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It's About Time: The Inequitable Distribution of Time as a Resource for College, by Gender and Race/Ethnicity

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Abstract

Existing qualitative research in higher education on students' work and family commitments already suggests that time as a resource for college is likely not distributed equitably by race/ethnicity or gender. However, the relationship between race/ethnicity, gender, and time as a resource for college has yet to be quantitatively measured in large-scale higher education research. This study explored whether gender or race/ethnicity correlated with differences in time as a resource for college; and further, the extent to which differences in time as a resource for college may be explained by other factors such as age, number of children, and access to childcare. Retrospective survey responses (n = 41,579) on self-reported time use were merged with institutional data records from students at the City University of New York (CUNY), a large diverse public university in the U.S. Women, Black, and Hispanic students were all significantly more time poor than male, White, or Asian students. Age accounted for significant portions of these differences, perhaps because it correlates with increased work and family responsibilities. Having children as well as a student's access to childcare also explained a significant portion of inequitable distributions of time as a resource for college.

Keywords Equity · Gender · Race and ethnicity · Age · Childcare · Time poverty · Time capital

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It is likely that time as a resource for college is inequitably distributed by gender and race/ethnicity. Having sufficient time for college has been shown to have a direct impact on college outcomes for student parents (Wladis et al., 2018), and there is evidence that women and students of color are more likely to have family responsibilities and to work full-time due to financial necessity while enrolled in college (Ross-Gordon, 2011). However, the extent to which time as a resource for college is inequitably distributed has not yet been explored in larger-scale quantitative higher education research.

Considering whether time is inequitably distributed among college students is important regardless of whether it leads to differential academic outcomes. Requiring certain racial/ethnic or gender groups to systematically invest significantly higher proportions of their free time to attain the same academic outcomes as others may lead to inequitable non-academic outcomes, such as overwork, which also leads to higher stress and poorer health (Kuroda & Yamamoto, 2019; Yamada et al., 2014). In this study, we investigated the extent to which time as a resource for college is inequitably distributed among college students by gender and race/ethnicity, and intersections of the two. We then explored potential explanations for differential distributions of time. Results provide evidence for future researchers who aim to design and test interventions to address the time poverty of the hardest hit groups in college.[1]

Conceptual Framework: Time Poverty

In the context of higher education, Wladis et al. (2018) conceptualize time poverty as insufficient time to devote to college work (i.e., insufficient time to maintain academic well-being). Research suggests that time poverty negatively impacts both college outcomes (Wladis et al., 2018, 2023) and other measures of well-being (e.g., mental and physical health (Wladis et al., 2023)). Time poverty may also interfere with students' ability to engage in the academic social community, potentially impacting retention (e.g., Mathuews, 2018; Tinto, 1975). Time in higher education tends to be viewed as a commodity free from constraint, ignoring structural and environmental factors which impact students' access to *time as a resource* for college (Bennett & Burke, 2017). We posit that time poverty, a byproduct of demographic and environmental factors (e.g., gender, age, financial resources), generates competing time demands (e.g., work and family commitments) that reduce the quantity and quality of time that students can spend on their studies (see Fig. 1).

While time poverty can be operationalized in different ways, we measure *non-discretionary time*, or time spent on paid work, housework (all unpaid work necessary to sustain the household, except childcare), and childcare (Aas, 1978; Kalenkoski et al., 2011; Wladis et al., 2018).[2] Thus, the higher the non-discretionary time, the *less* time that a student has available for college, and the higher the time poverty by our definition.

[1] In this paper, we use the terms "time poverty" and "time poor" because they are in line with terminology from the current literature; however, we acknowledge that these terms could be viewed as implying a deficit view of students. This terminology is not meant indicate an immutable characteristic of students or to downplay the structural factors that contribute to time inequities, but rather to identify the ways in which different groups are inequitably resourced for college, often as a result of inequitable societal and structural factors.

[2] Commuting to/from paid work and commuting related to childcare is included in this study as non-discretionary time; commuting related to university attendance is included in education time.

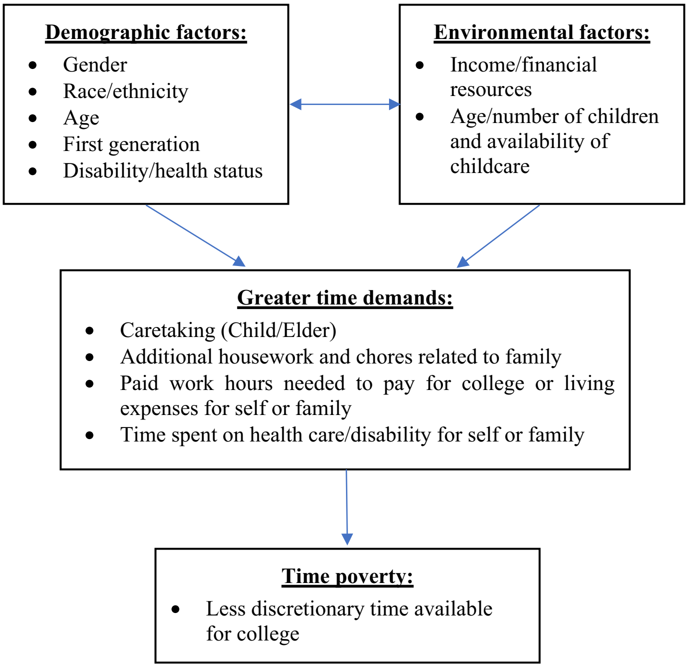

Fig. 1 Conceptual framework: time poverty in higher education

Since paid work and childcare were non-voluntary for the majority of this population, in line with prior research we include them in non-discretionary time categories. While some students may choose to prioritize other things above their studies, for many the commitments (e.g., work, childcare) that contribute to their time poverty are not a choice but a necessity (Mathuews, 2018; Robotham, 2013). For example, at The City University of New York (CUNY) where this study was conducted, three quarters of students who work do so to pay for living expenses (CUNY, 2018) and only one in five parents in this dataset agreed that available childcare provided enough time for their studies. We cannot always determine whether time poverty is voluntary or not. However, we can consider the extent to which time poverty is inequitably distributed.

Intersectionality

Our investigation first looks at distributions of time poverty by gender and then by race/ethnicity. In reality, gender and race/ethnicity may not have completely independent relationships with time poverty. We note that Crenshaw (1989) contends that single-axis analysis of Black Women (and we expand this to include all marginalized groups in higher education), serves to distort the lived experiences of those who face multiple forms of inequity. Scholarship on intersectionality suggests that researchers should endeavor to move intersectionality to unexplored places (Carbado et al., 2013; Schudde, 2018), of which we contend that time as a resource for college is once such area. Because of this, our subsequent analyses take an intercategorical approach (Schudde, 2018) to examine how identities combine to produce individual experience by looking at the intersection of gender and race/ethnicity. For these analyses, we draw on the theoretical framework of intersectionality (Crenshaw, 1989, 1991), examining how time as a resource may be the product of intersecting patterns not represented by gender or race/ethnicity inequities alone.

Research Questions

In this study, we asked:

RQ1 To what extent is time poverty unequally distributed by gender and/or race/ethnicity among college students?
RQ2 How does the distribution of demands that contribute to time poverty (i.e., time spent on work, childcare and housework) differ by gender or race/ethnicity for college students?
RQ3 To what extent do age, number of children, or rated childcare availability explain any observed differences in time poverty by gender and/or race/ethnicity?

Literature Review

There is currently little empirical literature on time poverty in higher education. What does exist tends to focus on individual characteristics that increase time demands (e.g., work or childcare responsibilities in isolation) without measuring time poverty as a unified construct. The few studies that operationalize time poverty as a unified construct by measuring non-discretionary time (Conway et al, 2021; Wladis et al, 2018) report that time poverty is significantly higher for parents than non-parents, particularly for parents of the youngest children. Further, time poverty is higher for mothers than fathers, explaining significant differences in full-time vs. part-time enrollment, college retention and credit accumulation by gender. In (Wladis et al., 2023), students who voluntarily enrolled in online courses were significantly more time poor compared to those who did not, and this explained differences in college outcomes.

Working and College Outcomes

Two factors that by definition impact the amount of discretionary time a student has for college are: working while in college; and family responsibilities. These have typically been considered separately. Research on time spent on paid work and college outcomes suggests that time poverty may play a role in explaining this relationship. Moderate levels of work hours have been positively associated with GPA (Darolia, 2014; Mathuews, 2018); yet working long hours/multiple jobs has been connected to missing classes, late/missing assignments, lower grades and course dropout (Burston, 2017; Goldrick-Rab, 2016). Darolia (2014), utilizing nationally representative data, found reduced study time and rates of course completion for students who worked more than 5 hours. Generally, evidence indicates that working 20 or more hours a week has a negative impact on college outcomes (Mathuews, 2018; Neyt et al, 2019). Robotham (2013) contends that working even part-time while attending college can decrease time for studies and for social/leisure activities; this can negatively impact academic performance and well-being. However, some mixed outcomes have been found as to how work relates to college outcomes (e.g., Neyt et al., 2019); this may be because measuring work hours alone is an imperfect partial measure of time poverty, which may be the more relevant explanatory variable.

Family Responsibilities and College Outcomes

Research on students' family commitments also suggests that time poverty may play a role in their relationship to college outcomes. Parents are more likely to enroll part-time and to drop out of college in comparison to their childless peers (Conway et al, 2021; Wladis et al., 2018). Wladis et al. (2018) found that student parents had significantly higher rates of time poverty, and that non-discretionary hours explained significant differences in college outcomes for parents versus non-parents. In qualitative work, Goldrick-Rab (2016) and Mathuews (2018) describe how the time pressure of competing demands of school, work and family responsibilities (particularly caring for children and the need to financially support parents/other family) contributed to student difficulties in finding time for college, and ultimately led to decisions to drop out.

Time Poverty as a Potential Source of Inequity by Gender and Race/Ethnicity

Certain student groups may be more likely to have higher time poverty than others. Burston (2017) suggests time demands for working students may be gendered, with women having more competing time demands than men. Time-use studies in the general population show that women are on average more time-poor than men, particularly after they have children (Chatzitheochari & Arber, 2012; Zilanawala, 2013). Student parents, who are more likely to be time poor because of time spent on childcare (Conway et al, 2021; Wladis et al., 2018), are more likely to Black or Hispanic women and single mothers (Institute for Women's Policy Research, 2019). Students from underrepresented racial/ethnic groups and poorer students also often delay college for financial reasons (Bozick & DeLuca, 2005), which makes them more likely to have significant life responsibilities that make demands on their time by the time that they enroll in college (Ross-Gordon, 2011). Further, poor and minoritized students often face many demands on their time, such as providing financially for their families; transportation issues, food and housing insecurity, and other caretaking responsibilities (Goldrick-Rab, 2016).

