisting backgrounds to accurately estimate the impact of student employment on the dropout decision, and propensity score matching can address this issue more effectively than conventional methodological approaches (Brand and Halaby 2006; Rosenbaum and Rubin 1983).[1]

Second, student employment has to be defined along several dimensions including quantity, timing, type, and purpose. This treatment heterogeneity complicates the implications of student employment on educational outcomes. This study defines student employment as work that a full-time student engages in outside of school, and particularly focuses on examining how work intensity differentially affects the dropout decision. That is, rather than analyzing a single counterfactual condition such as whether or not a student works, this study assumes complex counterfactual scenarios [intense work (20 h or more) vs. moderate work (less than 20 h) vs. no work] and aims to explore how the effects of employment on dropout vary by work intensity. In terms of timing, I examine first-year students. According to Tinto, the first year is the most critical period for a college student, as most college attrition is concentrated in the first year (Aughinbaugh and Gardecki 2008; Tinto 1993).

Lastly, along with estimating the average effects of student employment on dropout, I also examine how the effects of work vary by individual propensity to work. Varying effects of student employment on academic performance and persistence have been examined in many prior studies (D'Amico 1984; Entwisle et al. 2005; Lee and Staff 2007; Marsh 1991). Prior research has pointed out that effect heterogeneity can be attributed not only to treatment heterogeneity (i.e., quantity, purpose, and types of jobs), but also to students' social, demographic, educational, and institutional backgrounds. Therefore, assuming that the effect of work is the same for every student may produce inaccurate findings and limit our understanding of the impact of student employment on academic outcomes. Rather than examine interactions between student employment and each factor that might produce effect heterogeneity, this study examines interactions between student employment and students' propensity to work.

Students' propensity to work is an effective measure that reflects individual social positions. For example, those who are more likely to participate in work tend to have disadvantaged family backgrounds, poor prior academic achievements, unfavorable institutional characteristics, and often work in order to pay for their college expenses rather than for other reasons such as accruing work experience. On the other hand, those who are less likely to engage in work during college typically come from more advantaged social positions and are more likely to work to prepare for their future careers rather than to pay for college expenses. Therefore, by examining treatment effect heterogeneity by likelihood of participation in work, this study seeks to understand how the effects of student employment vary by students' social positions by simultaneously considering multiple dimensions of students' environments that may influence not only participation in student employment but also college persistence.

To examine these questions, I analyze data from the National Longitudinal Survey of Youth 1997 using propensity score matching and stratification-multilevel analysis (Xie et al. 2012). This study contributes to our understanding of persistence in postsecondary education by examining the effect of student employment on dropout, focusing on treatment effect heterogeneity. This study finds that engaging in intense work has deleterious

[1] The terms "effect" and "impact" in this study indicate an association or relationship between employment and dropout and do not imply a causal relationship. Propensity score matching depends on the ignorability assumption, which is the assumption that there are no additional confounders between treated and untreated units conditional on set of pretreatment covariates. However, there is always the possibility of unobserved factors that may simultaneously affect both treatment and outcome.

effects on first-year retention. However, the effect of intense work on college persistence varies significantly by likelihood of participation in intense work. The data show that those who are least likely to engage in intense work are penalized most from it. In other words, student employment is less harmful to those from most disadvantaged social backgrounds. As these findings indicate that the effects of student employment differ according to a student's socioeconomic status, policymakers should seek to establish policies regarding student employment that differ according to a given population's likelihood of participation in work.

Three General Perspectives on the Impact of Student Employment

The Deleterious Effects Perspective

The relationship between student employment and schooling has been examined from three general perspectives (Lee and Staff 2007). The deleterious effects perspective assumes that student employment has a direct and negative impact on school performance and persistence. This perspective relies on a zero-sum understanding of student employment, which is the understanding that when students engage in employment, they have less available time to devote to school activities such as studying, homework, and extracurricular activities (Coleman 1961; D'Amico 1984; Kablaoui and Paulter 1991; Marsh 1991; Schoenhals et al. 1998). Thus, this perspective assumes that time at work generally has a negative effect on school performance and completion since the time that a student can devote to schooling is reduced. Many prior studies that use this approach have identified deleterious effects of engaging in student employment on various aspects of education, including school grades, completion, and educational aspirations (Marsh and Kleitman 2005; Metzner and Bean 1987; Steinberg, Fegley, and Dornbusch, 1993; Steinberg et al. 1982). However, recent studies have found that the relationship between work intensity and academic outcomes is not linear and that moderate participation in the labor market can have positive consequences on college achievement. These studies concluded that only intensive participation is deleterious to academic outcomes and suggested that work intensity is a crucial factor in determining the deleterious effects of student employment (Bozick 2007; D'amico 1984; Marsh 1991; Orszag et al. 2001).

Greenberger and Steinberg (1986) suggested a somewhat different interpretation of the negative effects of engaging in student employment on academic outcomes. Their key point is that work environment and quality of student employment in contemporary America hinder the social and psychological development of student workers and actually promote pseudo-maturity without developing a corresponding psychological maturity. Students engaged in employment are, therefore, more likely to be involved in delinquent behavior such as alcohol and drug use and consequently have negative attitudes toward work itself (Greenberger and Steinberg 1986, p. 157). In this regard, they maintain that spending time on extracurricular activities or social activities with school friends is more beneficial than student employment for students to promote their psychosocial maturation.

Studies that employ this first perspective have found differing mechanisms that cause student employment to have deleterious effects on school performance; however, this first perspective commonly assumes that student employment detracts from the time the student has to dedicate to school-related activities and thus has a direct negative effect on individual students' schooling.

