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Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students

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ABSTRACT

A growing number of students are working while in college and to a greater extent. Using nationally representative data from the 1997 National Longitudinal Survey of Youth, I analyze the effect of working on grades and credit completion for undergraduate students in the United States. Strategies to identify the causal relationship between working and academic performance include student-level fixed effects to control for permanent, unobserved characteristics that may affect both work and study intensity, and system GMM models to account for potentially endogenous relationships between working and academic performance that vary over time. I examine the consequences of working for heterogeneous subgroups, with a particular focus on differences between full-time and part-time students. I find no evidence that students' grades are harmed by marginal work hours, but that full-time students complete fewer credits per term when increasing work.
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1. Introduction

A growing number of students turn to work in an effort to close the gap between college costs and available financial resources. Over 80 percent of all undergraduate students work while in school and recent students are both more likely to work and work more hours than in the past (Baum, 2010; Scott-Clayton, 2012). Even among "traditional" full-time college students less than 25 years of age, almost half work, with almost one in ten working at least 35 h a week (Perna, 2010). As working increasingly becomes commonplace among postsecondary students, the relationship between working and postsecondary educational outcomes has potentially important implications for the design and implementation of academic, vocational, and work-study programs, as well as for workforce training.

Working while in school can lead to better labor market outcomes for students through the accrual of work experience, professional connections, and the development of soft skills (such as time management, communication skills, and problem-solving) that contribute to academic and professional success (e.g., Light, 2001; Meyer & Wise, 1982; Molitor & Leigh, 2004; Ruhm, 1997). The complementary relationship between employment and academics may encourage colleges, employers, and public and private training providers to better coordinate cooperative training and workforce programs with postsecondary education. These vocational burdens on students, however, may impair academic achievement and experiences by substituting for time spent on studies and extracurricular activities.

In spite of the substantial postsecondary in-school work participation, only a few studies have used empirical approaches that control for potentially endogenous relationships among working and academic performance and there is little extant research examining the effects of working across heterogeneous types of students. In an

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effort to focus on closely comparable students, past research has frequently focused narrowly on samples from one school (e.g., Stinebrickner & Stinebrickner, 2003), while the few national studies have limited scopes (for example, Ehrenberg and Sherman (1987) analyze males who went to school full-time and Kalenkoski and Pabilonia (2010) focused on students in their first academic term). As such, extant research provides little evidence about the effects of working for a key segment of working students: students who attend school part-time. This gap in the literature is notable because part-time students work at higher rates and for more hours than their full-time counterparts, and these students comprise a large (almost 40 percent) and growing proportion of postsecondary students.[1]

Using a nationally representative sample of undergraduate students in the US from the National Longitudinal Survey of Youth 1997 ("NLSY97"), I analyze the effect of working on grades and credit completion across genders, races and ethnicities, and college types (four-year, two-year) for students' full tenure in college. In addition, the study provides some of the first estimates of the distinct effects of variation in work hours on academic performance between full-time and part-time students.

Determining the effects of working on academic performance is difficult, as students may endogenously choose the number of hours to allocate to work and study. Postsecondary academic performance can be correlated with personal background (e.g., Betts and Morell, 1999), such that unobserved personal characteristics, such as motivation or work ethic, may lead to strong academic performance as well as participation in the labor market. These factors could affect both the intensity of work (i.e., the intensive margin) and the decision to work or not (i.e., the extensive margin). To address this, I use student-level fixed effects to identify impacts based on variation in work behavior for each individual. Additionally, I use the system generalized methods-of-moments ("GMM") estimator to account for potentially dynamic relationships between hours worked and academic outcomes with and without instruments for plausibly exogenous determinants of financial resource availability.

I use two measures of academic performance as outcomes in this study: undergraduate students' grade point averages ("GPA") and credits completed. While the direct causal effect of grades on downstream outcomes is difficult to disentangle, college grades are transparently a determinant of admission into graduate schools, and evidence suggests that grades are associated with better labor market success (e.g., Loury & Garman, 1995; Wise, 1975). As well, grades can influence self-esteem and motivation (e.g., Crocker, Karpinski, Quinn, & Chase, 2003), which may affect persistence in school and overall well-being. Furthermore, an examination of credits contributes to the understanding of students' increasing time-to-degree over the last several decades (Bound, Lovenheim, & Turner, 2010). Policymakers have shown growing concern with increasing time-to-degree, with multiple states implementing legislation, initiatives, and studies to address college completion time.[2] Taking longer to complete degrees has macroeconomic implications by lowering the supply of college-educated workers and potentially raising public costs through federal and state subsidies for higher education (Turner, 2004). Taking fewer credits per term, moreover, may result in substantial forgone earnings for students, though these costs may be lesser for workers who are attending school as a secondary activity. Students who take longer to finish their degree also are less likely to graduate or complete their educational programs (Carroll, 1989; O'Toole, Stratton, & Wetzel, 2003).

I do not find harmful effects of marginal work hour increases on student grades in the sample. One reason for this could be a declining amount of time spent studying by students in recent years (e.g., Babcock & Marks, 2011), such that increased working is substituting for non-academic activities instead of study time. I find, however, a negative relationship between work hours and credit completion for full-time students. Therefore, students appear to reduce course loads when increasing work, which may be potentially concerning for policymakers. I find little conclusive evidence of effects of working on part-time students, suggesting that part-time student responses to working are distinct from those of full-time students.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical framework for the study and related literature. Section 3 presents the empirical identification strategy, and Section 4 describes the data. Section 5 discusses findings and Section 6 concludes.

2. Theoretical framework and related literature

Employment during school can have both negative and positive effects on students' academic performance. Since students have fixed time resources, time spent working might substitute for time spent on academic, social, leisure, or extracurricular activities. This can negatively affect academic performance, social integration, or student well-being. For example, time spent working may crowd out time spent studying. Given research demonstrates a positive relationship between study time and GPA (e.g., Stinebrickner & Stinebrickner, 2004, 2008), decreases in study time would be expected to have a negative impact on academic performance. Furthermore, time spent working may hinder students' opportunities to involve themselves in the academic and social community, with such integration believed to promote greater commitment to one's studies at the institution (e.g., Tinto, 1993).

Working, on the other hand, has benefits that could lead to improved academic performance for some students. Occupational activities can complement academic lessons by providing applied context, and work time could

[1] Author's calculations based on Snyder and Dillow (2011) and NLSY97.

[2] For example, "The Rhode Island Bachelor's Degree in Three Program Act" or Ohio's "Seniors to Sophomores" program, as well as initiatives in Connecticut, Texas, Florida, Tennessee, and North Carolina, among other states.

encourage students to use their time more efficiently by providing structure to students' schedules. Working can also aid in the development of soft skills that have value in both academic and vocational settings, such as communication, problem-solving, adaptability, responsibility, organization, and working under pressure. Some types of work, such as research opportunities with professors or jobs that employ a large number of students' peers, may aid in campus and social integration.