Thus, it seems likely that female college students, particularly those from underrepresented racial/ethnic groups, may have more time poverty than their male and/or White/Asian counterparts, leading to a potential differential impact by gender and/or ethnicity/race on college outcomes. If time poverty proves to be a critical inequity in college, current policies that focus solely on other factors may have the (unintended) result of widening existing inequities by disproportionately benefiting those without time poverty. Some examples are: policies that tie resources to full-time enrollment (i.e., US federal financial aid; childcare and development fund programs); or "academic momentum" initiatives that push students to enroll in more credits without also including supports to provide students with *more time* as a resource for college (e.g., "Keep On Moving On", 2018). Yet, existing research has not typically used a unified construct of time poverty (e.g., operationalized as total non-discretionary time commitments) to assess the extent to which time as a resource for college is distributed equitably by race/ethnicity and gender. This study addresses that gap.

Methods

Sample and Data Source

This study used a dataset from CUNY, the largest urban university system in the US (Boland, 2021). CUNY's 275,000 undergraduate students are extremely diverse: 45% are first-generation college students; 42% are non-native English speakers, and more than three-quarters identify as non-White. More than half are Pell grant recipients, 40% have household incomes under $20,000, roughly one-third work full-time, and 65% spend time during the week caring for others. While CUNY is not nationally-representative, because of its student body composition it is a reasonable choice for exploring the relationship between time poverty and gender/race/ethnicity among a diverse group of students.

The sample frame consisted of all students enrolled in courses that had sections offered in more than one medium at CUNY during fall or spring terms from fall 2015 to spring 2017. This sample was part of a larger study focused on how environmental factors, such as time poverty, may relate simultaneously to outcomes and students' decisions to enroll in online courses.[3] Students were invited to participate in an online survey near the end of the term and a response rate of 17.3% was achieved, roughly double that of institutional surveys with this population (e.g., CUNY, 2018). Institutional data, available for the full sample frame, was used to weight data to account for survey non-response, and combined with the 41,574 survey responses. Analysis indicates that the sample was roughly representative of the larger population (see Table 10 in the Appendix). Almost all minor differences were statistically significant because of the large sample frame size; however, overall survey respondents and non-respondents were comparable on all measures except gender. Respondents were more likely to be women (75% vs. 64%, respectively). Because there was adequate representation of both genders and we controlled for gender throughout analyses, we do not consider this to be a major limitation.

To adjust for non-response bias at both the student and survey question level, weighting and multiple imputation were used, respectively. Survey responses were weighted based on likelihood of responding to the survey by running a logistic regression model with a binary variable indicating whether the student submitted a completed survey as the dependent variable and all independent variables of interest in subsequent analyses used as independent variables. Weighting resulted in a reasonable weight distribution without significant outliers. The maximum weight across all values was 9.8; the 10th percentile weight was 0.6; and the 90th percentile weight was 2.5. Multivariate multiple imputation by chained equations imputed values for survey questions with missing responses, using all independent variables to be used in the subsequent analyses. Depending on variable type, logit models or predictive mean matching using three nearest neighbors was used. A median of 3.7% of data were missing across imputed variables (excluding variables with no missing values). The final imputed dataset contained 15 imputations. All subsequent results used the final imputed and weighted dataset.

[3] It is possible that this could bias the sample somewhat towards students who chose to take at least one course online; however, comparison of the CUNY population to the sample frame shows that they appear to be largely comparable (Wladis et al., 2024).

Measures

To record time use, students were asked the number of hours they spent on different activities during a typical week that term. Categories/descriptions were modeled after the American Time Use Survey [ATUS] (US Bureau of Labor Statistics, 2020), with survey categories reduced to those relevant to the study. For example, students were asked to report how many hours per week they spent "working for pay"; "directly engaged in caring for at least one child who required supervision or assistance"; "household tasks unrelated to childcare", among other time usage categories. Inputs for questions were restricted to numerical values that prevented students from entering invalid values (e.g., more than 168 h per week).

Analyses included both base models (with only the independent and dependent variables of interest) and full models (which contained control variables). Control variables were included to account for factors that may correlate with parental status, time poverty, or educational outcomes. These factors included: age, G.P.A., median household income of the student's zip code, first-generation college student status, whether the student was a first-time freshman, and whether the student was enrolled in at least one fully online course.

We also considered models that aim to understand to what extent inequalities in a specific third variable (e.g., age, rated availability of childcare) may explain race/ethnicity and/or gender disparities in time poverty. Following van der Weele and Robinson (2014), we conceptualize these third variables as mediators and employ statistical models from the mediation literature to decompose disparities into two parts. The first part is an "indirect" disparity that is a function of the combined effects of: (a) the relationship between the third variable and race/ethnicity (gender) and (b) the relationship between the third variable and time poverty. The second part is a "direct" disparity which quantifies the proportion of the total disparity that would remain even if the distribution of the third variable were to be equalized across racial/ethnic groups (gender).[4]

Equations and Software Packages Used for Analytical Models

All statistical analyses reported used Stata: *mi* for multiply-imputed data, *svy* for survey-weighted data, *logit* for logistic regression, *regress* for linear regression, and the *khb* package for KHB decomposition.

For logit models (survey completion as the dependent variable for survey weighting), the equation was:

$$\lambda(y) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \epsilon, \text{ logit link: } \lambda(y) = \frac{e^y}{1 + e^y}. \tag{1}$$

For linear regression (non-discretionary time) the equation was:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \epsilon. \tag{2}$$

For both equations, $x_1, \ldots, x_n$ represent the independent variables (e.g., age, ethnicity), and ϵ represents the difference between actual versus predicted probability (e.g., of survey

[4] Direct/indirect disparities are the same coefficients often referred to in mediation literature as direct/indirect effects; however, we avoid the term "effect" because this study is observational.

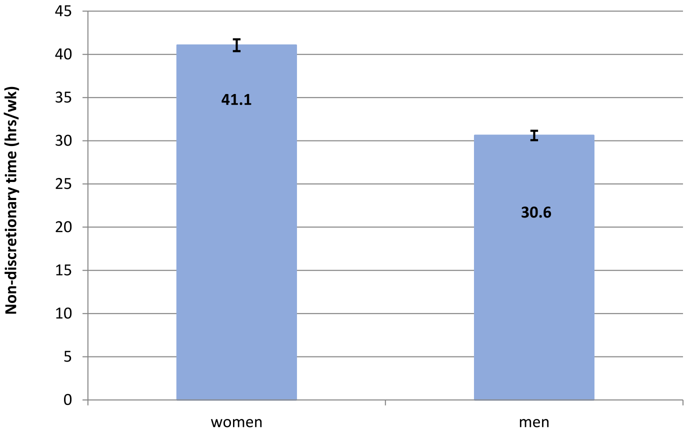

Fig. 2 Total non-discretionary time (hours/week) by gender. *Higher* amounts of non-discretionary time mean *less* time for college and *higher* time poverty. Linear regression model without controls on weighted imputed dataset; error bars indicate 95% confidence interval

Table 1 Predicted non-discretionary time (hours/week) by gender, linear regression coefficients reported (reference group: M)

Non-discretionary time (hours/week)		Coef.	SE	p
Base model	F	10.4	0.3	<0.001
Full model	F	8.4	0.3	<0.001

Full model includes the following control variables: ethnicity, age, GPA, income, first generation status, and online course enrollment status

completion) or values (e.g., non-discretionary hours) of the dependent variable for each student.

For mediation analysis, we used the KHB decomposition method, available in Stata (Karlson & Holm, 2011). The KHB method is a general decomposition method that is applicable in conjunction with either linear or logistic regression, and allows for inclusion of confounders (i.e., other covariates) in the models. While other methods can be used (Buis, 2010; Erikson et al., 2005; Long, 1997; Winship & Mare, 1984; Wooldridge, 2002), Monte Carlo studies have shown that the KHB method always performs as well or better than these methods in terms of recovering the degree of mediation net of the impact of any rescaling (Karlson & Holm, 2011; Karlson et al., 2010).

Results and Discussion

Time Poverty by Gender, and by Race/Ethnicity

Figure 2 and Table 1 show the total non-discretionary time commitments per week broken down by gender.

On average, women had 10.4 fewer hours/week for college than men ($p<0.001$). Controlling for race/ethnicity, age, GPA, first-semester-freshman status, first-generation-status,

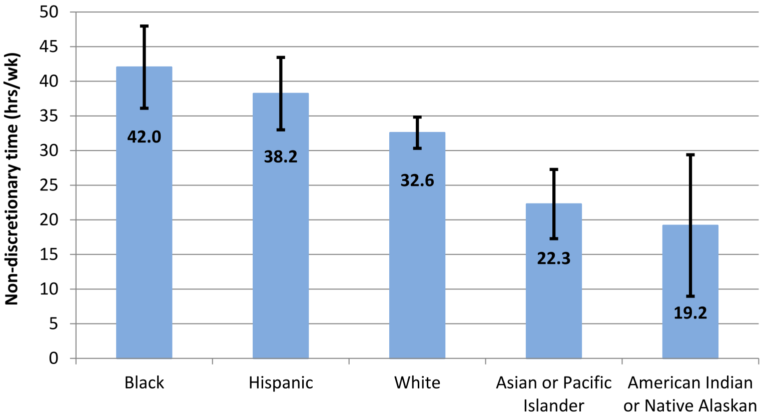

Fig. 3 Total non-discretionary time (hours/week) by race/ethnicity. Linear regression model without controls on weighted imputed dataset; error bars indicate 95% confidence interval

Table 2 Predicted non-discretionary time (hours/week) by race/ethnicity, linear regression coefficients reported (reference group: Asian/Pacific Islander)

Non-discretionary time (hours/week)		Coef.	SE	Ref. gp.*			
				Asian/PI	Black	Hispanic	White
				p	*p*	*p*	*p*
Base model	Black	18.8	0.5	***< 0.001***			
	Hispanic	15.4	0.4	***< 0.001***	***< 0.001***		
	White	13.5	0.5	***< 0.001***	***< 0.001***	***< 0.001***	
	AI/NA	4.4	2.9	0.133	***< 0.001***	***< 0.001***	**0.002**
Full model	Black	10.2	0.5	***< 0.001***			
	Hispanic	11.5	0.5	***< 0.001***	***0.007***		
	White	7.1	0.5	***< 0.001***	***< 0.001***	***< 0.001***	
	American Indian/ Alaskan Native	1.1	3.2	0.728	***0.004***	***0.001***	**0.059**

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and online course enrollment status

*p-values for each column were calculated by rotating through the reference group in the model

Bolding indicates p-values that are significant at the $\alpha \leq 0.1$ level

Bold italics indicates p-values that are still significant at the $\alpha \leq 0.1$ after adjusting for multiple significance tests in the given model using the Bonferroni method. (The Bonferroni method is a particularly conservative method, which is at greater risk of false negatives when the number of tests is high or test statistics are positively correlated (see e.g., Moran, 2003). In these tables it demonstrates that most coefficients remain significant even when one of the most conservative methods is used to adjust for multiple significance tests conducted on a single model; it also allows the reader to identify significance levels that may be more marginal once multiple significance tests are taken into account)

household income, and online-course-enrollment-status, this difference was reduced by a few hours, but still significant ($p < 0.001$). This reduction was likely due to control variables, such as number of children, which vary significantly by gender (see Table 11 in the Appendix); reasons for this gap are explored in the next section.