The Selection-to-Work Perspective

The selection-to-work perspective argues that the observed relationship between student employment and school performance reflects preexisting heterogeneity between students in terms of their family background, academic ability, motivation, aspirations, and so on (Lee and Staff 2007). This perspective assumes that if we consider the selection process that determines who enters the student workforce, the relationship between employment and school performance is no longer significant (Bachman and Schulenberg 1993; Schoenhals et al. 1998; Steinberg et al. 1993). The factors that affect both likelihood of participation in student employment and academic outcomes have been widely examined. These factors include socioeconomic background, demographic characteristics, prior academic achievements, and educational aspirations (Entwisle et al. 2000; Schoenhals et al. 1998; Steinberg et al. 1993; Warren et al. 2000). Accordingly, these studies have emphasized that the actual causes of poor academic performance or a high likelihood of school dropout can be found in students' preexisting backgrounds, their characteristics before entering school.

According to this perspective, the crucial point of analysis is controlling for preexisting heterogeneity between students. Unless research can fully control for various family and academic backgrounds that might simultaneously affect students' likelihood of engaging in student employment and academic performance, studies may arrive at inaccurate conclusions about the effect of student employment on dropout trends. Many prior studies have dealt extensively with this issue in the study of high school employment and academic performance using various advanced statistical methods (Lee and Staff 2007; Staff et al. 2010; Warren et al. 2000). However, only a few studies examining college student employment have considered this preexisting heterogeneity. Thus, one of the key research goals of this study is to provide less biased estimates of the impact of student employment on dropout while taking into account pretreatment heterogeneity by using propensity score matching.

The Heterogeneous Effects Perspective

The heterogeneous effects perspective assumes that student work has a direct effect on school performance but that its effect is heterogeneous by work characteristics and individual background. Therefore, this perspective emphasizes that assuming homogeneous effects of student employment on academic outcomes without considering sources of effect heterogeneity limits an accurate understanding of the impacts of student employment. The first source of effect heterogeneity is treatment heterogeneity. That is, characteristics of student employment differ greatly among students by type of job, timing of employment, hours, location (on campus vs. off campus), and so on. Due to the complicated patterns of work engagement among students, the effects of student employment can differ greatly according to how student employment is defined in the research design (Astin 1993; D'Amico 1984; Marsh 1991; Riggert et al. 2006; Steinberg et al. 1982; Worley 1995).

The second source of effect heterogeneity is pretreatment heterogeneity. That is, the effects of student employment on school performance are conditional upon students' preexisting backgrounds (Lee and Staff 2007). Prior studies have shown evidence of the conditional effects of student employment on academic performance and other delinquent behaviors. For example, the effects of student employment can differ by gender (D'Amico 1984), race and ethnicity (Canabal 1998; Johnson 2004), work purpose (Marsh 1991), socioeconomic background (Entwisle et al. 2005), institutional characteristics (Roksa

2011), and living arrangements (Bozick 2007). According to this perspective, any analysis that interprets only the average effects of student employment will have a limited understanding of the relevance and significance of student employment on college persistence.

In sum, the three general perspectives suggest important methodological and theoretical considerations when estimating the effects of student employment on dropout. Based on these three perspectives, I carefully considered three heterogeneity issues in the research design: pretreatment heterogeneity, treatment heterogeneity, and treatment effect heterogeneity. A more detailed discussion of how this study deals with these issues in the research design is provided in the following section.

Analytical Strategy: Methods, Data, and Measurement

Methods

In this study, I use propensity score matching and stratification-multilevel (SM) methods to examine the impact of student employment on dropout from the three perspectives. I use a four-step methodological approach. First, using a rich array of personal and academic data, I estimate individuals' propensity scores for participation in the student labor market (treatment condition). To effectively address treatment heterogeneity, I use a multiple counterfactual approach and define three sets of counterfactual scenarios. The key treatment condition is intensity of involvement in the student labor market. Thus, I estimate propensity scores by comparing intensive work (20 h or more) to (1) anything else (moderate work and no work), (2) moderate work (less than 20 h), and (3) no work by using the following equation:[2]

$$\mathrm{P} = p(d_i = 1|X_i)$$

where P is the propensity score, d_i indicates whether student i is engaged in intense work, and X_i is a vector of covariates observed prior to college entry. This propensity score provides estimates of an individual's propensity to engage in intense work relative to each control state. Then, I invoke an ignorability assumption, which means that conditional on my set of pretreatment covariates, I assume that there are no additional confounders between treated and untreated units.

Second, based on estimated propensity scores, I examine the average treatment effect on the treated (TT) under three counterfactual scenarios.

$$\tau_{tt} = E\left(y^{d=1} - y^{d=0}|d = 1\right)$$

TT represents average differences among those students who were actually engaged in intense work. I use nearest neighbor matching ($k = 1, 5$) and kernel matching to estimate TT for each counterfactual model. I also examine the average effects of intense work against three counterfactual conditions without matching and compare the results with those of the propensity score matching approach.

[2] This study defines three sets of counterfactual scenarios and all analyses are separately conducted for each sub-sample. While the intense versus anything else model includes all individuals, the intense versus moderate model does not include no-work individuals. Likewise, the intense versus no-work model does not include moderate work individuals.

Third, I construct a balanced propensity score stratum based on the estimated propensity scores found in the first step. The propensity score stratum is balanced when the mean value of each covariate and propensity score between those who are and are not involved in intense work within each stratum are not statistically different. This balanced propensity score stratum is used to estimate stratum-specific effects in the next step.

Fourth, I estimate propensity score stratum–specific employment effects on college dropout using logistic regression (level 1) and summarize effect trends across strata using a variance weighted least squares regression (level 2). This stratification-multilevel model assumes treatment effect heterogeneity and thus provides a linear trend in the variation of effects by propensity strata (Brand et al. 2014; Brand and Simon-Thomas 2013; Brand and Xie 2010). In sum, by using these two methods—propensity score matching and stratification-multilevel analysis—I examine the average effects of college student employment on dropout, as well as patterns of treatment effect heterogeneity by individual likelihood of participation in college employment.