Students' time-use will influence how much increased work time might substitute for study time. At a high school level, research indicates that working decreases academically productive study time and also non-academically productive time watching television, but has no effect on sleep time during school days (DeSimone, 2006; Kalenkoski & Pabilonia, 2009, 2012). Babcock and Marks (2011) present evidence that college students are allocating less time toward class and study time than in the past (down from 40 h per week in 1961 to 27 h per week in 2003). Therefore, with less time allocated toward academic studies, work hours may not be crowding out a substantial amount of current college students' study time, but instead substituting for leisure or other non-academically productive activities.

At a postsecondary level, descriptive research has generally found a positive association between moderate levels of work hours and grade point average (e.g., Hood, Craig, & Ferguson, 1992; Pascarella & Terenzini, 2005).[3] Using econometric approaches, however, researchers have generally, but not universally, found that each marginal hour worked reduces GPA by a small amount.[4] Kalenkoski and Pabilonia (2010) use a simultaneous equations strategy and find a negative impact of working on students' first semester GPA for both four-year and two-year college students using the NLSY97. An important contribution of these authors was their consideration of the financial reasons why students work, which had not been directly addressed in prior studies on the topic. Scott-Clayton (2011) examines specifically federal work-study employment using a difference-in-difference approach and finds that increases in hours result in reductions in GPA, on average. Using student-level fixed effect estimations, Stinebrickner and Stinebrickner (2003) find small positive effects of marginal work hours. A limitation to the broader inference of this latter study is that the authors use a sample of full-time students at one small liberal arts college with mandatory work requirements.

As discussed below in Section 3, concerns about time-invariant endogeneity of work and study time may bias estimates of the academic consequences associated with work. In response, some researchers use two-stage models to predict the number of hours worked by each student and then compare the relationship between predicted hours and academic outcomes. Stinebrickner and Stinebrickner (2003) use job type to instrument for the number of hours worked, while Ehrenberg and Sherman (1987) predict work hours from a model which includes a vector of student and family background variables, prior period GPA, and students' work hours in high school. The latter authors use more expansive national data from the National Longitudinal Survey of the High School Class of 1972, but narrow their focus to full-time male students only. Using this approach, both of these sets of researchers find small adverse consequences of each work hour on grades.

With respect to the evidence of effects of working on college persistence and credit completion in the existing literature, Scott-Clayton (2011) finds a positive relationship between federal work study and credits earned in students' first year. Ehrenberg and Sherman (1987) find that longer work hours are associated with lower persistence for two-year and four-year college students, but for those who stayed in school, longer hours increased the probability of graduating on time for two-year students. For four-year college students, on-campus work positively affected graduating on time, while off-campus work had the opposite effect.

3. Identification

3.1. Fixed effects models

I examine empirical relationships of interest using several approaches. I begin with a discussion of the following simple relationship between outcome y (GPA[5] or number of credits completed) for individual i in each year t as a linear function of the number of hours worked and student characteristics:

$$y_{it} = \beta_0 + \beta_1 Hours_{it} + \beta_2 PT_{it} + \beta_3 (PT \times Hours)_{it} + \eta X_{it} + d_t + \varepsilon_{it} \qquad (1)$$

Here *Hours* represents the number of hours each student worked in year t; *PT* is an indicator for being a part-time student; the X vector includes student-level controls that may affect academic outcomes (described in more detail below); d_t is a vector of year dummies to account for any effects that may vary over time that are common to all students in the sample; β_1, β_2, β_3, and η are

[3] See Riggert, Boyle, Petrosko, Ash, and Rude-Parkins (2006) for a review of qualitative literature.

[4] The literature studying the relationship between working and academic performance in high school is more developed than for college students. Ruhm (1997) provides a review of the literature and concludes that while there is no consensus on whether working results in net benefits or costs for high school students, small to moderate amounts of work appear to be associated with some benefits, while hindered academic performance is most likely associated with substantial work intensity. More recent research by Montmarquette, Viennot-Briot, and Dagenais (2007) find some detrimental effects of working more than fifteen hours for Canadian high school students.

[5] Though GPA is bounded by [0,4], I use OLS estimation for ease of interpretation and to be able to efficiently estimate a fixed effects model. Where corollary estimates are possible, results are similar when using a Tobit model. The use of OLS follows other literature examining the relationship between work and GPA (e.g., Oettinger, 1999; Stinebrickner & Stinebrickner, 2003) as well as many other papers in the economics of education literature (e.g., Betts & Morell, 1999; Jacob, 2004; Sacerdote, 2001).

parameter vectors; and ε is an error term. All estimates use survey weights.[6]

Because I am particularly interested in heterogeneity across full-time and part-time students, I allow the effects of these subgroups to differ.[7] Part-time students may respond to financial and time constraints distinctly from full-time students. Demographically, part-time students are more likely to be older, married, and financially independent, but with relatively disadvantaged academic and economic backgrounds (Chen & Carroll, 2007). Part-time students may enjoy lower per-term costs of attendance and greater flexibility to undertake nonacademic activities such as working. On the other hand, part-time students are associated with lower rates of persistence (e.g., Chen & Carroll, 2007; O'Toole et al., 2003) and nontraditional students (including adult, independent, and part-time students) may face different barriers to access financial aid (Seftor & Turner, 2002).

The coefficient β_1 can be interpreted as the relationship between academic outcome and each marginal hour worked for full-time students, while $(\beta_1 + \beta_3)$ is the marginal effect for part-time students. Given fixed time constraints to work and study, the choice of full-time or part-time status may be endogenously selected in the model. To account for this, I add a selection correction term based on Heckman (1976) and Lee (1978) that accounts for the probability students attend postsecondary coursework full-time or part-time in the fixed effects models.[8]

Eq. (1) relies on a selection on observables strategy, where the inclusion of observed personal characteristics in X is an attempt to diminish endogeneity and selection bias (e.g., Barnow, Cain, & Goldberger, 1980; Heckman & Hotz, 1989). Though a robust set of controls that can be included in X are available in the data, many other factors, such as motivation, energy levels, work ethic, social and peer networks, familiarity with labor market returns, parental connections, socioeconomic status and attitudes toward financial aid, that could plausibly affect both work decisions and academic outcomes are unobserved. For example, highly motivated students may choose high levels of both work time and study time. A less driven student or a student with long-term family care responsibilities may conversely have little time to devote to work or study. These unobserved factors are included in ε, and if $Cov(Hours, \varepsilon|X) \neq 0$, then estimates of the hours effects can be biased and it may not be possible to draw causal inference from estimation of the prior equations.

In an effort to mitigate omitted variable bias, I estimate Eq. (1) including a student-level fixed effect that controls for time invariant unobserved student specific factors that may affect both academic performance and work behavior. Some examples of these influences are inherent ability and family connections, and I assume that important characteristics such as an individual's motivation and work ethic do not vary substantially over the time a student is in school. By controlling for the student fixed effect, I identify the effect of working on GPA off changes over time for the same student. I note that the fixed effect comes at the cost of increased sampling variability. Since the student fixed effect controls for both unobserved and observed permanent characteristics, time invariant observed factors such as race/ethnicity or family socioeconomic background drop out of the model leaving in X only factors that can change over time: college sector (four-year, two-year), tuition, student attendance status (full-time, part-time), and indicators for college major (business, social sciences, humanities and arts, nursing and health, education, science and engineering, undecided/unknown).[9] In the estimations of GPA, I include in X the number of credits taken in the year to account for variation in grades due to lessening or increasing workload. From the student fixed effects model, one can interpret the parameter estimates β_1 and $(\beta_1 + \beta_3)$ as the marginal effects on GPA or credits for each additional hour worked by full-time and part-time students in the sample respectively, controlling for any time-invariant factors that may affect both work and study.