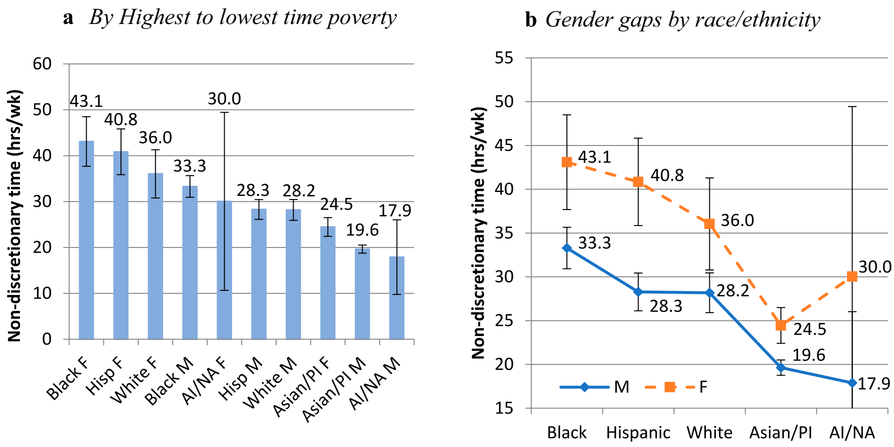

Fig. 4 Total predicted non-discretionary time (hours/week) by gender interacted with race/ethnicity. **a** By Highest to lowest time poverty. **b** Gender gaps by race/ethnicity. Linear regression model without controls on weighted imputed dataset; error bars indicate 95% confidence interval

Figure 3 and Table 2 show the total non-discretionary time commitments per week broken down by race/ethnicity.

In Fig. 3, Black students had the least time for college, followed by Hispanic, White, Asian/Pacific Islander (PI) and finally American Indian/Native American (AI/AN) students. Linear regression (Table A2) shows that all differences between groups were significant[5] except between Asian/PI and AI/AN students in base models. Black students had roughly double the amount of non-discretionary time commitments as Asian/PI or AI/NA students, and Hispanic students had only a little less non-discretionary time commitments than Black students. In full models, the relationship between Black and Hispanic students reversed, with Hispanic students significantly more time poor than Black students, yet all other differences remained significant (see Table 2). This reversal is likely due to significant differences in age between Black and Hispanic students, as Black students were significantly older and Hispanic students significantly younger (for more details, see Table 12 in the Appendix and the next section where the relationship between time poverty and age are explored).

Differences in time poverty by race/ethnicity remained highly significant even after controlling for a host of variables, but the control variables did reduce the gaps by one-third to one-half in many cases. This is in large part because older students and student parents are significantly more time poor, and there were differences in the mean age and mean number of children by racial/ethnic group (see Table 12 in the Appendix; these relationships are also explored in the next section).

[5] While error bars are included in Fig. 2, we remind the reader that they alone are not sufficient for assessing the significance of the difference (e.g., Austin & Hux, 2002) between two values on the graph (error bars can overlap even when differences are statistically significant)—regression model results are needed to assess these differences, reported separately in Table 2.

Table 3 Predicted non-discretionary time commitment (hours/week) by gender by race/ethnicity, separate intersected groups for pairwise comparison, linear regression coefficients reported (reference group: Asian/Pacific Islander M)

Interaction model	Coeff.	SE	Ref. gp.*								
			Asian/PI	Black M	Black F	Hispanic M	Hispanic F	White M	White F	Asian/PI F	AI/NA M
			p	*p*	*p*	*p*	*p*	*p*	*p*	*p*	*p*
Base model (no covariates)											
Black M	14.7	0.8	***<0.001***								
Black F	24.6	0.6	***<0.001***	***<0.001***							
Hispanic M	9.0	0.7	***<0.001***	***<0.001***	***<0.001***						
Hispanic F	22.3	0.6	***<0.001***	***<0.001***	***<0.001***	***<0.001***					
White M	11.3	0.8	***<0.001***	***<0.001***	***<0.001***	**0.003**	***<0.001***				
White F	19.1	0.7	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***			
Asian/PI F	4.9	0.6	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***		
AI/NA M	−0.4	3.9	0.928	***<0.001***	***<0.001***	**0.016**	***<0.001***	**0.003**	***<0.001***	0.182	
AI/NA F	10.5	3.7	**0.005**	0.263	***<0.001***	0.697	***0.001***	0.834	**0.021**	0.131	**0.043**
Full model (with controls)											
Black M	7.4	0.8	***<0.001***								
Black F	15.9	0.7	***<0.001***	***<0.001***							
Hispanic M	6.2	0.7	***<0.001***	0.114	***<0.001***						
Hispanic F	18.2	0.6	***<0.001***	***<0.001***	***<0.001***	***<0.001***					
White M	5.2	0.7	***<0.001***	**0.008**	***<0.001***	0.202	***<0.001***				
White F	12.3	0.7	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***			
Asian/PI F	4.1	0.6	***<0.001***	***<0.001***	***<0.001***	***0.002***	***<0.001***	0.124	***<0.001***		
AI/NA M	−1.5	4.3	0.734	**0.038**	***<0.001***	**0.075**	***<0.001***	0.121	***0.001***	0.193	
AI/NA F	6.7	4.0	**0.095**	0.851	**0.022**	0.894	**0.004**	0.706	0.160	0.517	0.161

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and whether the student chose to enroll in any online courses

*p-values for each row were calculated by rotating through the reference group in the model; to avoid misinterpretation these additional p-values are only displayed for the interaction terms, since the other terms are no longer interpretable in the same was as in a non-interaction model once an interaction term has been added

Bolding indicates p-values that are significant at the $\alpha \leq 0.1$ level

Bold italics indicates p-values that are still significant at the $\alpha \leq 0.1$ after adjusting for multiple significance tests in the given model using the Bonferroni method

Table 4 Predicted non-discretionary time commitment (hours/week) by gender by race/ethnicity, interaction model to illustrate relative significances of gender gap by race/ethnicity, linear regression coefficients reported (reference groups: M and Asian/Pacific Islander)

Interaction model	Base model (no covariates)						Full model (with controls)					
	Coeff.	SE	Ref. gp.*				Coeff.	SE	Ref. gp.*			
			Asian/PI	Black	Hispanic	White			Asian/PI	Black	Hispanic	White
			p	*p*	*p*	*p*			*p*	*p*	*p*	*p*
F	4.9	0.6	< 0.001				4.1	0.6	< 0.001			
Black	14.7	0.8	< 0.001				7.4	0.8	< 0.001			
Hispanic	9.0	0.7	< 0.001				6.2	0.7	< 0.001			
White	11.3	0.8	< 0.001				5.2	0.7	< 0.001			
AI/NA	− 0.4	3.9	0.928				− 1.5	4.3	0.734			
Black × F	5.1	1.0	***< 0.001***				4.3	1.0	***< 0.001***			
Hispanic × F	8.4	0.9	***< 0.001***	***< 0.001***			8.0	0.9	***< 0.001***	***< 0.001***		
White × F	3.0	1.0	***0.003***	**0.051**	***< 0.001***		3.0	0.9	***0.001***	0.222	***< 0.001***	
AI/NA × F	6.0	5.4	0.268	0.864	0.649	0.580	4.0	5.8	0.489	0.961	0.502	0.865

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and whether the student chose to enroll in any online courses

*p-values for each row were calculated by rotating through the reference group in the model; to avoid misinterpretation these additional p-values are only displayed for the interaction terms, since the other terms are no longer interpretable in the same was as in a non-interaction model once an interaction term has been added

Bolding indicates p-values that are significant at the $\alpha \leq 0.1$ level

Bold italics indicates p-values that are still significant at the $\alpha \leq 0.1$ after adjusting for multiple significance tests in the given model using the Bonferroni method

Table 5 Predicted time spent on childcare, paid work, and housework (hours/week) by gender, linear regression coefficients reported (reference group: M)

	Base			Full		
	Coeff.	SE	*p*	Coeff.	SE	*p*
Childcare (hours/week)						
F	6.2	0.2	< 0.001	5.8	0.2	< 0.001
Paid work (hours/week)						
F	0.8	0.2	< 0.001	−0.5	0.2	0.018
Housework (hours/week)						
F	3.9	0.1	< 0.001	3.6	0.1	< 0.001

Full model includes the following control variables: ethnicity, age, GPA, income, first generation status, and online course enrollment status

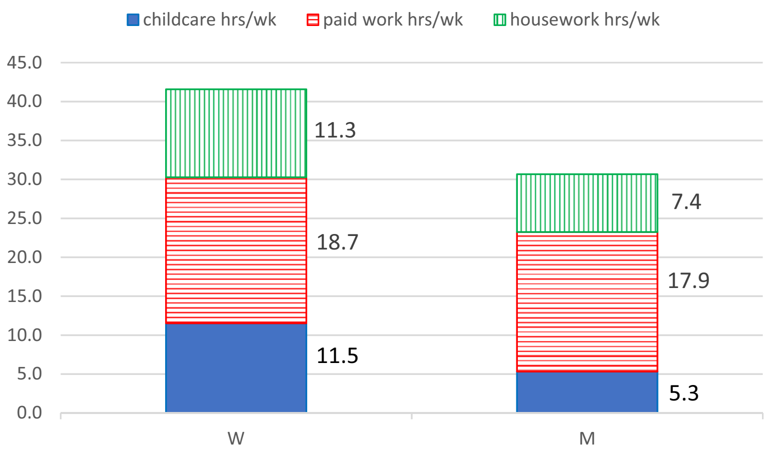

Fig. 5 Mean time (in hours) spent on childcare, paid work, and housework each week by gender

Time Poverty and Intersectionality: Combinations of Gender and Race/Ethnicity

In reality, race/ethnicity and gender may not have completely independent relationships with time poverty: the gender gap among students in different racial/ethnic groups may not be the same size or direction. These trends are shown in Fig. 4, Table 3 and 4. On the left (Fig. 4a), groups are listed from largest to smallest non-discretionary time commitments; on the right (Fig. 4b), data is displayed to illustrate the interaction between gender and race/ethnicity, so that gender gaps within each racial/ethnic group are easier to see and compare.

Black women had the highest non-discretionary time commitments, or 2.4 times more than Asian/PI and AI/NA men, who had the lowest levels (Fig. 4a). Except for comparisons between AI/NA students, the differences between each group and the one immediately next to it in Fig. 4a is statistically significant. While AI/NA subgroups do not have significantly different non-discretionary time compared to other immediately adjacent groups (likely because of small *n* for this group), AI/NA men had significantly less time poverty than white men students; and AI/NA women had significantly more time poverty than Asian/PI men and significantly less time poverty than White women.[6]

Gender gaps (Fig. 4b) are smallest for Asian/PI students and largest for Hispanic students. Black students have the second largest time poverty gender gap, and White students have the second smallest. The differences in the sizes of these gaps are statistically significant for all pairwise comparisons.[7] Linear regression models (Table 4) show that not only are differences by gender and race/ethnicity significant in predicting non-discretionary time commitments (and thus, time available for college), there is also a significant interaction between gender and race/ethnicity—the gender gap is larger for some racial/ethnic groups

[6] Reports of statistical significance come from a regression model in which each intersection group (gender by race/ethnicity) was treated as a separate category (see Table 3).