Data

In this analysis I use the National Longitudinal Survey of Youth 1997 (NLSY97) dataset. NLSY97 tracks a nationally representative sample of approximately 9000 youths who were 12–16 years old as of December 31, 1996, with annual interviews starting in 1997. NLSY97 contains a broad array of information, including social and family background, schooling, and demographic transitions, as well as labor market participation and outcomes. It also covers detailed information about the transition from high school to postsecondary education and from postsecondary education to the labor market. In terms of education, NLSY97 includes all schools that an individual attended since the preceding interview, the level and type of school, dates of enrollment, and school characteristics. Because first-year college retention is of key interest to my analysis, this extensive information on individuals' time in high school helps to estimate the individual's propensity to participate in the labor market during their first year of college.

The analysis that follows uses data collected through round 15 of the survey, at which time the respondents ranged in age from 26 to 32 years. Among 8984 individuals initially interviewed in round 1, about 83% (7423) were interviewed in round 15. I restrict the sample to those who ever attended a four-year college by 2005 and to those who did not have any missing data on treatment (employment history) and outcome variables (college history). It is important to note that this sampling scheme includes both timely college attendees who attended college right after high school graduation (83%) and non-traditional college students who attended college at older ages (17%). This heterogeneity may result in biased findings since timely college attendees and non-traditional college students have different socioeconomic and educational backgrounds. For example, non-traditional college students are likely to have more complex college histories and lower socioeconomic backgrounds than timely college attendees (Rosenbaum et al. 2006). Therefore, I conducted supplementary analyses separating the samples of timely college attendees and others. This supplementary analysis on both samples returned similar results to those reported in the current study.

While most control variables have only a few missing values, the four continuous variables—family income, GPA, Armed Services Vocational Aptitude Battery (ASVAB) test scores, and parents' education—have relatively large missing values. For individuals with missing data, I imputed the values based on the other variables in my models. Because using a multiple imputed dataset with stratification multi-level method lends an additional complexity of analysis, I use single imputations. A supplementary analysis using only those who had no missing information (i.e., listwise) showed very similar results with this study. The total sample includes 2613 individuals, but the final sample differs for each counterfactual model.

Measurement

My treatment variables are related to employment status outside of school in the first year. In this study, I focus only on paid employment outside of school. I calculate average work intensity by hours worked during the first year and divide employment into three categories: no work, moderate work (up to 20 h per week), and intensive work (over 20 h per week). These categories regarding work intensity have been used in several prior studies (Bozick 2007), which allows for a comparison of this study's findings with prior studies.

My outcome variable is whether or not a first-year student returned to school the following year. The NLSY97 contains data on school enrollment by month and thus I can examine whether the respondents finished their first year and returned to school for their second year. More specifically, if respondents first attended a four-year school (during August, September and October), I make note of the college identification number. When looking at that same respondent's enrollment the following year, I confirm that the identification number is the same, thus ensuring I capture continued enrollment at the same institution. If the student is enrolled the following year at a different four-year college, they are designated as transfer students. Dropout cases are identified as those who did not enroll in any postsecondary education for the start of the second academic year.[3]

To estimate an individual's propensity for employment, I use a rich array of background factors, including demographic, socioeconomic, educational, institutional, and individual financial conditions. Aside from some demographic variables, most of the variables are utilized from data one year before the respondent attended college.

Demographic Characteristics

Gender is a dummy variable (male = 1). The race variable includes White [reference category], Black, and Hispanic. Total family size is a continuous variable and family composition is a dichotomous variable where living with both biological parents is 1 and any other configuration is 0.

Socioeconomic Characteristics

Family income is a continuous variable that indicates annual household income. Parents' education is a continuous variable and is the average value of both parents' education.

[3] The mean dropout rate of the sample in this study is about 14% (see Table 1), which is lower than the national rate for first to second year retention. For example, the national first to second year retention rate of four-year colleges in 2005 was about 70% (ACT Institutional Data File, 2005). This gap is largely due to the fact that my sample do not include transfer students as dropout cases. If I include transfer students as dropout cases, the mean dropout rates of this sample increase to 25%. I conducted supplementary analyses including transfer students as dropouts, and the results were similar to the findings of this study.

Table 1 Descriptive statistics by student employment: National Longitudinal Survey of Youth 1997 (N = 2613)

	Full sample	Intense[a]	Moderate	No-work
Demographic characteristics				
Male	0.448 (0.497)[b]	0.441 (0.497)	0.388 (0.488)	0.529 (0.500)
White	0.661 (0.473)	0.644 (0.480)	0.687 (0.464)	0.646 (0.479)
Black	0.213 (0.410)	0.199 (0.399)	0.192 (0.394)	0.251 (0.434)
Hispanic	0.125 (0.331)	0.158 (0.365)	0.121 (0.326)	0.103 (0.305)
Family size	4.118 (1.356)	4.135 (1.496)	4.153 (1.352)	4.060 (1.232)
Both parents	0.604 (0.489)	0.511 (0.500)	0.641 (0.480)	0.634 (0.482)
Socioeconomic characteristics				
Family income	76301.87 (68179.71)	67844.99 (58258.12)	75435.25 (65409.75)	84418.32 (77682.39)
Parent's education	14.1 (2.701)	13.6 (2.525)	14.2 (2.644)	14.4 (2.854)
Educational characteristics				
High school GPA	3.215 (0.476)	3.126 (0.475)	3.271 (0.454)	3.221 (0.492)
ASVAB test	66.375 (24.579)	61.869 (24.524)	69.057 (23.438)	66.822 (25.483)
Institutional characteristics				
Public school	0.710 (0.454)	0.783 (0.412)	0.673 (0.470)	0.696 (0.460)
Urbanity	0.739 (0.440)	0.730 (0.445)	0.732 (0.443)	0.755 (0.431)
Northeast	0.204 (0.403)	0.210 (0.408)	0.215 (0.411)	0.187 (0.390)
North Central	0.279 (0.448)	0.311 (0.463)	0.288 (0.453)	0.241 (0.428)
South	0.349 (0.477)	0.332 (0.471)	0.320 (0.467)	0.399 (0.490)
West	0.168 (0.374)	0.147 (0.354)	0.178 (0.383)	0.174 (0.379)
Financial aid[c]				
Loan	0.274 (0.446)	0.249 (0.433)	0.308 (0.462)	0.252 (0.435)
Scholarship	0.463 (0.499)	0.414 (0.493)	0.504 (0.500)	0.453 (0.498)
Family support	0.522 (0.500)	0.435 (0.496)	0.555 (0.497)	0.556 (0.496)
Outcome[d]				
Dropout	0.142 (0.349)	0.235 (0.424)	0.094 (0.292)	0.123 (0.329)
N	2613	710	1051	852