In addition to the estimations on the pooled sample of students, I relax the assumption that estimated parameters in η from Eq. (1) are constant across gender and school sector (four-year vs. two-year) and estimate separate regressions for these groups to examine potentially different responses. Compared to males, females may have distinct characteristics or experiences that affect attitudes toward work and study, such as access to family resources, expectations regarding labor force participation, expected returns to college, or maturity levels that affect college preparation (Buchmann, DiPrete, & McDaniel, 2008; Goldin, 2006; Goldin, Katz, & Kuziemko, 2006). Extant research also provides evidence that female and

[6] Estimates with an indicator for working any hours are similar to estimates reported. Piecewise regression models using linear splines with various hour ranges reveal little evidence of statistically significant non-linear relationships.

[7] Full-time/part-time enrollment is defined using respondents' statuses as reported in the survey (see Section 4). Approximately 20 percent of students switch between full-time and part-time status at some point during their college tenure. For these students, I consider them in the attendance status group according to their status for that year.

[8] Specifically, for each student status, S (full-time, part-time), I first estimate by probit, $P(S_{it}|X_{it}) = \Phi(Z_{it}\gamma_s)$, where Φ is the standard normal cumulative density function and Z includes all covariates in X as well as the unemployment rate of the student's resident county (similar to Kalenkoski and Pabilonia (2010)) to satisfy the exclusion restriction. Here, $\hat{\lambda}_{it}^{S} = \lambda(Z_{it}\hat{\gamma}_S))$ is the inverse Mills ratio (i.e., $\lambda(Z_{it}\hat{\gamma}_S) = \phi(Z_{it}\hat{\gamma}_S)/\phi(Z_{it}\hat{\gamma}_S)$, where ϕ is the standard normal probability density function and Φ is the standard normal cumulative density function), with parameter, ρ. The second stage of the estimation is estimated using OLS, following Lee (1978). I note that in certain circumstances, standard errors may not be efficiently estimated, but both Wooldridge (2003) and Lee (1978) note that this will typically not result in important differences. As well, in my preferred estimations with student-fixed effects, tests of selection bias (H_0: $\rho = 0$) reveal little sample selection problem, such that OLS standard errors should be correctly estimated (Wooldridge, 2003).

[9] I display estimates from OLS models without fixed effects in Appendix Table A1 to provide a comparison against prior research. In these estimations, in addition to the covariates included in the fixed effects model, X includes race/ethnicity, gender, state, Armed Services Vocational Aptitude Battery ("ASVAB") score percentile, parents' income, and parents' education. The ASVAB is an academic and occupational aptitude test. More information is available at http://official-asvab.com/index.htm.

male students respond differently to financial incentives and constraints in a postsecondary setting, such that students of different genders may also deal with work demands distinctly (e.g., Angrist, Lang, & Oreopoulos, 2009; Dynarski, 2008).

The effects of working may vary across school sector (four-year vs. two-year in this study) as well. Socioeconomic backgrounds are on average different, with wealthy students increasingly concentrated in selective four-year colleges and poor students increasingly concentrated in two-year colleges (e.g., Bastedo & Jaquette, 2011). Students at two-year schools are more likely to be older, attend part-time, and come from families with lower educational attainment (Kane & Rouse, 1999). Moreover, academic programs may be different at four-year and two-year colleges. Two-year colleges may be more likely to offer academic programs with strong vocational connections and also provide class schedules convenient to working students.

3.2. Dynamic models and exogenous determinants of financial resource availability

If unobserved time-invariant factors are the only source of bias in the model, results from the fixed effects estimations should allow causal inference of the effect of work hours on academic performance. In addition to time-invariant factors, however, another potential source of endogeneity may remain with ambiguous expected bias. Students may endogenously determine work and study time use allocations in a manner that varies by period. For example, students may choose to work less in periods when they expect to have particularly difficult academic responsibilities or to work more in periods when they expect to have less difficult academic responsibilities. As well, health, financial, or lifestyle shocks may affect both work and study intensity in any period. For example, a death in a student's family may cause students to exert low levels of effort, while a new diet or exercise routine may provide a student with extra energy to devote to work and study. These actions in prior and current periods, moreover, may influence decisions on behavior in future periods. Failure to consider these factors could potentially result in biased estimates, though it is difficult *a priori* to predict the direction of such bias, if it exists.

To address this potential issue, one strategy used in past research is to treat the choice of work hours as endogenously determined. In this approach, researchers have used observable and/or exogenous factors to predict hours worked for each student and then examined the relationship between predicted hours and academic performance (e.g., Ehrenberg & Sherman, 1987; Stinebrickner & Stinebrickner, 2003).[10] In a similar spirit, I use the system GMM estimator to account for the potentially dynamic relationship between hours worked and outcomes.[11] A lagged term for the outcome variable is added on the right hand side of the equation,

$$y_{it} = \alpha y_{i,t-1} + \delta_1 Hours_{it} + \delta_2 PT_{it} + \delta_3 (PT \times Hours)_{it} + \eta X_{it} + d_t + \varepsilon_{it} \tag{2}$$

In difference GMM estimation (e.g., Arellano & Bond, 1991), Eq. (2) is first-differenced to eliminate time-invariant unobserved effects and the lagged endogenous outcome variable is instrumented with earlier lags. The system GMM estimator adds first-differenced regressors as instruments in the original equation, such that a system of both the levels and differences equations is estimated. An assumption with the system GMM estimator is that the first-differences of the instruments are uncorrelated with time-invariant student fixed effects. Because hours worked may also be endogenous, I analogously instrument current and lagged full-time and part-time hours with earlier lags of these variables. Year dummy variables and the same time-variant covariates included in X from Eq. (1) are included, with state indicators excluded to reduce the number of instruments.

A concern with the dynamic model is serial correlation in errors. The estimator differences out the time invariant component of the error term, such that autocorrelation in the remaining idiosyncratic error would indicate potentially invalid instruments. To test for this, I report the second-order Arellano–Bond (1991) test for serial correlation in differences. To examine support for exogeneity assumptions, I report the Hansen (1982) *J*-test. The number of instruments used in system GMM can also give rise to concern about the use of too many instruments (e.g., Roodman, 2009b). Because of the large sample sizes, however, all estimations have numbers of observations and groups that well exceed the number of instruments (Roodman, 2009a,b). As well, I report the difference-in-Sargan test of instrument subsets.