[7] Reports of statistical significance of gaps come from a gender by race/ethnicity interaction model (see Table 4). Tables 3 and 4 produce the same estimates, but present data differently. We include both tables since the significance values allow for different types of comparisons (between individual intersectional groups, vs. comparison of gender gaps for each racial/ethnic group).

than others. The time poverty gender gap was 3.0 h, 5.1 h, and 8.4 h *greater*, respectively, for White, Black and Hispanic versus Asian/PI students. Adding controls to these models reduced the size of the differences in time poverty by gender and race/ethnicity, but these differences remained significant.

Exploring Potential Explanations for Differential Rates of Time Poverty

One possible reason for the inequitable distribution of time poverty by gender and race/ethnicity is that other demographics that correlate with high time poverty may also correlate with race/ethnicity or gender. We considered a few variables to investigate how these might explain differential time poverty rates.

Time Spent on Work, Childcare, and Housework, by Gender and Race/Ethnicity

Separate weighted linear regression models (Table 5) were used to predict the mean time spent each week on childcare, paid work, and housework by gender. We also explored the weighted mean time spent on each activity (Fig. 5), which yielded practically identical results.

Women students spent significantly more time on each of these activities than men ($p < 0.001$, Table 5), although the relative magnitude of these differences varied. Childcare was the biggest relative difference, with women spending more than double the time each week compared to men; housework was the second biggest relative difference, with women spending 52% more time; and paid work showed the least difference, with women spending only 5% more time. This is in line with previous findings that have shown that women on average spend more time on childcare and shoulder more unpaid domestic work (Chatzitheochari & Arber, 2012; Mattingly & Bianchi, 2003; Zilanawala, 2013).

We next considered the distribution of these three types of time commitments by race/ethnicity, based on weighted means (see Fig. 6) and linear regression models (Table 6).

In all three categories, Black, Hispanic and White students spent significantly more time on each of these activities than Asian/PI students ($p < 0.001$, based on weighted linear regression model); Black and Hispanic students spent significantly more time on each of these than White students ($p < 0.001$ for all except childcare, which was $p = 0.030$); and Black students spent significantly more time on paid work than Hispanic students ($p < 0.001$). The relative magnitude of these differences also varied by group. Black and Hispanic students both spent roughly double the time on childcare than Asian/PI students, whereas White students spent only 39% more. Similarly, for housework, Black and Hispanic students spent 45% and 41% more, respectively, than Asian/PI students, while White students spent 27% more. Black, Hispanic, and White students also spent more time on paid work than Asian/PI students, at 85%, 63% and 80% more, respectively. Thus, the largest burden relative to other groups for Black and Hispanic students appears to be childcare, followed by paid work; whereas for White students, the largest contributor to their higher rates of time poverty compared to Asian students is the time spent on paid work.

The implications of these patterns suggest that childcare is one of the major contributing factors related to differential rates of time poverty. Paid work is also a factor, and may be related to parental status, as student parents work more hours to pay for their families' expenses (Huelsman & Engle, 2013). The living expenses of dependents are not counted as a cost of attending (COA) college in US federal financial aid formulas (Wladis et al., 2018), so current US federal financial aid rules do not allow student parents to reduce their work hours to spend more time on their education if they are working by necessity to support their families.

Some may note that the Estimated Family Contribution (EFC) (and its replacement, the Student Aid Index) formula does include household size and number of dependents. However, this is only used to calculate the proportion of the already estimated cost of attendance (COA) that a student is able to pay. But the COA under-estimates the true cost of attendance for many students because the lost hours that a student must spend working to feed, house, clothe, and provide healthcare for their dependents, which they now cannot spend on college, are not accounted for in the COA to begin with (US Department of Education, 2022). In addition, even childcare—which is allowed to be included in the COA—is not automatic and has to be petitioned for on an individual basis, a fact about which many students are unaware (Emrey-Arras, 2019; US Department of Education, 2022). Thus, there are many unaccounted-for time costs to attending college under federal financial aid (even after recent reforms) because on top of working whatever hours are needed to fulfil their federally calculated expected family contribution, students must also: (1) work extra to pay for dependent living expenses that are not included in the COA; (2) petition specially for childcare to be included in the COA (if they are even aware that this is allowed); and (3) work whatever hours are needed to make up the gap between the (often under-estimated) federally-calculated financial need and actual awarded aid (roughly 75% of current students have unmet need; Walizer, 2018).

The results from this section thus suggest that interventions may be needed that provide students (1) better access to affordable childcare; and (2) more financial aid targeted at allowing them to reduce their work hours. The latter would be important not just for student parents, but also for lower-income students who often must work to support their parents, siblings, or extended families (Goldrick-Rab, 2016).

The reasons for many of these differences in the distribution of time commitment type by gender and race/ethnicity appear to be related to age, parental status, and access to childcare, so we explored each of these factors.

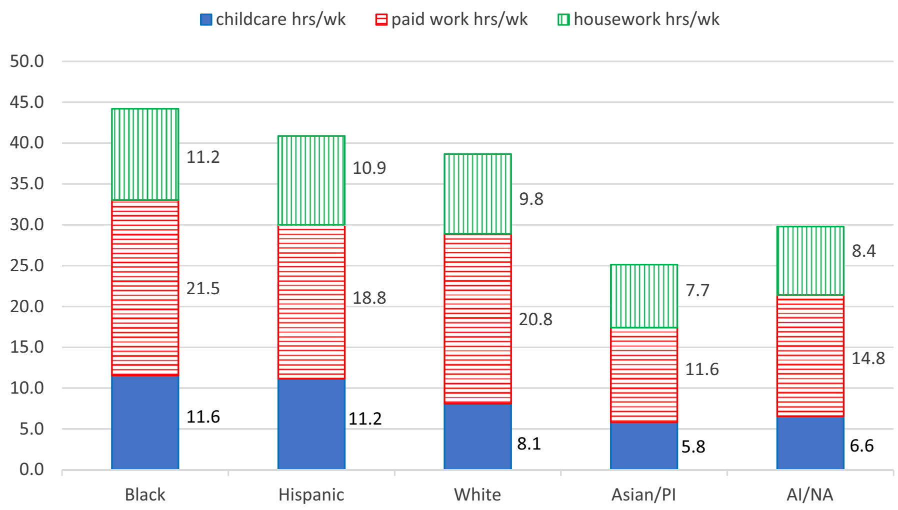

Fig. 6 Mean time (in hours) spent on childcare, paid work, and housework each week by race/ethnicity

Table 6 Predicted childcare, paid work and housework time (hours/week) by race/ethnicity, linear regression coefficients reported (reference group: Asian/Pacific Islander)

Interaction model	Base model						Full model (with controls)					
	Coeff.	SE	Ref. gp.*				Coeff.	SE	Ref. gp.*			
			Asian/PI	Black	Hispanic	White			Asian/PI	Black	Hispanic	White
			p	*p*	*p*	*p*			*p*	*p*	*p*	*p*
Childcare (hours/week)												
Black	5.7	0.3	***<0.001***				2.8	0.3	***<0.001***			
Hispanic	5.3	0.2	***<0.001***	0.140			3.7	0.3	***<0.001***	***0.002***		
White	2.3	0.3	***<0.001***	***<0.001***	***<0.001***		0.7	0.3	**0.012**	***<0.001***	***<0.001***	
AI/NA	0.7	1.3	0.581	***<0.001***	***<0.001***	0.234	−1.2	1.4	0.372	***0.004***	***<0.001***	0.161
Paid work (hours/week)												
Black	9.9	0.3	***<0.001***				6.2	0.3	***<0.001***			
Hispanic	7.3	0.3	***<0.001***	***<0.001***			6.1	0.3	***<0.001***	0.842		
White	9.2	0.3	***<0.001***	**0.030**	***<0.001***		5.5	0.3	***<0.001***	**0.066**	**0.078**	
AI/NA	3.3	1.6	**0.045**	***<0.001***	**0.014**	***<0.001***	2.5	1.8	0.167	**0.037**	**0.039**	**0.082**
Housework (hours/week)												
Black	3.5	0.2	***<0.001***				6.2	0.3	***<0.001***			
Hispanic	3.2	0.2	***<0.001***	**0.075**			6.1	0.3	***<0.001***	***0.001***		
White	2.1	0.2	***<0.001***	***<0.001***	***<0.001***		5.5	0.3	***<0.001***	0.015	***<0.001***	
AI/NA	0.7	1.1	0.551	**0.014**	0.0028	0.224	2.5	1.8	0.167	0.344	0.155	0.566

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and online course enrollment status

*p-values for each column were calculated by rotating through the reference group in the model

Bolding indicates p-values that are significant at the $\alpha \leq 0.1$ level

Bold italics indicates p-values that are still significant at the $\alpha \leq 0.1$ after adjusting for multiple significance tests in the given model using the Bonferroni method

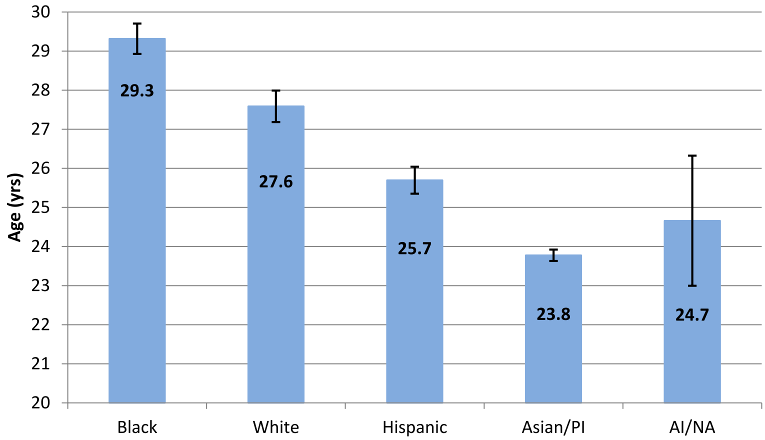

Fig. 7 Mean age by race/ethnicity. Linear regression model (without controls on weighted imputed dataset); error bars indicate 95% confidence interval

Age as a Mediator Between Gender or Race/Ethnicity, and Time Poverty

According to weighted linear regression models, for every additional year of age, a student's non-discretionary time commitments went up by 1.5 h/week, and this correlation is highly significant ($p < 0.001$).[8] This is likely due to a complex host of factors, including needing to work as well as childcare responsibilities. Using the same weighted linear regression models to predict differences in age by gender, we found that women in the sample were on average seven months older than the men, which was significant ($p < 0.001$)—this is also coupled with the fact that women on average tend to have children five years earlier than men (Bui & Miller, 2018). In Fig. 7, the average age for different racial/ethnic groups in the sample is listed—the differences between each of these is pairwise statistically significant ($p < 0.001$; Table 7), with only the exception of AI/NA vs. Asian/PI comparison (where the numbers of AI/NA students in the sample may simply be too small to accurately assess pairwise significance).