[a] Work intensity is measured by average work hours per week during the academic year (intense work: 20 h or more; moderate work: less than 20 h; no work: 0 h)

[b] Standard deviations in *parentheses*

[c] All financial aid variables are dichotomous (receiving aid = 1)

[d] Outcome variable indicates whether or not a freshmen student returned for their sophomore year

Educational Characteristics

GPA is a continuous variable, and the NLSY provides credit-weighted overall high school GPAs. I also include ASVAB math verbal scores as a continuous variable to capture students' cognitive abilities.

Institutional Characteristics

Three variables are used for measuring college characteristics: urbanity (1 = urban, 0 = rural), private or public school [reference category], and school region (Northeast [reference category], North central, South and West).

The student's financial situation

I utilize three variables to measure a student's financial condition regarding education. All three measures are dummy variables where 1 indicates that the student received financial aid and 0 indicates that they did not. The three variables are loans, fellowships, and family support.

Results

Descriptive Statistics

Table 1 shows descriptive statistics by student employment condition. The overall trend suggests that those who engaged in intense work during the first year had the most disadvantaged social backgrounds compared with the moderate and no-work groups. For example, annual family income was about $84,418 for the no-work group and $67,844 for the intense work group. Parents' education followed a similar trend. Parents' average years of schooling for the no-work group was about 14 and 13 years for the intense work group. Also, the percentage of those who received family support was the smallest for the intense work group among the three groups, as was the percentage of those living with both parents. In sum, it is apparent that socioeconomic background is negatively associated with work intensity and that those who engaged in intense work came from the most disadvantaged families.

While there are significant differences between the intense work group and the other two groups, the moderate and no-work groups have somewhat mixed trends along several dimensions. For example, while the no-work group comprised individuals from more advantaged socioeconomic backgrounds than the moderate group (according to indicators such as family income and parents' education), other factors such as family composition, educational background, and college financial condition indicate the reverse. For example, the moderate group had most advantaged educational backgrounds according to indicators such as high school GPA and ASVAB test scores. This group also received the most scholarship and loan support during college. The moderate group also had the lowest dropout rate among the three groups. These trends coincide with prior studies that moderate participation in work has a positive impact on educational outcomes (Bozick 2007; D'amico 1984; Marsh 1991; Orszag et al. 2001).

In sum, the descriptive statistics indicate that those who engaged in intense work were comparatively disadvantaged socioeconomically, educationally, and financially. However, the distinction between the moderate and no-work groups is less clear: while the no-work group had more advantaged socioeconomic backgrounds, the moderate group had better educational and financial support.

Determinants of Participation in Student Employment

To estimate the average and heterogeneous effects of intense work, I first estimate the propensity scores for a student engaging in intense work compared with three counterfactuals using probit regression. Table 2 shows the results of probit regression estimates.

The three models return similar results. In terms of socioeconomic variables, both family income and parents' education negatively affected the probability of engaging in intense work in all three models. Parents' education was statistically significant in every model; however, family income was only significant in the intense versus no-work model.

Table 2 Probit regression estimates for models predicting engagement in intense work

	Intense versus[a]		
	Anything else	Moderate	No-work
Demographic characteristics			
Male	−0.052 (0.055)[c]	0.090 (0.064)	−0.232**[b] (0.067)
Black	−0.304*** (0.081)	−0.222* (0.093)	−0.431*** (0.098)
Hispanic	0.080 (0.090)	0.061 (0.102)	0.102 (0.111)
Family size	0.026 (0.020)	0.014 (0.023)	0.050† (0.026)
Both parents	−0.274*** (0.061)	−0.272*** (0.070)	−0.288***† (0.075)
Socioeconomic characteristics			
Family income	$-6.03e^{-7}$ ($4.56e^{-7}$)	$-2.76e^{-7}$ ($5.44e^{-7}$)	$-1.17e^{-6}$* ($5.37e^{-7}$)
Parent's education	−0.029* (0.012)	−0.023† (0.014)	−0.038** (0.014)
Educational characteristics			
High school GPA	−0.200** (0.069)	−0.230** (0.081)	−0.194* (0.083)
ASVAB test	−0.003* (0.001)	−0.004* (0.002)	−0.002 (0.002)
Institutional characteristics			
Public school	0.280*** (0.063)	0.294*** (0.072)	0.290*** (0.077)
Urbanity	−0.019 (0.064)	0.001 (0.073)	−0.059 (0.079)
North Central	0.070 (0.079)	0.034 (0.090)	0.094 (0.098)
South	−0.071 (0.080)	−0.020 (0.092)	−0.157 (0.097)
West	−0.197* (0.094)	−0.191† (0.107)	−0.240* (0.115)
Financial aid[d]			
Loan	−0.035 (0.068)	−0.086 (0.077)	0.029 (0.083)
Scholarship	−0.046 (0.064)	−0.076 (0.073)	−0.010 (0.077)
Family support	−0.147* (0.061)	−0.133† (0.071)	−0.176* (0.075)
Constant	0.749** (0.269)	1.135*** (0.315)	1.398*** (0.326)
LR chi2	149.58	123.70	144.03
Prob > chi2	0.000	0.000	0.000
N	2613	1761	1562

[a] Work intensity is measured by average work hours per week (intense work: 20 h or more; moderate work: less than 20 h; no work: 0 h)

[b] † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[c] Standard errors in *parentheses*

[d] All financial aid variables are dichotomous (receiving aid = 1)

Both educational background variables were statistically significant in all three models except for the ASVAB test score in the intense versus no-work model. High school GPA and ASVAB test scores were negatively associated with engaging in intense work. This result clearly indicates that those who had disadvantaged academic backgrounds were more likely than the other groups to engage in intense work. In terms of institutional characteristics, only public schools had a statistically significant effect—those who attended public colleges were more likely to engage in intense work.