In addition to estimates from the dynamic model, I present estimates where I add two exogenous instruments that affect students' available financial resources and therefore work behavior to the dynamic panel estimation. Bound et al. (2010) present evidence that a rationale for increased working by students in recent years is in response to higher college costs. As such, students with less access to financial resources to meet college costs will likely be more constrained in their ability to adjust work hours. I instrument for hours worked using plausibly exogenous factors that affect financial need – variation in area house prices and credit scores. When house prices increase, families have increased ability to tap into home equity to transfer to students for use against postsecondary educational expenses, lessening the need for students to work in order to cover college costs. Lovenheim (2011) provides evidence that fluctuations in house prices affect financial decisions related to college, with rises in housing

[10] Estimates of the relationship between academic performance and working for full-time students using lagged hours of work as internal instruments are included in Appendix Table A2, though results are imprecisely estimated.

[11] See Arellano and Bover (1995) and Blundell and Bond (1998). For more recent application in the economics of education literature, see, for example, Bachmann and Boes (2012). I use estimation based on the *xtabond2* Stata command (Roodman, 2009a).

wealth increasing the likelihood of college enrollment. The effect of house price changes on enrollment is attributed to credit constraints and not wealth effects since increases in housing wealth appear to most positively affect low-income families.

Changes in creditworthiness can also affect financial resource availability through access to student loans and other credit. Private lenders may differentially provide access to neighborhoods based on area credit quality, where, as consistent with average cost pricing, lenders would charge higher average prices and/or restrict credit in areas with higher risk of default. While this relationship is yet to be empirically examined in great detail, Ionescu and Simpson (2010) find evidence suggesting that higher individual credit scores are associated with more investment in college education.

Though exclusion restrictions are difficult to empirically prove, I argue that variation in housing prices and credit quality are largely out of the individual's control and should not affect academic performance, except through work behavior. Possibly, financial resource availability could affect the ability to buy a car and therefore may affect the costs to the student of commuting to campus or a job. A potential concern may be the effect of residential sorting on college decisions (e.g., Nelson, 2010). However, it is likely that families choose neighborhoods based on absolute levels of area house prices and general creditworthiness, and not short term changes in the levels of these factors. Therefore, the use of deviations from average housing prices and creditworthiness for each student arguably mitigates concerns about residential sorting. As with the prior estimations, I report overidentifying restriction tests to consider exogeneity.

4. Data

I use the nationally representative 1997 National Longitudinal Survey of Youth collected by the US Bureau of Labor Statistics as the source of student level records in this study. The NLSY97 annually surveys approximately 9000 youth who were 12–16 years of age in 1996. The data contain information on educational outcomes and experiences, as well as demographic and financial data. I exclude from the sample graduate students and survey responses that report no college attendance in that year. I include only students with work hours up to 40 h per week and GPAs in the range [0.0, 4.0] (with all GPAs converted to a 0–4 scale). I average the GPA for each student in each year. Credits completed in each year include both credits toward bachelor's and associate's degrees, but not toward graduate degrees. As the measure of hours worked, I take the average hours worked for each student in each year during two reference weeks (the second weeks of February and October). Full-time/part-time enrollment is defined using respondents' statuses as reported in the survey (using the *sch_college_degree* family of event history variables). Therefore, it should be noted that this distinction reflects respondents' own identification of their enrollment status.

Parental transfers in the data include money received from parents (as well as grandparents, friends, and others) to pay for educational expenses that the student does not expect to repay. Loans include both government-subsidized loans and other types of loans (but not loans from family members) for postsecondary education purposes. I obtained access to restricted NLSY97 geo-coded data containing information on students' geographic location (state, county, MSA) and postsecondary school identifier. Using this identifier, I obtain from the Integrated Postsecondary Education Data System ("IPEDS") (an annual survey of postsecondary institutions collected by the US Department of Education), the average gross tuition (based on in-state tuition for full-time students) as a measure of the relative cost of the institution for each school attended.

Unemployment rates come from the Local Area Unemployment Statistics program from the US Bureau of Labor Statistics. The house price index comes from yearly MSA level data provided by the Federal Housing Finance Agency. These data are constructed through a repeat sales index of single family homes that have been purchased by Freddie Mac or Fannie Mae. As the data source for area credit scores, I merge the NLSY97 with private credit score data from one of the three major credit score providers. These data include a random sample of proprietarily created credit scores for 5,000,000 individuals in each year from 1999 through 2008 across the United States, which I aggregate at a county-urban/rural level.

I include in Table 1 summary statistics for the analysis sample. Full-time students have an average GPA of 3.18 with a standard deviation of 0.48, while part-time students have an average GPA of 3.13 with a standard deviation of 0.52. Part-time students work about six hours per week more on average than full-time students (21.9 h as compared to 15.9 h), and with more variance of work hours (standard deviations of 12.7 h vs. 10.6 h). Students in the sample also have substantial "within-student" variation in hours worked, with the average range of hours worked of about 13 h.

Part-time students have lower average ASVAB scores, lower high school GPAs, and come from households with lower incomes and parental education levels. Full-time students are more likely to attend a four-year college and are more likely to be non-Hispanic white. Full-time students are more likely than part-time students to major in science and engineering and the social sciences, while part-time students are more likely to major in nursing and health disciplines.

While the NLSY97 is among the most robust national data sets available to examine this topic, many key data fields, including GPA, credits, and work hours are self-reported, leaving open the possibility of measurement error. Grubb (1997) compares self-reported to transcript-reported education and finds that groups less likely to enroll in postsecondary education tend to overstate educational achievement. Kane, Rouse, and Staiger (1999) review other national longitudinal surveys and generally find inaccuracies between transcript and self-reported data. Kuncel, Crede, and Thomas (2005) find that response bias may be associated with student success, as those with higher grades appear to report data more accurately. Because of the focus on "within student" effects, however, I expect response bias to be relatively consistent for each individual over time.

Table 1
Sample summary statistics.

	All students (N = 4082)		Full-time (N = 3323)		Part-time (N = 759)	
	Mean	SD	Mean	SD	Mean	SD
College GPA (yearly)	3.17	0.48	3.18	0.48	3.13	0.52
Credit hours (yearly)	21	13	22	13	18	14
Average hours worked weekly	16.9	11.1	15.9	10.6	21.9	12.7
Range in hours worked (per student)	13.0	12.0	13.7	11.9	9.5	11.8
HS GPA (cumulative)	3.18	0.67	3.24	0.65	2.91	0.70
ASVAB math & verbal percentile	64	25	66	25	53	25
Parents' 1997 income ($000)	64	49	67	51	52	41
% of students						
Male	46%		46%		44%	
Female	54%		54%		56%	
2-year college	42%		35%		75%	
4-year college	73%		79%		41%	
Non-Hispanic White	72%		74%		63%	
African American	13%		12%		15%	
Hispanic or Latino	10%		8%		17%	
Asian	3%		3%		3%	
Missing race/ethnicity	6%		6%		6%	
Parents Ed: some college or higher	69%		70%		60%	
Parents Ed: HS graduate	23%		22%		27%	
Parents Ed: Some HS	5%		4%		8%	
Parents Ed: Missing	4%		3%		5%	
Major: Business	24%		24%		22%	
Major: Social Sciences	20%		21%		16%	
Major: Humanities & Arts	16%		17%		13%	
Major: Nursing & Health	14%		13%		20%	
Major: Education	11%		11%		8%	
Major: Science & Engineering	27%		28%		22%	
Major: unknown/undecided	41%		39%		49%	

Source: NLSY97. Survey weights used.
Notes: Reported majors and occupation types may not add up to 100 percent, as students may report multiple majors or occupation types over their time in school. For purposes of this summary table, students are included in the summaries of either full-time or part-time students based on their attendance status for the majority of their studies.