Because women and Black students attend college at later ages, and age is strongly correlated with higher rates of time poverty, it may be that conditioning on age changes the relationship between gender or race/ethnicity and time poverty. Adding age to regression models that predict non-discretionary time commitments by gender or ethnicity reduced the time poverty gaps both by gender and ethnicity.

Using KHB mediation analysis, Table 8 shows that conditioning on age does not significantly change the gap in non-discretionary time by gender, explaining only about 2% of the difference (because the indirect disparity is non-significant and only about 2% of the total disparity). The major differences in non-discretionary time commitments by gender were for childcare and housework, so age may not be a good proxy for childcare-related time commitments by gender (which makes sense, since as previously noted, women on average have children five years earlier than men). This suggests that age does not explain

[8] We also considered non-linear representations of age, but a linear model fit the data better.

Table 7 Age (in years) by race/ethnicity, linear regression coefficients reported (reference group: Asian/Pacific Islander)

Age	Coef.	SE	Ref. gp.*			
			Asian/PI	Black	Hispanic	White
			p	*p*	*p*	*p*
Black	3.8	0.1	***< 0.001***			
Hispanic	5.5	0.1	***< 0.001***	***< 0.001***		
White	1.9	0.1	***< 0.001***	***< 0.001***	***< 0.001***	
AI/NA	0.9	0.8	0.254	***< 0.001***	***< 0.001***	***< 0.001***

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and online course enrollment status

*p-values for each column were calculated by rotating through the reference group in the model

Bolding indicates p-values that are significant at the $\alpha \leq 0.1$ level

Bold italics indicates p-values that are still significant at the $\alpha \leq 0.1$ after adjusting for multiple significance tests in the given model using the Bonferroni method

much of the gender gap in time available for college, and other explanatory factors need to be explored.

However, in Table 8 age *is* a significant mediator of the relationship between race/ethnicity and time poverty for various groups (because the indirect disparity is significant). Age explains 37%, 20% and 45% of the differences in time poverty between Black, Hispanic and White vs. Asian/PI students, respectively, and 42% of the difference between Black and White students (because the indirect disparity is this proportion of the total disparity for each group compared to the reference group). The pattern for Hispanic vs. White students is more complex: after we control for age, the time poverty gap (or total disparity) between Hispanic and White students is about twice as large as it originally appeared. This is because Hispanic students in this study are on average younger than White students, but they are even more time poor when compared to White students of the same age. Thus, the fact that Hispanic students attend college at younger ages actually masks the fact that they are significantly more time poor than comparable-age White students.

These results indicate that age is a significant mediating factor in the relationship between race/ethnicity and time poverty, but not between gender and time poverty. This has implications for practice and future research. This suggests that delayed entry into college may have a significant negative impact in terms of the time that a student can dedicate to their studies. This is particularly problematic for groups that enter college later because of a lack of financial resources, or because they lack appropriate advisement about college admissions or financial aid at the secondary school level (Bozick & DeLuca, 2005; Castro, 2019; St. Amour, 2020). Black students in this sample were particularly likely to be older, and therefore, also to suffer higher rates of time poverty. If students could be helped to enter college earlier, this might alleviate some time poverty. Future causal research would be needed to investigate this possibility. Also, once time poverty interventions have been successfully developed, age might be one way of initially identifying students who could benefit from time poverty interventions, since age is a variable that is readily available in institutional research data.

Table 8 Mediation analysis (KHB Method) of the extent to which age explains the relationship between gender, or race/ethnicity and time poverty, linear regression coefficients reported

Non-disc. time (h/week)	Base			Full		
	Coeff.	SE	*p*	Coeff.	SE	*p*
Gender (ref. gp. M)						
Total disparity	9.3	0.4	< 0.001	7.3	0.4	< 0.001
Direct disparity	9.1	0.4	< 0.001	7.8	0.4	< 0.001
Indirect disparity	0.2	0.2	0.315	− 0.5	0.6	0.362
Black vs. Asian/PI (ref. gp.)						
Total disparity	19.5	0.6	< 0.001	17.8	0.6	< 0.001
Direct disparity	12.3	0.6	< 0.001	12.0	0.7	< 0.001
Indirect disparity	7.2	0.4	< 0.001	5.8	0.7	< 0.001
Hispanic vs. Asian/PI (ref. gp.)						
Total disparity	15.5	0.5	< 0.001	14.5	0.6	< 0.001
Direct disparity	12.4	0.5	< 0.001	11.7	0.6	< 0.001
Indirect disparity	3.1	0.3	< 0.001	2.7	0.8	< 0.001
White vs. Asian/PI (ref. gp.)						
Total disparity	14.6	0.6	< 0.001	11.4	0.6	< 0.001
Direct disparity	8.0	0.6	< 0.001	6.6	0.6	< 0.001
Indirect disparity	6.6	0.4	< 0.001	4.8	1.0	< 0.001
Black vs. White (ref. gp.)						
Total disparity	5.0	0.6	< 0.001	4.8	0.7	< 0.001
Direct disparity	3.0	0.6	< 0.001	3.2	0.7	< 0.001
Indirect disparity	2.1	0.2	< 0.001	1.6	0.7	0.016
Hispanic vs. White (ref. gp.)						
Total disparity	1.1	0.6	0.038	2.2	0.7	0.001
Direct disparity	4.7	0.6	< 0.001	4.9	0.7	< 0.001
Indirect disparity	− 3.6	0.3	< 0.001	− 2.7	0.8	< 0.001

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and whether the student chose to enroll in any online courses

However, even if helping students enter college earlier were to reduce their time poverty, this approach would not help students who are currently enrolled and already older than their peers. Another approach would be to develop interventions to improve the time poverty of students who are currently enrolled in college, whatever their age. One possible type of targeted time poverty intervention would be to provide student parents better access to childcare. We assessed the potential importance of such an intervention in improving gender and racial/ethnic gaps in time poverty by exploring the extent to which conditioning on the following two measures of parental time commitments may change the relationship between gender or race/ethnicity and time poverty: (1) number of children, and (2) student ratings of whether available childcare was sufficient.

Number of Children and Childcare Access as a Mediator Between Gender or Race/Ethnicity, and Time Poverty

In this sample, women had significantly more children than men on average (almost twice as many). In comparison to Asian/PI students, Black students had roughly 3.5 times as many children, Hispanic students had roughly 2.5 times as many, and White students had roughly twice as many children; all pairwise comparisons were significant ($p < 0.001$). These trends mirror those for time poverty. We explored potential mediation using the KHB method and found that the gender and race/ethnicity gaps in non-discretionary hours as measured by linear regression models went down significantly after controlling for number of children (model coefficients are not reported here because of space constraints—see Table 9 for results from related models). However, it is unclear the extent to which the differential time poverty distribution for students with children by gender and racial/ethnic group is related to the extent to which a student had access to childcare, or the extent to which students have voluntarily chosen to reduce the time spent on their college education in order to spend more time with their children. If the relationship between student ratings of available childcare and their time poverty is strong, it would suggest that the higher rates of time poverty are *not* entirely voluntary, and that many student parents might prefer to increase their available time for college by utilizing childcare if it were available to them.

On the survey, we asked students to rate on a 7-point Likert scale the extent to which they agreed with the statement "The childcare available to me (through family, friends, daycare or paid caretakers) provided me with enough time for my schoolwork". Higher ratings on this scale symbolized stronger disagreement with the statement. Student responses were both highly correlated with their discretionary time and helped to explain many of the differences by gender and by race/ethnicity and time poverty (see Table 9).

In Table 9, the total, direct, and indirect gender disparities are all significant ($p < 0.001$) and controlling for student ratings of available childcare reduced the gap in non-discretionary time by gender by 38.0%, from 9.7 h/week (the total disparity) to 6.0 h/week (the direct disparity remaining after accounting for childcare availability ratings). When comparing Black and Hispanic students to either White or Asian/PI students, and when comparing White to Asian/PI students, the total, direct, and indirect disparities are all significant ($p < 0.001$). Controlling for student ratings of childcare reduces the gap in non-discretionary time by race/ethnicity substantially: by 40%, 37% and 26% for Black, Hispanic and White vs. Asian/PI students; and by 89% and 100% for Black and Hispanic vs. White students, in base models (because this describes the difference between the total and direct disparities in these models). Most of these patterns were preserved once covariates were added, with two exceptions: there was no mediation for White vs. Asian students after adding controls, and for Hispanic vs. White students the mediation changed from total to partial after adding controls (because Hispanic students were largely younger than White students). The direct disparity was no longer significant when comparing Black vs. White students, either with or without controls, so student ratings of childcare completely mediated the relationship between race and time poverty in this case. For both gender and race/ethnicity, conditioning on student ratings of childcare reduced disparities more than conditioning on number of children.

These results suggest that lack of access to childcare is likely a significant barrier to many student parents, and that significant portions of the inequitable distribution of time as a resource for college by gender and by race/ethnicity, especially for women, Black, and Hispanic students, are likely related to insufficient access to childcare. This indicates that interventions that attempt to provide affordable and convenient high-quality childcare may be critical to closing

Table 9 Mediation analysis (KHB Method) of the extent to which student rating of childcare availability explains the relationship between gender or race/ethnicity and time poverty, linear regression coefficients reported

Non-disc. time (hours/week)	Base			Full		
	Coef.	SE	*p*	Coef.	SE	*p*
Gender (ref. gp. M)						
Total disparity	9.7	0.4	< 0.001	8.1	0.4	< 0.001
Direct disparity	6.0	0.4	< 0.001	5.6	0.4	< 0.001
Indirect disparity	3.6	0.2	< 0.001	2.6	0.7	< 0.001
Black vs. Asian/PI (ref. gp.)						
Total disparity	19.7	0.6	< 0.001	12.0	0.6	< 0.001
Direct disparity	11.9	0.6	< 0.001	9.5	0.7	< 0.001
Indirect disparity	7.8	0.3	< 0.001	2.4	0.9	0.005
Hispanic vs. Asian/PI (ref. gp.)						
Total disparity	15.8	0.5	< 0.001	11.8	0.6	< 0.001
Direct disparity	9.9	0.5	< 0.001	9.2	0.6	< 0.001
Indirect disparity	5.8	0.3	< 0.001	2.7	0.8	0.001
White vs. Asian/PI (ref. gp.)						
Total disparity	14.6	0.6	< 0.001	6.5	0.6	< 0.001
Direct disparity	10.9	0.6	< 0.001	6.9	0.6	< 0.001
Indirect disparity	3.7	0.4	< 0.001	– 0.4	0.9	0.664
Black vs. White (ref. gp.)						
Total disparity	5.2	0.6	< 0.001	3.4	0.7	< 0.001
Direct disparity	0.6	0.6	0.315	0.8	0.7	0.224
Indirect disparity	4.6	0.3	< 0.001	2.6	0.9	0.004
Hispanic vs. White (ref. gp.)						
Total disparity	1.4	0.5	0.009	5.2	0.6	< 0.001
Direct disparity	– 1.0	0.5	0.054	1.7	0.7	0.007
Indirect disparity	2.5	0.3	< 0.001	3.4	0.8	< 0.001

Full model includes the following control variables: gender, ethnicity, age, GPA, income, first generation status, and whether the student chose to enroll in any online courses

time poverty gaps. Future causal studies should explore the potential effectiveness of such interventions.