Although most financial aid variables negatively affected the probability of engaging in intense work, only family support had a statistically significant effect in every model. Furthermore, compared with scholarships and loans, family support had a greater effect on selection into intense work.

Lastly, among the demographic variables, family composition had a significant effect in every model. That is, the intense work group was less likely to be living with both biological parents. Family size was only significant when comparing the intense and no-work models: it had a positive effect on engaging in intense work compared with the no-work group. In every model, Black students were less likely to engage in intense work compared with White students and Hispanic students were more likely to engage in intense work compared with White students.

In sum, probit regression results confirm that the intense work group was less likely have advantaged socioeconomic, demographic, and educational backgrounds compared with the moderate and no-work groups. These results also indicate that several key background factors such as parents' education, family composition, prior academic achievements, and family financial support are major determinants of engaging in intense work during college.

Average Effects of Intense Work

Based on estimated propensity scores, I examine the average treatment effect on the treated. Table 3 shows the results of matched and unmatched estimates of engaging in intense work along the three counterfactual models. Intense work had a deleterious effect on first-year retention in both the matching and unmatched models and in every counterfactual scenario. Unmatched differences suggest that the intense work group experienced a dropout rate that was 14% points higher than the moderate work group and 11% points higher than the no-work group. The matching model reduced these estimates for each counterfactual scenario. For example, nearest neighbor matching with five controls suggests that the intense work group experienced a statistically significant dropout rate that was 11% points higher than the moderate work group and a dropout rate that was 7% points higher than the no-work group.

Although the matched estimates were relatively smaller than those of the unmatched model, which lends weight to the selection to work perspective, the overall results clearly favor the deleterious effect perspective. That is, pretreatment heterogeneity does not fully explain the negative relationship between student employment and first-year retention. Considering that the estimates were larger for the intense versus moderate model than for the intense versus no-work model, it appears that the deleterious effects of intense work do not simply result from constraints on the use of time, which is a key argument of the zero-sum explanation of the deleterious effects perspective. If time constraints were the key factor in the negative effects of intense work, the effects of intense work would be greater in the intense versus no-work model. Thus, this result suggests that intensive student

Table 3 Matching estimates of engaging intense work on first-year retention

	Intense versus[a]		
	Anything else	Moderate	No-work
Unmatched differences	0.128***[b] (0.015)[c]	0.141*** (0.017)	0.112*** (0.019)
Nearest neighbor matching ($K = 1$)	0.099*** (0.025)	0.087** (0.026)	0.086** (0.028)
Nearest neighbor matching ($K = 5$)	0.093*** (0.020)	0.112*** (0.021)	0.065** (0.024)
Kernel matching	0.098*** (0.018)	0.109*** (0.019)	0.068** (0.021)

[a] Work intensity is measured by average work hours per week (intense work: 20 h or more; moderate work: less than 20 h; no work: 0 h)

[b] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[c] Standard errors in *parentheses*

employment affects college persistence in more ways than by just reducing the amount of available time to devote to schoolwork.

Heterogeneous Effects of Intense Work

Next, to examine the heterogeneous effects of intense work based on propensity to engage in intense work, I construct a balanced propensity score stratum based on estimated propensity scores. Table 4 summarizes the individual characteristics for those who did or did not engage in intense work by propensity stratum (the intense vs. anything else model). This result confirms again that those who are more likely to engage in intense work have disadvantaged socioeconomic, educational, and demographic backgrounds. For instance, a representative student in stratum 1 had parents with some college, a family income of around $100,000, a 3.5 or greater high school GPA, lived with both parents during high school, and received financial support for college from family. In contrast, a typical student in stratum 5 had parents who are high school dropouts, a family income of around $50,000, a 2.7 high school GPA, lived with a single parent during high school, and did not receive financial support for college from family. This overall trend is very similar to the intense versus moderate and intense versus no-work models.

Based on propensity score strata, I estimate treatment effect heterogeneity using the stratification-multilevel method. Within stratum–specific treatment effects are estimated using a logit model (level 1), then the linear trends of treatment effects are summarized using variance weighted least squares regression (level 2). Figure 1 includes three graphs, one for each counterfactual scenario (Table 5 presents every coefficient and significance for the level 1 and level 2 slopes for all three counterfactual scenarios). The dots in Fig. 1 represent point estimates of level 1 slopes, and the linear plots are the level 2 variance-weighted least squares slopes.

All three graphs clearly depict a decreasing pattern across propensity strata. These results indicate that those who were least likely to engage in intense work faced the most negative consequences from it. That is, the effect of intense work was most deleterious for students from the most advantaged social backgrounds and the least deleterious for those from the most disadvantaged social backgrounds. For example, in Fig. 1a, the level 2 slope for the intense versus anything else model was −0.229. This indicates that a unit change in stratum rank was associated with a −0.229 reduction in the treatment effects, which

Table 4 Mean covariate values by propensity score strata and treatment condition: intense versus anything else