5. Findings

I begin with a review of graphical evidence of the association between academic performance and work hours. Observed unconditional relationships may be subject to selection bias without accounting for factors that can affect both educational and work behavior. Fig. 1 contains a plot of the average GPA for each hour worked for full-time and part-time students in the sample with a fitted locally weighted regression line of GPA on work hours (with bin size equal to 0.3 h).

For both groups, there is a positive association between grades and working up to about five hours worked (more pronounced for part-time students), then a declining

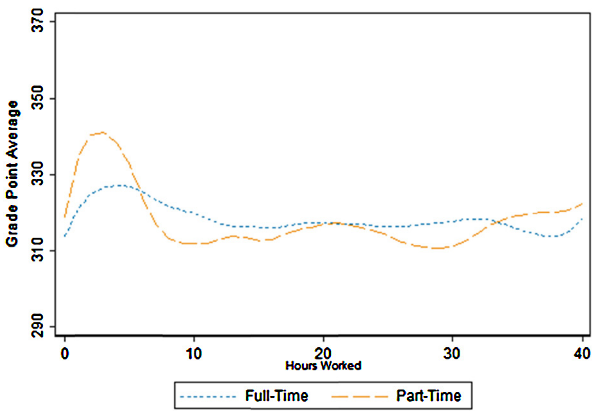

Fig. 1. Relationship between GPA and hours worked. *Note*: Lines represent a locally weighted regression for the average GPA per hour worked, with bin size = 0.3.
Source: NLSY97. Survey weights used.

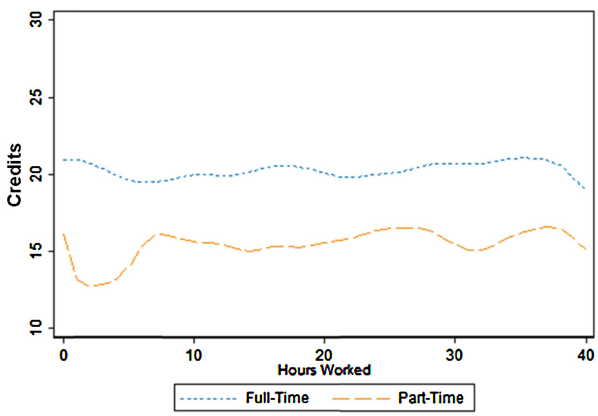

Fig. 2. Relationship between credits and hours worked. *Note*: Lines represent a locally weighted regression for the average credits per hour worked, with bin size = 0.3.
Source: NLSY97. Survey weights used.

Table 2
Student fixed effects estimates of the effect of hours worked on GPA.

	All (1)	4-year (2)	2-year (3)	Male (4)	Female (5)
Hours worked – FT student	−0.032	−0.016	−0.166	−0.079	−0.011
	(0.084)	(0.090)	(0.303)	(0.129)	(0.112)
Hours worked – PT student	0.253	0.174	0.442	0.274	0.149
	(0.210)	(0.311)	(0.397)	(0.330)	(0.285)
Observations	8338	6204	2134	3634	4704
Adj. R-sq.	0.601	0.617	0.618	0.582	0.613

Source: NLSY97. Survey weights used.
Notes: GPA is scaled [0,400]. Heteroskedasticity robust standard errors are clustered by student and included in parentheses. Models include student fixed effects, a selection correction term, and controls for school sector (4-year, 2-year), year, credits, college major indicator, tuition, and state.

Table 3
Student fixed effects estimates of the effect of hours worked on credits.

	All (1)	4-year (2)	2-year (3)	Male (4)	Female (5)
Hours worked – FT student	−0.124***	−0.107***	−0.081	−0.102**	−0.149***
	(0.034)	(0.037)	(0.120)	(0.050)	(0.047)
Hours worked – PT student	−0.036	0.021	−0.014	−0.047	−0.059
	(0.085)	(0.121)	(0.174)	(0.134)	(0.118)
Observations	8338	6204	2134	3634	4704
Adj. R-sq.	0.105	0.070	0.291	0.113	0.097

Source: NLSY97. Survey weights used.
Notes: GPA is scaled [0,400]. Heteroskedasticity robust standard errors are clustered by student and included in parentheses. Models include student fixed effects, a selection correction term, and controls for school sector (4-year, 2-year), year, college major indicator, tuition, and state.
** Significant at 5%.
*** Significant at 1%.

relationship between grades and working, flattening out around 15 h worked for full-time students and about 10 h worked for part-time students. There also appears to be a slight upward trending relationship between grades and working over 30 h for part-time students. One explanation for the peaks in the graph is that working helps develop useful skills that can be applied to an academic setting. Alternatively, the trends may simply reflect the choices of intelligent, motivated, responsible students who select themselves into certain intensities of work participation. Graphical analysis of the relationship between credits and hours worked in Fig. 2 provides little notable discernible unadjusted trend for number of credits a full-time student takes over the range of hours worked. Part-time students appear to have lower credits if they work a few hours, followed by a rise and a relatively flat trend over the 10–40 h range.

Tables 2 and 3 present estimates of the effect of working on GPA and credits respectively using OLS models with fixed effects for student subgroups.[12] I find little evidence that marginal hours affect students' grades after accounting for time-invariant personal characteristics that may affect both work behavior and GPA. One explanation could be the decreasing amount of time students allocate to their studies, such that increasing work hours is not crowding out study time. Point estimates in Table 2 largely follow existing literature in finding negative consequences for all the full-time student subgroups, though findings from this study are generally of lower magnitude than much of the prior research and are not statistically significant. In contrast, while not statistically significant, point estimates for part-time students are all positive, though imprecisely estimated. The increase in standard errors for this group could be a function of sample size, but also may indicate that part-time students have wider variation in responses to work demands.

Turning next to an examination of the effect of working on credits completed each term, I display the effect of marginal work hours in Table 3. Results indicate that each marginal work hour is negatively associated with credit completion for all full-time student subgroups. All subgroup results are statistically significant and range from 0.10 to 0.15 fewer credits per year for each hour increase in work, with the exception of smaller negative point estimate at 2-year colleges (0.08) with a relatively large standard error. With an average standard deviation of approximately 12 h worked by

[12] GPAs are converted from a range [0,4] to a range of [0,400] in the tables. However, in the text, discussions of the magnitudes of coefficients are based on a 4.0 scale.

Table 4
System GMM estimates of the effect of hours worked on GPA.