Limitations

This study did not explore the relationship between time and income poverty. Student household income was controlled in full models, but we have not attempted to tease apart the complex relationship between financial and time poverty in this study. Running an analysis with income as the sole measure of financial need is problematic because income in isolation can have both a positive (more work hours = greater income but also less discretionary time) as well as a negative (more income = greater ability to work less or outsource household work) relationship with time poverty. These two effects can confound one another, making it impossible to interpret average effects. The more relevant and equitable comparison would focus on financial *need*, not income. However, current student financial need calculations have been especially poor at accurately reflecting the needs of marginalized groups in college (Goldrick-Rab, 2016; Kelchen et al., 2017).

The CUNY dataset in this study is also not necessarily nationally representative. CUNY is more diverse than the average U.S. College; while this may impact representativeness, it also makes the dataset an excellent source for investigating time poverty and college outcomes among traditionally underrepresented groups. However, this dataset does have some limitations in how gender and race/ethnicity were recorded. CUNY institutional data had at the time only a binary category for gender and used limited federal race/ethnicity categories; therefore, these variables likely do not accurately represent how all students self-identify—further research that includes more nuanced race/ethnicity and gender categories is necessary. It is also important to note that New York state provides a higher proportion of on-campus childcare than 47 other US states (Eckerson et al., 2016). Early in data collection, it began offering universal pre-kindergarten, and New York City spends more on public benefits than any other US municipality. Thus, some of the time poverty relationships explored in this study may *underestimate* national trends.

We also note that the time measures utilized in this study are retrospective and self-reported; while there is ample evidence that these methods can produce valid results (for a more detailed discussion, see Wladis et al., 2024), it is possible that other approaches could result in different time use data (e.g., experience sampling method, see e.g., Sonnenberg et al., 2012). Further, we note that our measure of non-discretionary time commitments could be improved by including time spent on eldercare or healthcare. These time commitments could be viewed as non-discretionary, and both are likely also inequitably distributed by gender and race/ethnicity. Because these components of time use were not measured in this study, all results based on total non-discretionary time commitments in this study likely *underestimate* the inequitable distribution of time poverty. These non-discretionary tasks have been added to measures of time poverty in ongoing research.

Finally, it is important to be aware that the data reported here were collected prior to the COVID-19 pandemic. There is a possibility of shifts in time poverty distributions post-pandemic. There may be some alleviation of time issues due to the flexibility provided by a continuation of online courses. However, while research does show that students who are more time poor tend to take online courses (Wladis et al., 2023), there is currently no empirical evidence to suggest that online course-taking can close time poverty gaps. Further, we note that nationally there are mixed outcomes in terms of childcare-availability post-pandemic, with improved childcare access for some age groups in some states, and worse childcare availability in others (Crouse et al., 2023; Region Track, 2024). Thus, the potential impacts of current childcare on student time poverty needs further investigation. At the same time, many ethnic/racial-based and gender-based inequities worsened during the pandemic (Laster Pirtle & Wright, 2021; Olaniyan et al, 2023; US Department of Education, 2021), and how this may have impacted longer-term time poverty among college students is as-yet unclear and requires further research.

Implications and Directions for Future Research

This study reveals that students at large public universities like CUNY are largely time poor: the average student in this sample spent a total of 63.3 h/week on non-discretionary tasks together with their college studies, before accounting for time for meals, sleep, exercise, healthcare, or eldercare. Women, Black and Hispanic students were significantly more time poor than other groups. These results suggest that if colleges wish to address gender- and race/ethnicity-based inequities, supports that address time poverty are likely essential.

From the data, two factors that appear to significantly but partially explain differential rates of time poverty by gender and race/ethnicity are student age and childcare availability, although hours spent on paid work were also a contributing factor.

The fact that some student groups (e.g., Black students) enter college at older ages suggests that supports that help students to attend college as early as possible might produce more equitable distributions of time as a resource for college. Older students often have work and caretaking responsibilities, both of which are significant time investments (Ross-Gordon, 2011). However, many students, especially students from underrepresented racial/ethnic groups and lower-SES students, delay college for financial reasons (e.g., Bozick & DeLuca, 2005). If college were more affordable and financial aid were improved to provide *every* student the opportunity to attend college immediately after high school, this might improve inequitable rates of time poverty observed here. First generation and low-SES students (many of whom are students of color) may also need more assistance applying to college and financial aid programs if they are to attend college earlier, because despite documented need, they are less likely to do so (Gewertz, 2018).

We note, however, that disparities persisted even after controlling for age, suggesting that women, Black and Hispanic students still had higher time poverty than comparable peers of the same age, and therefore, supports that focus only on reducing the age of college enrollment are unlikely to fully address time inequities. In particular, women and Hispanic students were relatively time poor even at younger ages.

Having children was a significant predictor of time poverty and explained a significant proportion of differential rates of time poverty by gender and race/ethnicity. Results suggest that students with children (particularly Black and Hispanic women who are disproportionately more likely to be parents (Institute for Women's Policy Research, 2019)) may have a specific need for access to low- or no-cost on-campus childcare if they are to increase the time they have for their studies. Yet, the amount of available childcare on campuses in the U.S. has shrunk over the past decades, and those colleges that offer on-campus daycare centers (20.7% of all 2- and 4-year colleges) meet on average only about 5% of student need (Gault et al., 2014; Miller et al., 2011). Increasing on-campus childcare or increasing financial aid to offset childcare costs may serve to increase the time student parents (particularly Black and Hispanic mothers) devote to their studies and help alleviate the inequitable time poverty burden they carry. While current financial aid packages at many US colleges theoretically can be made to include the cost of childcare, such inclusion is not automatic and requires students to petition individually for this adjustment to their financial aid; information about how this works is often hidden and is not listed on many college websites (Emrey-Arras, 2019). There is also no standard procedure for accurately estimating childcare costs; financial aid personnel are not necessarily trained in this kind of cost-assessment, likely leading to underestimation in some cases, as has been observed already with financial aid offices' calculations of students' living expenses (Kelchen et al., 2017). Furthermore, this adjustment only serves to increase a student's need, and thus only has an effect if financial aid covers a student's need; in reality, roughly 3 out of 4 current US college students already have unmet financial need (Walizer, 2018), even before adjusting the cost of attendance to more accurately reflect students' college expenses. Therefore, if we wish to improve the ability of students to pay for childcare using their financial aid resources, we must *both* increase those resources to cover their actual need *and* adjust estimates of need to be more accurate.

Time spent on paid work was also a significant factor in the inequitable distribution of time poverty by both race/ethnicity and gender. Thus, to increase the time that time-poor students have for their studies, more financial aid may be necessary so that they can reduce time spent on paid work. Many older students must work full-time to support their families, yet this is not typically included in US financial aid calculations of expenses (only the student's own living expenses are included in federal cost-of-attendance [COA] calculations). Some research has shown that increasing aid to students can result in reduced hours spent on paid work (Broton et al., 2016; DesJardins & McCall, 2009; Scott-Clayton, 2011) and may increase hours spent studying (DesJardins & McCall, 2009). The federal cost of attendance (COA) could be adjusted to account for the time costs of students working extra hours to pay for the living expenses of their dependents. Research has demonstrated that even when just accounting for childcare and children's food costs, existing estimates of the cost of college attendance radically underestimate student parents' net price by tens of thousands of dollars per year per child (California Competes, 2020; Williams et al., 2022), and it would require on average 53–54 h/week of work at minimum wage just to cover the childcare costs for one child while attending college full-time (Williams et al., 2022); this does not even account for the work hours needed to pay for children's living expenses, or childcare for multiple children.

Time-poverty inequities in college are related to many wider systemic inequities. For example, as already noted, economic inequities, which are correlated with race/ethnicity, lead to delayed college entry resulting in older ages at college entry (Bozick & DeLuca, 2005) and they also correlate with higher-levels of time-consuming work and family responsibilities (Ross-Gordon, 2011), leading to higher time poverty.

Higher education culture also tends to frame working off-campus or having children in college as a deviation from the norm. This can impact the likelihood that older students, economically-disadvantaged students, or student parents obtain the supports that they need through federal financial aid and other resources such as on-campus childcare. For example, the Federal Student Aid Handbook (US Department of Education, 2022, Chapter 2) refers to dependent care costs as an "exceptional expense" and requires students to petition for these costs on a case-by-case basis, suggesting that having children while attending college is non-normative. Reinforcing this, information about including childcare costs in financial aid calculations is often hidden or unavailable on college websites, and students are often unaware that they can petition to include childcare in their COA (Emrey-Arras, 2019). Students who work to pay for college or living expenses can also be framed as non-normative by higher education institutions, through implicit or explicit messages that they do not "belong" in college. For example, as the Federal Student Aid Handbook (US Department of Education, 2022, Chapter 2, Step 3) explains, "The law governing the FSA programs is based on the premise that the family is the first source of the student's support". This "premise" establishes a norm, reinforced by federal higher education practices (and subsequently reinforced by higher education institutions) that "normal" students can depend on their parents to pay college expenses. However, this is directly contradicted by data on current college students, where according to the US National Center for Education Statistics (2020), the majority of college students (55.6%) received no financial assistance from parents/family/friends to pay for college. Even among dependent students, 39.9% reported receiving no financial assistance from parents/family/friends to pay for college (National Center for Education Statistics, Institute of Education Statistics, 2020), yet the Federal Student Aid Handbook (US Department of Education, 2022, Chapter 2, Step 3) states that financial aid administrators can only determine that a student who "doesn't meet any of the independence criteria" can be treated as an independent student "in unusual cases". The use of the word "unusual" is another example of how higher education structures frame students who must work to pay for college as non-normative. This presents both issues of stigma (student parents and students who must work to pay for college, are sent implicit or explicit messages that they do not "belong" in college) as well as practical barriers to obtaining sufficient time to invest in college.

There are many ways that this could be addressed. For example, information about the number and age(s) of every student's children could be collected in advance on the FAFSA, and childcare costs could subsequently be automatically calculated by combining this information with a student's registration information and federal information on local childcare costs to automatically add childcare expenses to the COAs of all student parents. The federal Department of Labor already maintains a database of childcare costs by zip code that is publicly available (US Department of Labor, 2023). Currently this is offered in a technical form aimed at researchers, but this data could be put into a user-friendly web interface, updated based on federally-calculated inflation rates to provide cost estimates for the current academic year, and adjusted to display hourly costs; it could be accompanied by interactive tools and simple instructions that individual colleges and financial aid officers could then use to determine accurate childcare costs for students based on number and age(s) of children and student enrollment hours. Automatically collecting data on the age/number of students' children on the FAFSA and using this data to automatically calculate childcare costs both de-stigmatizes student parents' college attendance, and provides critical changes needed to automate student access to necessary childcare for college. This would require providing financial aid professionals with standardized tools for calculating childcare costs (US Department of Labor, 2023), which has already been suggested as an important approach for correcting observed inequities in living expense calculations for financial aid (Kelchen et al., 2017).