Variables	Propensity score strata									
	Stratum1		Stratum2		Stratum3		Stratum4		Stratum5	
	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1
Demographic characteristics										
Male	0.473	0.483	0.437	0.464	0.456	0.393	0.443	0.452	0.414	0.413
Black	0.231	0.267	0.216	0.247	0.227	0.230	0.228	0.187	0.127	0.126
Hispanic	0.034	0.059	0.104	0.124	0.123	0.131	0.151	0.139	0.304	0.315
Family size	4.110	4.246	4.041	4.175	4.094	3.984	4.133	3.987	4.282	4.385
Both parents	0.873	0.898	0.711	0.711	0.586	0.590	0.417	0.396	0.232	0.175
Socioeconomic characteristics										
Family income	109496.6	97159.07	76953.71	81943.03	66891.14	67942.39	57653.58	57155.28	47358.89	51202.88
Parent's education	15.745	15.039	14.402	14.240	14.063	14.036	13.186	13.478	11.720	11.803
Educational characteristics										
High school GPA	3.467	3.429	3.345	3.225	3.181	3.210	3.080	3.088	2.747	2.796
ASVAB test	79.843	77.568	71.070	71.425	67.401	64.918	57.345	58.434	44.666	45.354
Institutional characteristics										
Public school	0.446	0.483	0.689	0.639	0.757	0.795	0.888	0.909	0.950	0.916
Urbanity	0.770	0.746	0.740	0.804	0.722	0.730	0.724	0.678	0.702	0.748
North Central	0.175	0.136	0.252	0.247	0.317	0.328	0.338	0.322	0.387	0.469
South	0.383	0.364	0.396	0.381	0.366	0.344	0.317	0.335	0.221	0.259
West	0.258	0.254	0.158	0.175	0.126	0.115	0.125	0.135	0.122	0.084
Financial aid[a]										
Loan	0.351	0.347	0.318	0.258	0.246	0.246	0.228	0.261	0.155	0.147
Scholarship	0.614	0.593	0.544	0.485	0.408	0.434	0.353	0.400	0.287	0.224
Family support	0.775	0.763	0.641	0.639	0.502	0.525	0.338	0.344	0.177	0.098

Table 4 continued

Variables	Propensity score strata									
	Stratum1		Stratum2		Stratum3		Stratum4		Stratum5	
	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1	d = 0	d = 1
Outcome[b]										
Dropout rates	0.048	0.144	0.097	0.258	0.107	0.230	0.146	0.196	0.254	0.364
N	590	118	412	97	309	122	391	230	181	143

[a] All financial aid variables are dichotomous (receiving aid = 1)

[b] Outcome variable indicates whether or not a freshmen student return for their sophomore year

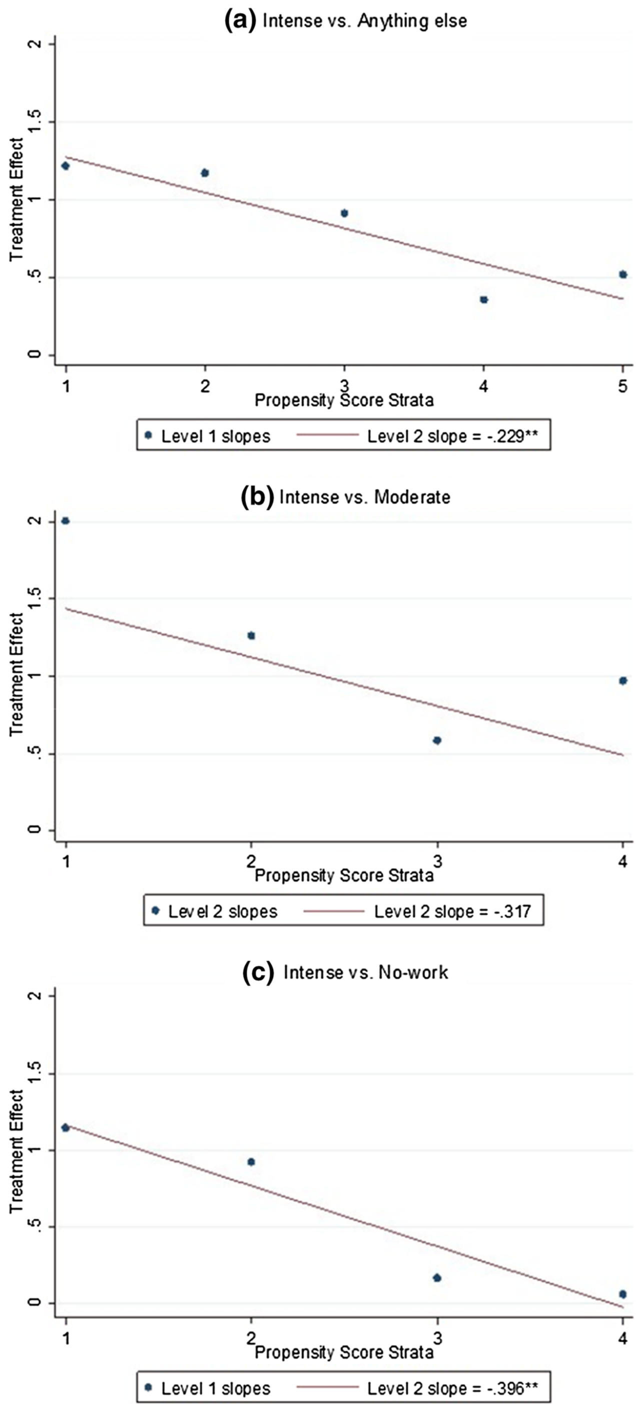

Fig. 1 Stratification multilevel (SM) method for heterogeneous treatment effects

Table 5 Stratification multilevel (SM) estimates of engaging in intense work on first-year retention

	Intense versus		
	Anything else	Moderate	No-work
Level-1			
Stratum1	1.217***[a] (0.326)[b]	2.007 (1.458)	1.143*** (0.251)
Stratum2	1.172*** (0.286)	1.262*** (0.237)	0.918** (0.313)
Stratum3	0.913** (0.283)	0.584** (0.197)	0.162 (0.294)
Stratum4	0.354 (0.219)	0.973* (0.401)	0.056 (0.281)
Stratum5	0.517* (0.244)		
Level-2	−0.119** (0.086)	−0.317 (0.210)	−0.396** (0.120)
N	2613	1761	1562

[a] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[b] Standard errors in *parentheses*

suggests that the risk of dropout by engaging in intensive work decreased as propensity score increased. This decreasing pattern is similarly observed in the intense versus moderate and intense versus no-work models. The level 2 slope of intense versus moderate was −0.317, and the level 2 slope of intense versus no-work model was −0.396.