	All	4-year	2-year	Male	Female
	(1)	(2)	(3)	(4)	(5)
Panel A: Dynamic models					
Hours worked – FT student	0.296	0.307	0.123	0.483*	0.213
	(0.237)	(0.262)	(0.427)	(0.275)	(0.275)
Hours worked – PT student	−0.516	−0.844	0.596	0.861	0.434
	(0.688)	(0.914)	(0.473)	(0.597)	(0.734)
AB AR(2) test	0.660	0.550	0.821	0.897	0.548
Overidentification test	0.320	0.617	0.270	0.766	0.000
Difference-in-Sargan test	0.458	0.766	0.849	0.833	0.000
Observations	5407	4500	907	2343	3064
Panel B: Dynamic models with additional IVs					
Hours worked – FT student	0.265	0.176	0.740	0.347	0.391
	(0.244)	(0.258)	(0.630)	(0.270)	(0.294)
Hours worked – PT student	−0.774	−0.792	0.811	0.766	0.308
	(0.694)	(0.866)	(0.491)	(0.550)	(0.742)
AB AR(2) test	0.563	0.548	0.334	0.654	0.887
Overidentification test	0.405	0.448	0.531	0.546	0.538
Difference-in-Sargan test	0.568	0.795	0.605	0.818	0.166
Observations	4348	3591	757	1918	2430

Source: NLSY97. Survey weights used.
Notes: Standard errors included in parentheses. Models include controls for lagged hours worked, lagged hours worked interacted with part-time status, school sector (4-year, 2-year), year, tuition, credits, and college major indicator. Models are estimated by system GMM using all available lags, and instruments are first-differenced regressors (as listed above) and lags of the outcome variable and hours worked. Instruments added in Panel B are variation in house prices and credit scores. AB AR(2) test is the *p*-value for the Arellano and Bond (1991) autocorrelation test of order 2. Overidentification test is the *p*-value for the Hansen (1982) *J*-test. Difference test is the *p*-value for the difference-in-Sargan test of the exogeneity of instrument subsets.
* Significant at 10%.

full-time students in the sample, this indicates that a one standard deviation increase in work hours results in a reduction of about one fewer three credit course every two to three years. For part-time students, I find no statistically significant effects of marginal work hours on credits taken.

In an effort to control for potential endogenous selection of hours, I next provide results for estimations

Table 5
System GMM estimates of the effect of hours worked on credits.

	All	4-year	2-year	Male	Female
	(1)	(2)	(3)	(4)	(5)
Panel A: Dynamic models					
Hours worked – FT student	−0.629***	−0.611***	−0.236	−0.529***	−0.573***
	(0.088)	(0.086)	(0.183)	(0.101)	(0.117)
Hours worked – PT student	0.048	−0.039	−0.104	−0.266	0.122
	(0.187)	(0.193)	(0.249)	(0.228)	(0.192)
AB AR(2) test	0.910	0.817	0.267	0.654	0.863
Overidentification test	0.235	0.090	0.546	0.260	0.000
Difference-in-Sargan test	0.492	0.224	0.943	0.038	0.000
Observations	4657	3898	759	2035	2622
Panel B: Dynamic models with additional IVs					
Hours worked – FT student	−0.624***	−0.608***	−0.011	−0.466***	−0.606***
	(0.087)	(0.086)	(0.195)	(0.097)	(0.128)
Hours worked – PT student	−0.150	−0.176	−0.212	−0.404	0.071
	(0.219)	(0.156)	(0.221)	(0.221)	(0.214)
AB AR(2) test	0.958	0.929	0.228	0.810	0.563
Overidentification test	0.223	0.266	0.728	0.283	0.075
Difference-in-Sargan test	0.297	0.123	0.868	0.287	0.459
Observations	3738	3102	636	1655	2083

Source: NLSY97. Survey weights used.
Notes: Standard errors included in parentheses. Models include controls for lagged hours worked, lagged hours worked interacted with part-time status, school sector (4-year, 2-year), year, tuition, and college major indicator. Models are estimated by system GMM using all available lags, and instruments are first-differenced regressors (as listed above) and lags of the outcome variable and hours worked. Instruments added in Panel B are variation in house prices and credit scores. AB AR(2) test is the *p*-value for the Arellano and Bond (1991) autocorrelation test of order 2. Overidentification test is the *p*-value for the Hansen (1982) *J*-test. Difference test is the p-value for the difference-in-Sargan test of the exogeneity of instrument subsets.
*** Significant at 1%.

based on the dynamic system GMM models. In Table 4, results are displayed for estimates of hours worked on GPA. Similar to the fixed effect models, I find few statistically significant results for either full-time or part-time students in either dynamic model in Panel A or in the dynamic model with additional IVs in panel B. It is worth noting that point estimates are generally higher than fixed effect estimates, but imprecisely estimated. I find one statistically significant effect, with marginal work hours for male students associated with an approximately 0.005 GPA point increase. While this increase is small enough to potentially be considered practically insignificant, the result suggests that male students can benefit from working, perhaps because of the increased organizational structure it provides and is consistent some past research that also found a small positive effect of working (e.g., results from student fixed effect models in Stinebrickner and Stinebrickner (2003)).

Included at the bottom of each panel are *p*-values from tests for autocorrelation and overidentification. These tests indicate that second order autocorrelation is not problematic in any of these estimations, and that overidentification test *p*-values are generally comfortably above conventional significance levels. The exception to this is for the estimates for female students in Panel A, column 5, where the Hansen *J* and difference-in-Sargan tests indicate that instruments in the dynamic model may not be exogenous. After adding the additional instruments, however, *p*-values for these tests exceed conventional significance levels (Panel B, column 5).

Next, I consider the system GMM estimates of hours on credits earned in Table 5. These estimates suggest a larger working penalty for full-time students than found in the fixed effects models. Coefficients stay relatively consistent when adding the additional instruments in Panel B. For example, these results indicate that the average effect of each marginal hour worked is about 0.62–0.63 fewer credits per year (Panels A and B, column 1), such that a student who adds an average of an extra five hours of work each week is expected to complete about one fewer course in that year. As with the fixed effects models, the point estimates for full-time students at 2-year colleges are directionally consistent with the other subgroups, though of a smaller magnitude and without statistical significance. I continue to find no statistically significant effects of marginal work hours on the credit accumulation of part-time students in either specification.

Autocorrelation tests reveal no apparent issues across any of the subgroups, but overidentification tests call for caution when interpreting results for certain subgroups. In particular, in the dynamic models displayed in Panel A, the estimates for 4-year, male, and female students all have Hansen *J* or difference-in-Sargan tests that indicate some potential for concern with instrument exogeneity assumptions. When adding the additional instruments in Panel B, *p*-values from these tests exceed conventional significance levels, with the exception of the female student estimates.

6. Summary and conclusions

Working students have become commonplace on college campuses and hours worked by each student have increased substantially (Baum, 2010; Perna, 2010; Scott-Clayton, 2012). Given the increasing rates of work participation and policy initiatives to expand postsecondary education, it is critical to understand the costs and benefits of working while in school, especially for heterogeneous segments of student bodies. Working while in school can have future labor market payoffs and improve soft skills, such as time efficiency, communication, problem solving ability, and personal responsibility (e.g., Light, 2001; Molitor & Leigh, 2004; Ruhm, 1997). On the other hand, time spent working may crowd out time spent on studies or other academically enriching activities. Lower grades may hinder students' graduate school or labor market prospects (e.g., Loury & Garman, 1995; Wise, 1975) and extending time-to-degree can lead to forgone earnings and lower persistence. Conclusions about the effects of working based on restricted or pooled samples of students may miss or mask divergent responses from students with diverse goals, backgrounds, and constraints. In this study, I analyze annual grades and credit completion from a nationally representative sample of undergraduate students in the US; across genders, races and ethnicities, college types (four-year, two-year), and student attendance status (full-time vs. part-time) for students' full tenure in college.