Currently financial aid professionals are provided no concrete guidance on how they should estimate the costs of childcare for student parents; the Federal Student Aid Handbook (US Department of Education, 2022, vols. 3, Chapter 2) says only that "this allowance covers actual costs expected to be incurred for dependent care during periods that include but are not limited to class time, study time, field work, internships, and commuting time for the student. The amount of the allowance should be based on the number and age of the student's dependents and should not exceed reasonable cost in the community for the type of care provided". While financial aid administrators are admonished to not allow too-high estimates, no equivalent warning about the dangers of under-estimating costs is included, suggesting an implicit bias towards under- rather than over-estimating costs. Further, financial aid administrators are left on their own to research local childcare costs in their area and correctly estimate students' costs, which is problematic both with respect to workload/efficiency (every college or financial aid administrator must calculate these costs individually) and with respect to accuracy (research on how colleges calculate living expenses has already revealed that roughly one-third of colleges underestimate costs (Kelchen et al., 2017).

Similarly, changes to dependency status criteria in federal financial aid so that they better reflect the realities of current students could help to improve calculations of expected family contributions so that they better reflect the true cost of attending college; this would allow students to work fewer hours while attending college, therefore providing them more time for academics. Currently students are automatically classified as "dependent" for financial aid purposes, regardless of their individual circumstances if they are undergraduates under 24 years old, with only a few specific exceptions (married, have dependents, are active-duty or veterans of the US military, orphan/foster child/ward of the court, emancipated minor, or unaccompanied homeless youth) (US Department of Education, 2022, Chapter 2, step 3). This policy could be revised to provide concrete ways for students currently classified as "dependent" to provide evidence of their independence without needing to be part of the narrow set of categories currently designated in the federal aid definition of "independent". This is critical given that roughly 2 out of every 5 "dependent" students currently receive no financial assistance from friends or family (National Center for Education Statistics, Institute of Education Statistics, 2020).

Further, the hours that students must work in order to support dependents' living expenses could be reclassified in federal financial aid formulas as a cost of college attendance, since the hours spent working to pay for these expenses directly displace time needed to be spent on academics in college. With this change, students' calculated need would better reflect the time costs, in addition to other financial costs, of attending college. This would allow aid packages to be increased to allow students to work fewer hours to support their families, and in turn invest more hours in their studies. This could help to bring hours spent on paid work down to reasonable levels that are still compatible with college study.

Other societal structures beyond federal financial aid also contribute to time poverty inequities. For example, administrative burden (or time/energy/information costs necessary to receive public services, both within and outside higher education) has been shown to have the greatest negative impacts on the most marginalized groups, including people of color (e.g., Bell & Jilke, 2024). The time needed to obtain external public services (e.g., healthcare, housing subsidies, childcare) as well as college services (e.g., financial aid, disability accommodations, on-campus childcare) can then drain time that could otherwise be invested in academics, and reducing this administrative burden is a critical equity issue. There are also structural inequities related to work that could impact time poverty for students in college. For instance, workers of color (and particularly women of color) (Harknett & Schneider, 2019) are exposed to more unstable/unpredictable work scheduling practices and higher job turnover compared to their White co-workers (Harknett & Schneider, 2019), which may contribute to higher levels of time poverty and poorer quality of time available for academics in college. Perhaps even more important, low minimum wage rates can drastically increase the number of hours that students need to work in order to obtain the necessary funds to pay college-related costs (Williams et al., 2022). While increasing minimum wage improves the economic situation of all low-wage workers, it is particularly critical for improving racial wage gaps (Derenoncourt & Montialoux, 2020). Thus, while there is much that individual institutions and federal financial aid policies can do to improve inequity in time as a resource for college, attaining true equity will also require broader structural and societal changes beyond just educational institutions.

Inequitable distribution of time as a resource for college is a serious equity issue. Particularly considering the intersection of gender and race/ethnicity, the group with the highest levels of time poverty (Black women) vs. lowest levels of time poverty (AI/NA men) had more than double the non-discretionary time commitments, or about 25 h/week less time for their studies. Not only does lack of time reduce the time that students may spend on their studies, it also likely has other negative consequences. Overwork has been linked to negative mental and physical health outcomes (Kuroda & Yamamoto, 2019; Yamada et al., 2014); thus, the relationship between time poverty and other sources of inequity such as mental and physical health, stressors, and financial poverty, is likely complex and strongly interrelated, and should be investigated in future research. Regardless of the complexities involved, if we truly hope to provide equal opportunities for every student to succeed, it is critical that we fundamentally re-think the extent to which current models include all types of inequity that college students currently face, including addressing the inequitable distributions of time as a resource for college that were found in this study.

Appendix

See Table 10, 11 and 12

Table 10 Summary statistics comparing survey sample to students in sample frame who did not complete the survey

	Submitted survey	Did not submit survey
Female	75.2%	64.0%
Race/ethnicity		
Black	26.1%	26.8%
Hispanic	33.7%	34.2%
White	20.0%	19.8%
Asian/PI	19.8%	18.9%
Age	24.4	23.7
First-time fresh	23.5%	26.2%
GPA		
< 2.0	9.6%	12.9%
2.0–2.49	12.6%	12.9%
2.5–2.99	17.0%	16.3%
3–3.49	19.0%	17.6%
3.5–4.00	18.3%	16.4%
Median income of zipcode	$50,334	$50,232
Enrolled in a fully online course	14.1%	11.0%
Credits enrolled that semester	11.4	11.0
College retention	80.6%	75.5%
Credits earned that semester	8.8	8.1

Table 11 Distribution of control variables by gender, with 95% confidence intervals

	M		F	
	Mean	CI (95%)	Mean	CI (95%)
Age	26.3	[26.1, 26.4]	26.8	[26.7, 26.9]
First term fresh	21%	[20.6%, 22.0%]	20%	[19.5%, 20.4%]
GPA	3.0	[3.02, 3.05]	3.1	[3.07, 3.08]
Median household income of zip code	$51,351	[$50,980, $51,723]	$50,242	[$49,999, $50,486]
First generation college student	56%	[54.9%, 56.8%]	59%	[58.3%, 59.6%]
Took at least one fully online course	18%	[17.2%, 18.5%]	23%	[22.6%, 23.6%]
Number of children	0.3	[0.30, 0.33]	0.5	[0.51, 0.54]
n	12,844		28,730	

Table 12 Distribution of control variables by race/ethnicity, with 95% confidence intervals

	Black		Hispanic		White		Asian/PI		AI/PI	
	Mean	CI (95%)	Mean	CI (95%)	Mean	CI (95%)	Mean	CI (95%)	Mean	CI (95%)
Age	29.1	[28.9, 29.3]	25.6	[25.5, 25.8]	27.5	[27.3, 27.7]	24.0	[23.8, 24.2]	24.7	[23.1, 26.2]
First term fresh	19%	[18.5%, 20.1%]	20%	[19.4%, 20.8%]	20%	[18.8%, 20.6%]	23%	[22.0%, 23.9%]	13%	[7.5%, 19.1%]
GPA	2.96	[2.95, 2.98]	2.94	[2.92, 2.95]	3.33	[3.32, 3.35]	3.16	[3.14, 3.18]	2.76	[2.60, 2.92]
Median household Income of zip code	$47,168	[$46,811, $47,525]	$44,749	[$44,431, $45,067]	$62,758	[$62,203, $63,314]	$53,416	[$52,989, $53,844]	$51,437	[$48,821, $54,054]
First generation College student	57%	[56.3%, 58.5%]	67%	[66.1%, 67.8%]	42%	[40.9%, 43.2%]	57%	[56.0%, 58.4%]	72%	[63.7%, 81.1%]
Took at least one Fully online course	23%	[22.7%, 24.3%]	19%	[18.5%, 19.8%]	28%	[27.4%, 29.5%]	17%	[15.7%, 17.4%]	19%	[12.5%, 26.0%]
Number of children	0.6	[0.62, 0.66]	0.5	[0.46, 0.49]	0.4	[0.36, 0.40]	0.2	[0.18, 0.21]	0.2	[0.10, 0.32]
n	11,207		13,863		8,234		8,134		136	

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Data availability Restrictions apply to the availability of the data that support the findings of this study, due to subject privacy concerns and legal restrictions. The data are available from the authors upon reasonable request if permission can be obtained from the City University of New York.

References

Aas, D. (1978). Households and dwellings: New techniques for recording and analyzing data on time use. In W. Michelson (Ed.), *Public policy in temporal perspective.* Den Haag.

Austin, P. C., & Hux, J. E. (2002). A brief note on overlapping confidence intervals. *Journal of Vascular Surgery, 36*(1), 194–195. https://doi.org/10.1067/mva.2002.125015

Bell, E., & Jilke, S. (2024). Racial discrimination and administrative burden in access to public services. *Scientific Reports, 14*(1), 1071. https://doi.org/10.1038/s41598-023-50936-1

Bennett, A., & Burke, P. J. (2017). Re/conceptualizing time and temporality: An exploration of time in higher education. *Discourse: Studies in the Cultural Politics of Education, 39*(6), 1–13. https://doi.org/10.1080/01596306.2017.1312285

Boland, W. C. (2021). *New York: Minority serving institutions in the Empire State*. Rudgers Graduate School of Education - Center for Minority Serving Institutions. https://cmsi.gse.rutgers.edu/sites/default/files/NewYorkReport.pdf

Bozick, R., & DeLuca, S. (2005). Better late than never? Delayed enrollment in high school to college transition. *Social Forces, 84*(1), 531–544. https://doi.org/10.1353/sof.2005.0089

Broton, K. M., Goldrick-Rab, S., & Benson, J. (2016). Working for college: The causal impacts of financial grants on undergraduate employment. *Educational Evaluation and Policy Analysis, 38*(3), 477–494. https://doi.org/10.3102/0162373716638440

Bui, Q., & Miller, C. C. (2018). The age that women have babies: How a gap divides America. *The New York Times, 4*, 1.

Buis, M. L. (2010). Stata tip 87: Interpretation of interactions in nonlinear models. *The Stata Journal, 10*(2), 305–308. https://doi.org/10.1177/1536867X1001000211

Burston, M. A. (2017). I work and don't have time for that theory stuff: Time poverty and higher education. *Journal of Further and Higher Education, 41*(4), 516–529. https://doi.org/10.1080/0309877X.2015.1135885

California Competes. (2020). *Clarifying the true cost of college for student parents*. California Competes. https://californiacompetes.org/wp-content/uploads/2023/01/CACompetes_Clarifying-the-True-Cost-of-College-for-Student-Parents_Final.pdf

Carbado, D. W., Crenshaw, K. W., Mays, V. M., & Tomlinson, B. (2013). Intersectionality: Mapping the movements of a theory. *Du Bois Review: Social Science Research on Race, 10*(2), 303–312. https://doi.org/10.1017/S1742058X13000349

Castro, A. (2019). *Early decision harms students of color and low-income students*. Center for American Progress. https://www.americanprogress.org/issues/race/news/2019/11/04/476789/early-decision-harms-students-color-low-income-students/

Chatzitheochari, S., & Arber, S. (2012). Class, gender and time poverty: A time-use analysis of British workers' free time resources. *The British Journal of Sociology, 63*(3), 451–471.