Discussion and Conclusion

This study explores how student employment affects dropout rates and how these effects differ by the likelihood that an individual will participate in the labor market as a student. These two questions arise from concerns of stratification and from those seeking to address issues such as how marginalized students manage their disadvantaged economic situation and bring about positive results from their time in college. The key findings of this study are as follows. First, engaging in intense work has significant deleterious effects on first-year retention. The magnitude of the average effects is larger for the intense versus moderate than the intense versus no-work model, and this provides some evidence that the effects of student employment vary by work intensity. Second, the effects of intense work vary significantly by propensity to participate in intense work, and the patterns of treatment effect heterogeneity suggest that those who are least likely to engage in intense work are penalized most from it. This means that engaging in intense work has a more negative impact on students from more advantaged social backgrounds, while its effects are very small for students from the most disadvantaged social backgrounds.

There are two possible explanations for the patterns of treatment effect heterogeneity observed in this study. First, different counterfactuals between low and high propensity students may influence this pattern. High propensity students who do not engage in intense work already have extremely high dropout rates, and this can mask the effects of intense work on dropout. That is, regardless of work engagement, disadvantaged students often drop out for other reasons. In contrast, dropouts for low propensity students is relatively rare, and thus the impact of intense work on dropout is relatively larger for high propensity students. Second, the fact that high propensity, intense work students are penalized the least from engaging in intense work could be due to their low socioeconomic status. That is, without engaging in intense work during college, they would not be able to pay their tuition or living expenses. Considering that low- and high-propensity students have vastly different financial situations, it is reasonable to expect that the purpose of work is significantly different between those two groups. Therefore, different financial conditions and purpose of work between low and high propensity students may affect the observed patterns of treatment effect heterogeneity.

These results have two key implications. First, for advantaged students, engagement in intense work should be carefully considered. Although job experience is considered to be an important requirement for labor market entrance, it can also threaten bachelor's degree completion. Therefore, unless it is necessary for financial purposes for college retention, advantaged students should carefully consider their employment options when deciding to participate in student employment. Second, although disadvantaged students are less penalized from engaging in intense work, participating can still be problematic for several reasons. For example, spending a great amount of time on work reduces time for school, which can contribute to bad grades or a lack of socialization in college (Pike et al. 2008; Tinto 1993). Considering that one's grades can also affect successful transition from college to work, this could reduce returns to education for disadvantaged students, even if they do complete a bachelor's degree. Given these findings, the provision of sufficient financial aid to disadvantaged students to help them to balance work and study would be one way to address educational inequality in the United States.

This study has several limitations. First, the key methodological approaches employed in this study—propensity score matching and stratification multilevel methods—rely on the ignorability assumption. Although I carefully considered both the theoretical backgrounds and prior studies to include various covariates to predict engagement in student employment, there is always the possibility of unobservable causal mechanisms. Thus, it is important to note that the causal effects of student employment on dropout have not been established, and the validity of findings of this study greatly depends on the plausibility of the covariates of the current model.

Second, I focus only on full-time students who attended 4-year colleges. Since this sample selection is restrictive, the results of this study cannot be generalized to a broader population that includes those who attend community colleges or part-time students. Lastly, due to data limitations, this study cannot utilize the purpose of work and job types as a treatment variable. Further research that considers employment type and work purpose is necessary to more fully assess the effect heterogeneity of intense work.

In conclusion, this study deepens our understanding of student employment by demonstrating that the effect of employment on dropout is heterogeneous depending on not only work intensity but also on the individual's propensity to work outside of school. Many prior studies have identified two factors regarding the relationship between college student employment and dropout: disadvantaged students are more likely to engage in employment during college and the average effect of student employment on dropout is negative. These two findings could be easily interpreted to mean that student employment is a major factor in exacerbating educational inequality between students of differing socioeconomic status. However, the observed heterogeneous effects of college employment in the current study suggest a more complex relationship between student employment and first-year retention. For example, the most disadvantaged students often have to work to fund their schooling, and the data indicate that doing so does not greatly increase their risk of dropout. However, there is still the possibility that engagement in intense work by disadvantaged students may have a deleterious effect on other factors of school life. Given the high prevalence of student employment in the current educational context, therefore, the findings of this study emphasize that the effort to reduce the deleterious effects of intense work should be practiced with careful consideration for sub-populations that have different reasons for and effects of student employment.

References

Astin, A. W. (1993). *Preventing students from dropping out*. San Francisco: Jossey-Bass.

Aughinbaugh, A., & Gardecki, R. M. (2008). *Attrition in the National Longitudinal Survey of Youth 1997* (Working Paper).

Bachman, J. G., & Schulenberg, J. (1993). How part-time work intensity relates to drug use, problem behavior, time use, and satisfaction among high school seniors: Are these consequences or merely correlates? *Developmental Psychology, 29*(2), 220.

Bean, J. P. (1985). Interaction effects based on class level in an explanatory model of college student dropout syndrome. *American Educational Research Journal, 22*(1), 35–64.

Bozick, R. (2007). Making it through the first year of college: The role of students' economic resources, employment, and living arrangements. *Sociology of Education, 80*(3), 261–285.

Brand, J. E., & Halaby, C. N. (2006). Regression and matching estimates of the effects of elite college attendance on educational and career achievement. *Social Science Research, 35*(3), 749–770.

Brand, J. E., Pfeffer, F. T., & Goldrick-Rab, S. (2014). Interpreting community college effects in the presence of heterogeneity and complex counterfactuals. *Sociological Science, 1,* 448–465.

Brand, J. E., & Simon-Thomas, J. (2013). Causal effect heterogeneity. In S. L. Morgan (Ed.), *Handbook of causal analysis for social research*. New York: Springer.

Brand, J. E., & Xie, Y. (2010). Who benefits most from college? *American Sociological Review, 75*(2), 273–302.