As well, this study is among the first to specifically analyze differences in the effect of working on academic performance for full-time and part-time students, whereas previous studies paid little attention to part-time students. In addition to informing policymakers regarding working learners, a focus on part-time students may also have important equity implications for students of different races and ethnicities, as a major reason for the increase in part-time postsecondary students is due to an increase in enrollment by minority students (O'Toole et al., 2003). There appears to be distinct effects of hours worked on the academic performance of full-time and part-time students. In general, I find little conclusive evidence that working affects the average outcomes of part-time students overall and for any part-time student subgroup, or for students that attend 2-year colleges. The large standard errors associated with these groups' estimates suggest that further understanding of the heterogeneous responses to working is needed for students who do not attend full-time or are in the sub-baccalaureate sector.

Though magnitudes differ, interpretation of results across methods (OLS estimations with and without student fixed effects and dynamic models with and without IVs) generally point to consistent conclusions. Findings from this study indicate little discernible impact of working on students' grades for either full-time or part-time students. This result is perhaps not surprising given time use studies (e.g., Babcock & Marks, 2011) that document the falling time-cost of college studies, such that increased working time may not be crowding out study time. It is worth noting that the average range in increases in student hours worked in the sample is approximately thirteen hours, such that results might not be viably extrapolated to students who increase hours well beyond that range.

Nevertheless, initiatives that encourage working can be financially rewarding and, given prior research on the labor market returns to in-school work, may have future professional benefits with potentially little penalty to students' GPAs. These complementary relationships may inspire policymakers to promote initiatives that closely align academic and vocational pursuits. For example, academic curricula that successfully integrates and accommodates professional experiences, such as cooperative education programs, may be particularly beneficial for some students. Workforce training providers might choose to encourage students to seek work while going to school or while participating in skills training.

Increased work behavior, however, has costs. Increases in job commitments may substitute for other school-related activities that may contribute to academic and social integration, and therefore other measures of academic success, or crowd out leisure activities that contribute to overall welfare. Furthermore, policymakers who undergo efforts to expand the integration of academic and professional programs need to consider the interaction of working with federal, state, and institutional financial aid programs. Federal financial aid formulas penalize many working students by offsetting earnings with reduced need-based financial aid (Baum, 2010). The penalty is particularly problematic for part-time students who are more likely to be financially independent.

Moreover, working students may take fewer credits per term because of work commitments. While I find little evidence that increasing work affects credit accrual for part-time students, results indicate that increased work intensity results in fewer credits completed in each term by full-time students, particularly at 4-year institutions. This may contribute to increasing time-to-degree, costing the student in forgone earnings, higher college expenses, and lower persistence (Bound et al., 2010). As such, policies that encourage the integration of professional experiences with schooling should be accompanied with appropriate academic support services. This might take the form of increased academic credit for work, close coordination with employers to encourage mutually beneficial work and school schedules, or concerted efforts by schools to create and promote professional opportunities that are complementary to academic programs.

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This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

Appendix A

See Tables A1 and A2.

Table A1
Estimates of the effect of hours worked on GPA & credits (without student fixed effects).

	All (1)	4-year (2)	2-year (3)	Male (4)	Female (5)
Panel A: GPA					
Hours worked – FT student	0.068	0.043	0.214	−0.024	0.053
	(0.062)	(0.070)	(0.136)	(0.093)	(0.081)
Hours worked – PT student	0.123	−0.231	0.417	0.085	0.152
	(0.142)	(0.206)	(0.192)	(0.209)	(0.195)
Adj. *R*-sq.	0.072	0.076	0.072	0.073	0.088
Panel B: Credits					
Hours worked – FT student	−0.069***	−0.077***	−0.044	−0.064***	−0.077***
	(0.015)	(0.017)	(0.039)	(0.022)	(0.022)
Hours worked – PT student	0.008	−0.023	0.038	−0.043	0.055
	(0.142)	(0.206)	(0.192)	(0.209)	(0.195)
Adj. *R*-sq.	0.042	0.039	0.060	0.036	0.045
Observations	8338	6204	2134	3634	4704

Source: NLSY97 and IPEDS. Survey weights used.
Notes: GPA is scaled [0,400]. Heteroskedasticity robust standard errors are clustered by student and included in parentheses. Models include a selection correction term and controls for race/ethnicity, gender, school sector (4-year, 2-year), student attendance status (full-time, part-time), credits (GPA model only), tuition, year, major, state, ASVAB score quartile, parents' 1997 income quartile, and parental education level.
*** Significant at 1%.

Table A2
Internal instrument estimates of the effect of hours worked on GPA & credits.

	GPA	Credits
	(1)	(2)
Full-time students		
Hours worked – FT student	−0.148	0.347
	(0.446)	(0.216)
Overidentification test	0.655	0.315
Cragg–Donald Wald *F* statistic	29.7	27.9
Observations	2352	2352

Source: NLSY97. Survey weights used.
Notes: Standard errors included in parentheses. Models include controls for school sector (4-year, 2-year), year, tuition, credits, and college major indicator, but coefficients are not displayed. Uses one and two period lags of hours worked as instruments for hours worked. Overidentification test is the *p*-value for the Hansen (1982) *J*-test.

References

Angrist, J., Lang, D., & Oreopoulos, P. (2009). Incentives and services for college achievement: Evidence from a randomized trial. *American Economic Journal: Applied Economics, 1*(1), 136–163.
Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economics and Statistics, 58*, 277–297.
Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29–51.
Babcock, P., & Marks, M. (2011). The falling time cost of college: Evidence from half a century of time use data. *The Review of Economics and Statistics, 93*(2), 468–478.
Bachmann, A., & Boes, S. (2012). *Private transfers and college students' decision to work*. SSRN Working Paper. Available at http://ssrn.com/abstract=2145262.
Barnow, B. S., Cain, G. C., & Goldberger, A. S. (1980). Issues in the analysis of selectivity bias. In Stromsdorfer, E. W., & Farkas, G. (Eds.), *Evaluation Studies Review Annual* (Vol. 5). Beverly Hills, CA: Sage.
Bastedo, M. N., & Jaquette, O. (2011). Running in place: Low-income students and the dynamics of higher education stratification. *Educational Evaluation and Policy Analysis, 33*(3), 318–339.
Baum, S. (2010). Student work and the financial aid system. In L. W. Perna (Ed.), *Understanding the working college student*. Sterling, VA: Stylus Publishing.
Betts, J. R., & Morell, D. (1999). The determinants of undergraduate grade point average: The relative importance of family background, high school resources, and peer group effects. *Journal of Human Resources, 34*(2), 268–293.
Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143.
Bound, J., Lovenheim, M. F., & Turner, S. (2010). *Increasing time to baccalaureate degree in the United States. NBER Working Paper 15892*. Cambridge, MA: NBER.
Buchmann, C., DiPrete, T. A., & McDaniel, A. (2008). Gender inequalities in education. *Annual Review of Sociology, 34*, 319–337.
Carroll, C. D. (1989). *College persistence and degree attainment for 1980 high school graduates: Hazards for transfers, stopouts and part-timers*. Washington, DC: US Department of Education, Office of Educational Research and Improvement.
Chen, X., & Carroll, C. D. (2007). *Part-time undergraduates in postsecondary education: 2003–04*. Washington, DC: US Department of Education.
Crocker, J., Karpinski, A., Quinn, D. M., & Chase, S. K. (2003). When grades determine self-worth: Consequences of contingent self-worth for male and female engineering and psychology majors. *Journal of Personality and Social Psychology, 85*(3), 507–516.
DeSimone, J. (2006). Academic performance and part-time employment among high school seniors. *Topics in Economic Analysis & Policy, 6*(1), 1–34.
Dynarski, S. (2008). Building the stock of college-educated labor. *Journal of Human Resources, 43*(3), 576–610.
Ehrenberg, R., & Sherman, D. (1987). Employment while in college, academic achievement, and postcollege outcomes: A summary of results. *Journal of Human Resources, 22*(1), 1–23.
Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American Economic Review, 96*(2), 1–21.
Goldin, C., Katz, L. F., & Kuziemko, L. (2006). The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic Perspectives, 20*(4), 133–156.
Grubb, W. N. (1997). The returns to education in the sub-baccalaureate labor market, 1984–1990. *Economics of Education Review, 16*(3), 231–246.
Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica, 50*, 1029–1054.
Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models. *Annals of Economic Social Measurement, 5*(4), 475–492.
Heckman, J. J., & Hotz, J. V. (1989). Choosing among alternative nonexperimental methods for estimating the impact of social programs: The case of manpower training. *Journal of the American Statistical Association, 84*(408), 862–874.
Hood, A. B., Craig, A. F., & Ferguson, B. W. (1992). The impact of athletics, part-time employment and other activities on academic achievement. *Journal of College Student Development, 33*, 447–453.
Ionescu, F., & Simpson, N. (2010). *Credit scores and college investment*. Unpublished manuscript.
Jacob, B. A. (2004). Public housing, housing vouchers, and student achievement: Evidence from public housing demolitions in Chicago. *American Economic Review, 94*(1), 233–258.
Kalenkoski, C. M., & Pabilonia, S. W. (2009). Does working while in high school reduce US study time? *Social Indicators Research, 93*, 117–121.
Kalenkoski, C. M., & Pabilonia, S. W. (2010). Parental transfers, student achievement, and the labor supply of college students. *Journal of Population Economics, 23*, 469–496.
Kalenkoski, C. M., & Pabilonia, S. W. (2012). Time to work or time to play: The effect of student employment on homework, sleep, and screen time. *Labour Economics, 19*, 211–221.
Kane, T., & Rouse, C. (1999). The community college: Educating students at the margin between college and work. *Journal of Economic Perspectives, 13*(1), 63–84.
Kane, T., Rouse, C., & Staiger, D. (1999). *Estimating returns to schooling when schooling is misreported. NBER Working Paper 7235*. Cambridge, MA: NBER.
Kuncel, N., Crede, M., & Thomas, L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research, 75*(1), 63–82.
Lee, L. (1978). Unionism and wage rates: A simultaneous equations model with qualitative and limited dependent variables. *International Economic Review, 19*(2), 415–433.
Light, A. (2001). In-school work experience and the returns to schooling. *Journal of Labor Economics, 19*(1), 65–93.
Lovenheim, M. (2011). The effect of liquid housing wealth on college enrollment. *Journal of Labor Economics, 29*(4), 741–771.
Loury, L. D., & Garman, D. (1995). College selectivity and earnings. *Journal of Labor Economics, 13*(2), 289–308.
Meyer, R. H., & Wise, D. A. (1982). High school preparation and early labor force participation. In R. B. Freeman (Ed.), *The youth labor market problem: Its nature, causes, and consequences*. Chicago: University of Chicago Press.
Molitor, C. J., & Leigh, D. E. (2004). In-school work experience and the returns to two-year and four-year colleges. *Economics of Education Review, 24*, 459–468.
Montmarquette, C., Viennot-Briot, N., & Dagenais, M. (2007). Dropout, school performance, and working while in school. *The Review of Economics and Statistics, 89*(4), 752–760.
Nelson, A. A. (2010). Credit scores, race, and residential sorting. *Journal of Policy Analysis and Management, 29*(1), 39–68.
Oettinger, G. S. (1999). Does high school employment affect high school academic performance. *Industrial and Labor Relations Review, 53*(1), 136–151.
O'Toole, D. M., Stratton, L. S., & Wetzel, J. N. (2003). A longitudinal analysis of the frequency of part-time enrollment and the persistence of students who enroll part time. *Research in Higher Education, 44*(5), 519–537.
Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students: A third decade of research*. San Francisco, CA: Jossey-Bass.
Perna, L. W. (Ed.). (2010). *Understanding the working college student*. Sterling, VA: Stylus Publishing.
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.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136.
Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics, 71*(1), 135–158.
Ruhm, C. J. (1997). Is high school employment consumption or investment? *Journal of Labor Economics, 15*(4), 735–776.
Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *Quarterly Journal of Economics, 116*(2), 681–704.
Scott-Clayton, J. (2011). The causal effect of federal work-study participation: Quasi-experimental evidence from West Virginia. *Educational Evaluation and Policy Analysis, 33*(4), 506–527.
Scott-Clayton, J. (2012). *What explains trends in labor supply among US undergraduates, 1970–2009? NBER Working Paper 17744* Cambridge, MA: NBER.
Seftor, N., & Turner, S. (2002). Back to school: Federal student aid policy and adult college enrollment. *Journal of Human Resources, 37*, 337–352.
Snyder, T. D., & Dillow, S. A. (2011). *Digest of Education Statistics 2010*. Washington, DC: US Department of Education.
Stinebrickner, R., & Stinebrickner, T. (2003). Working during school and academic performance. *Journal of Human Resources, 38*(3), 473–491.
Stinebrickner, R., & Stinebrickner, T. (2004). Time-use and college outcomes. *Journal of Econometrics, 121*(1–2), 243–269.
Stinebrickner, R., & Stinebrickner, T. (2008). The causal effect of studying on academic performance. *The B.E. Journal of Economic Analysis & Policy, 8*(1), 1–55.
Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago, IL: University of Chicago Press.
Turner, S. E. (2004). Going to college and finishing college: Explaining different educational outcomes. In C. Hoxby (Ed.), *College choices: The economics of where to go, when to go, and how to pay for it*. Chicago: University of Chicago Press.
Wise, D. A. (1975). Academic achievement and job performance. *American Economic Review, 65*(3), 350–366.
Wooldridge, J. M. (2003). *Introductory econometrics: A modern approach*. Cincinnati, OH: South-Western College Publishing.