Braxton, J. M. (1988). Causal modeling and path analysis: An introduction and an illustration in student attrition research. *Journal of College Student Development, 29*(3), 263–272.

Braxton, J. M. (2000). *Reworking the student departure puzzle*. Nashville: Vanderbilt University Press.

Canabal, M. E. (1998). College student degree of participation in the labor force: Determinants and relationship to school performance. *College Student Journal, 32*(4), 597–605.

Coleman, J. S. (1961). *The adolescent society*. Glencoe: Free Press.

D'Amico, R. (1984). Does employment during high school impair academic progress? *Sociology of Education, 57*(3), 152–164.

Entwisle, D. R., Alexander, K. L., & Olson, L. S. (2000). Early work histories of urban youth. *American Sociological Review, 65*(2), 279–297.

Entwisle, D. R., Alexander, K. L., & Olson, L. S. (2005). Urban teenagers. *Youth & Society, 37*(1), 3–32.

Greenberger, E., & Steinberg, L. D. (1986). *When teenagers work: The psychological and social costs of teenage employment*. New York: Basic Books.

Hebel, S. (2000). States without affirmative action focus on community-college transfers. *Chronicle of Higher Education*.

Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology, 38,* 379–400.

Iwai, S. I., & Churchill, W. D. (1982). College attrition and the financial support systems of students. *Research in Higher Education, 17*(2), 105–113.

Johnson, M. K. (2004). Further evidence on adolescent employment and substance use: Differences by race and ethnicity. *Journal of Health and Social Behavior, 45,* 187–197.

Kablaoui, B. N., & Pautler, A. J. (1991). The effects of part-time work experience on high school students. *Journal of Career Development, 17*(3), 195–211.

Lee, J. C., & Staff, J. (2007). When work matters: The varying impact of work intensity on high school dropout. *Sociology of Education, 80*(2), 158–178.

Marsh, H. W. (1991). Employment during high school: Character building or a subversion of academic goals? *Sociology of Education, 64*(3), 172–189.

Marsh, H. W., & Kleitman, S. (2005). Consequences of employment during high school: Character building, subversion of academic goals, or a threshold? *American Educational Research Journal, 42*(2), 331–369.

Metzner, B. S., & Bean, J. P. (1987). The estimation of a conceptual model of nontraditional undergraduate student attrition. *Research in Higher Education, 27*(1), 15–38.

National Center for Education Statistics [NCES]. (2010). *Digest of education statistics*. Washington, DC: U.S. Department of Education.

National Research Council. (1998). *Protecting youth at work: Health, safety, and development of working children and adolescents in the United States*. Washington, DC: National Academy Press.

Orszag, J. M., Orszag, P. R., & Whitmore, D. M. (2001). *Learning and earning: Working in college*. Newton: Upromise Inc.

Pascarella, E. T., & Chapman, D. W. (1983). A multiinstitutional, path analytic validation of Tinto's model of college withdrawal. *American Educational Research Journal, 20*(1), 87–102.

Perna, L. W. (2010). Toward a more complete understanding of the role of financial aid in promoting college enrollment: The importance of context. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (Vol. 25, pp. 129–179). New York, NY: Springer.

Pike, G. R., Kuh, G. D., & Massa-McKinley, R. C. (2008). First-year students' employment, engagement, and academic achievement: Untangling the relationship between work and grades. *Journal of Student Affairs Research and Practice, 45*(4), 1012–1034.

Rampell, C. (2011). Are young college grads too lazy to work? *New York Times*.

Riggert, S. C., Boyle, M., Petrosko, J. M., Ash, D., & Rude-Parkins, C. (2006). Student employment and higher education: Empiricism and contradiction. *Review of Educational Research, 76*(1), 63–92.

Roksa, J. (2011). Differentiation and work: Inequality in degree attainment in US higher education. *Higher Education, 61*(3), 293–308.

Roksa, J., & Velez, M. (2010). When studying schooling is not enough: Incorporating employment in models of educational transitions. *Research in Social Stratification and Mobility, 28*(1), 5–21.

Rosenbaum, J. E., Deli-Amen, R., & Person, A. E. (2006). *After admission: From college access to college success*. New York: Russell Sage Foundation.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Schoenhals, M., Tienda, M., & Schneider, B. (1998). The educational and personal consequences of adolescent employment. *Social Forces, 77*(2), 723–761.

Spady, W. G. (1970). Dropouts from higher education: An interdisciplinary review and synthesis. *Interchange, 1*(1), 64–85.

Staff, J., Schulenberg, J. E., & Bachman, J. G. (2010). Adolescent work intensity, school performance, and academic engagement. *Sociology of Education, 83*(3), 183–200.

Stage, F. K. (1988). University attrition: LISREL with logistic regression for the persistence criterion. *Research in Higher Education, 29*(4), 343–357.

Stage, F. K., & Hossler, D. (1989). Differences in family influences on college attendance plans for male and female ninth graders. *Research in Higher Education, 30*(3), 301–315.

Steinberg, L. D., Fegley, S., & Dornbusch, S. M. (1993). Negative impact of part-time work on adolescent adjustment: Evidence from a longitudinal study. *Developmental Psychology, 29*(2), 171.

Steinberg, L. D., Greenberger, E., Garduque, L., & McAuliffe, S. (1982). High school students in the labor force: Some costs and benefits to schooling and learning. *Educational Evaluation and Policy Analysis, 4,* 363–372.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*(1), 89–125.

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago: University of Chicago Press.

Warren, J. R., LePore, P. C., & Mare, R. D. (2000). Employment during high school: Consequences for students' grades in academic courses. *American Educational Research Journal, 37*(4), 943–969.

Worley, L. P. (1995). Working adolescents: Implications for counselors. *The School Counselor, 42*(3), 218–223.

Xie, Y., Brand, J. E., & Jann, B. (2012). Estimating heterogeneous treatment effects with observational data. *Sociological Methodology, 42*(1), 314–347.