Conway, K. M., Wladis, C., & Hachey, A. C. (2021). Time poverty and parenthood: Who has time for college? *AERA Open, 7*, 233285842110116. https://doi.org/10.1177/23328584211011608
Crenshaw, K. (1989). *Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics*. University of Chicago Legal Forum. https://chicagounbound.uchicago.edu/uclf/vol1989/iss1/8
Crenshaw, K. (1991). Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stanford Law Review, 43*(6), 1241. https://doi.org/10.2307/1229039
Crouse, G., Ghertner, R., & Chien, N. (2023). *Child care industry trends during the recovery from the COVID-19 pandemic*. Assistant Secretary for Planning and Evaluation, US Department of Health and Human Services.
CUNY. (2018). *2018 Student experience survey: A survey of CUNY undergraduate students*. https://public.tableau.com/app/profile/oira.cuny/viz/2018StudentExperienceSurvey/CoverPage
Darolia, R. (2014). Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and pare-time students. *Economics of Education Review, 38*, 38–50. https://doi.org/10.1016/j.econedurev.2013.10.004
Derenoncourt, E., & Montialoux, C. (2020). Minimum wages and racial inequality. *The Quarterly Journal of Economics, 136*(1), 169–228. https://doi.org/10.1093/qje/qjaa031
DesJardins, S. L., & McCall, B. P. (2009). The impact of Washington state achievers scholarship on student outcomes. In *Annual Meeting of the Association for the Study of Higher Education*.
Eckerson, E., Talbourdet, L., Reichlin, L., Sykes, M., Noll, E., & Gault, B. (2016). *Childcare for parents in college: A state-by-state assessment (No. IWPR #C445)*. Institute for Women's Policy Research.
Emrey-Arras, M. (2019). *Higher education: More information could help student parents access additional federal student aid. Report to congressional requesters. GAO-19-522*. US Government Accountability Office.
Erikson, R., Goldthorpe, J. H., Jackson, M., Yaish, M., & Cox, D. R. (2005). On class differentials in educational attainment. *Proceedings of the National Academy of Science of the United States of America, 102*(27), 9730–9733. https://doi.org/10.1073/pnas.0502433102
Gault, B., Reichlin, L., Reynolds, E., & Froehner, M. (2014). *Campus childcare declining even as growing numbers of parents attend college (No. IWPR #C425)*. Institute for Women's Policy Research.
Gewertz, C. (2018). Why don't students apply for financial aid? *Education Week*. https://www.edweek.org/teaching-learning/why-dont-students-apply-for-financial-aid/2018/12
Goldrick-Rab, S. (2016). *Paying the price: College costs, financial aid, and the betrayal of the American dream*. University of Chicago Press.
Harknett, K., & Schneider, D. (2019). *It's about time: How work schedule instability matters for workers, families and racial inequities (the shift project)*. Harvard University. https://shift.hks.harvard.edu/its-about-time-how-work-schedule-instability-matters-for-workers-families-and-racial-inequality/
Huelsman, M., & Engle, J. (2013). *Student parent and financial aid. Working paper June 2013*. Institute for Women's Policy Research.
Institute for Women's Policy Research. (2019). *Parents in college by the numbers: Today's student parent population*. https://iwpr.org/iwpr-issues/student-parent-success-initiative/parents-in-college-by-the-numbers/
Kalenkoski, C., Hamrick, K., & Andrews, M. (2011). Time poverty thresholds and rates for the US population. *Social Indicators Research, 104*(1), 129–155. https://doi.org/10.1007/s11205-010-9732-2
Karlson, K. B., & Holm, A. (2011). Decomposing primary and secondary effects: A new decomposition method. *Research in Social Stratification and Mobility, 29*(2), 221–237. https://doi.org/10.1016/j.rssm.2010.12.005
Karlson, K. B., Holm, A., & Breen, R. (2010). *Total, direct, and indirect effects in logit models (CSER WP No. 0005)*. Aarhus Universitet. Retrieved from http://www.forskningsdatabasen.dk/en/catalog/2353728899
Keep On Moving On. (2018). *CUNY matters*. Spring 2018. http://www1.cuny.edu/sites/matters/2018/02/16/keep-on-moving-on/
Kelchen, R., Goldrick-Rab, S., & Hosch, B. (2017). The costs of college attendance: Examining variation and consistency in institutional living cost allowances. *The Journal of Higher Education, 88*(6), 947–971. https://doi.org/10.1080/00221546.2016.1272092
Kuroda, S., & Yamamoto, I. (2019). Why do people overwork at the risk of impairing mental health? *Journal of Happiness Studies, 20*(5), 1519–1538. https://doi.org/10.1007/s10902-018-0008-x
Laster Pirtle, W. N., & Wright, T. (2021). Structural gendered racism revealed in pandemic times: Intersectional approaches to understanding race and gender health inequities in COVID-19. *Gender & Society, 35*(2), 168–179. https://doi.org/10.1177/08912432211001302
Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Sage Publications.

Mathuews, K. B. (2018). *The working time-poor: Time poverty implication for working students' involvement.* [Doctoral dissertation, Ohio University]. OhioLINK Electronic Theses and Dissertations Center. http://rave.ohiolink.edu/etdc/view?acc_num=ohiou1540829773983031

Mattingly, M. J., & Bianchi, S. M. (2003). Gender differences in the quantity and quality of free time: The US experience. *Social Forces, 81*(3), 999–1030.

Miller, K., Gault, B., & Thorman, A. (2011). *Improving childcare access to promote postsecondary success among low-income parents (No. IWPR #C378)*. Institute for Women's Policy Research. https://iwpr.org/iwpr-general/improving-child-care-access-to-promote-postsecondary-success-among-low-income-parents/

Moran, M. D. (2003). Arguments for rejecting the sequential Bonferroni in ecological studies. *OIKOS, 100*(2), 403–405. https://doi.org/10.1034/j.1600-0706.2003.12010.x

National Center for Education Statistics & Institute of Education Statistics. (2020). *National Postsecondary student aid study*. Institute of Education Sciences. https://nces.ed.gov/surveys/npsas/

Neyt, B., Omey, E., Verhaest, D., & Baert, S. (2019). Does student work really affect education outcomes? A review of the literature. *Journal of Economic Surveys, 33*(3), 896–921. https://doi.org/10.1111/joes.12301

Olaniyan, M., Magnelia, S., Coca, V., Abeyta, M., Vasquez, M., Harris, F., & Gadwah-Meaden, C. (2023). *Two pandemics: Racial disparities in basic needs insecurity among college students during the COVID-19 pandemic*. The Hope Center at Temple University. https://hope.temple.edu/racial-disparities-basic-needs-insecurity-college-students-covid-19-pandemic

Region Track. (2024). *Child care in state economies (2024 update)*. Committee for Economic Development. https://cdn2.assets-servd.host/ced-microsite/production/documents/Ex-Summ-Part-1_Child-Care-in-State-Economies-2024.pdf?dm=1706542767

Robotham, D. (2013). Students' perspective on term-time employment: An exploratory qualitative study. *Journal of Further and Higher Education, 37*(3), 431. https://doi.org/10.1080/0309877X.2012.666892

Ross-Gordon, J. M. (2011). Research on adult learners: Supporting the needs of a student population that is no longer nontraditional. *Peer Review, 13*(1), 26.

Schudde, L. (2018). Heterogeneous effects in education: The promise and challenge of incorporating intersectionality into quantitative methodological approaches. *Review of Research in Education, 42*(1), 72–92. https://doi.org/10.3102/0091732X1875904

Scott-Clayton, J. (2011). On money and motivation: A quasi-experimental analysis of financial incentives for college achievement. *Journal of Human Resources, 46*, 614–646.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. In S. Leinhardt (Ed.), *Sociological Methodology* (pp. 290–312). American Sociological Association.

Sonnenberg, B., Riediger, M., Wrzus, C., & Wagner, G. G. (2012). Measuring time use in surveys—Concordance of survey and experience sampling measures. *Social Science Research, 41*(5), 1037–1052. https://doi.org/10.1016/j.ssresearch.2012.03.013

St. Amour, M. (2020). *What happens before college matters*. Inside Higher Eduaction. https://www.insidehighered.com/news/2020/10/20/black-students-need-changes-policies-and-structures-beyond-higher-education

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*(1), 89–125. https://doi.org/10.3102/F00346543045001089

US Bureau of Labor Statistics. (2020). *American time use survey [ATUS]*. https://www.bls.gov/news.release/atus.toc.htm

US Department of Education. (2021). *Education in a pandemic: The disparate impacts of COVID-19 on America's Students*. https://www2.ed.gov/about/offices/list/ocr/docs/20210608-impacts-of-covid19.pdf

US Department of Education. (2022). 2023–2024 federal student aid handbook. U.S. Dept. of Education, Federal Student Aid, Washington

US Department of Labor. (2023). *National database of childcare prices*. DOL. Retrieved February 15, 2024, from http://www.dol.gov/agencies/wb/topics/featured-childcare

van der Weele, T. J., & Robinson, W. R. (2014). On the causal interpretation of race in regressions adjusting for confounding and mediating variables. *Epidemiology, 25*(4), 473–484. https://doi.org/10.1097/EDE.0000000000000105

Walizer, L. (2018). *When financial aid falls short*. CLASP. https://www.luminafoundation.org/wp-content/uploads/2019/01/when-financial-aid-falls-short.pdf

Williams, B., Bitar, J., Polk, P., Nguyen, A., Montague, G., Gillispie, C., Waller, A., Tadesse, A., & Elliott, K. C. (2022). *For student parents, the biggest hurdles to a higher education are costs and finding child care (student parent affordability)*. The Education Trust, Generation Hope. https://edtrust.org/wp-content/uploads/2014/09/For-Student-Parents-The-Biggest-Hurdles-to-a-Higher-Education-Are-Cost-and-Finding-Child-Care-August-2022.pdf

Winship, C., & Mare, R. D. (1984). Regression models with ordinal variables. *American Sociological Review, 49*(4), 512–525.
Wladis, C., Hachey, A. C., & Conway, K. (2018). No time for college? An investigation of time poverty and parenthood. *The Journal of Higher Education, 89*(6), 807–831. https://doi.org/10.1080/00221546.2018.1442983
Wladis, C., Hachey, A. C., & Conway, K. (2023). Time poverty: A hidden factor connecting online enrollment and college outcomes? *The Journal of Higher Education, 94*(5), 609–637. https://doi.org/10.1080/00221546.2022.2138385
Wladis, C. W., Hachey, A. C., & Conway, K. M. (2024). It's about time, Part II: Does time poverty contribute to inequitable college outcomes by gender and race/ethnicity. *AERA Open*, *10*(1), 1–20.https://doi.org/10.1177/233285842412379
Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. The MIT Press.
Yamada, T., Yamada, T., Chen, C. C., & Zeng, W. (2014). Overwork and adverse effects on health. *Journal of Global Economics, 2*(1), 1–8. https://doi.org/10.4172/2375-4389.1000106
Zilanawala, A. (2013). *Women's time poverty: Differences by family structure, employment, and gender ideology.* Doctoral dissertation, Columbia University. https://doi.org/10.7916/D8HX1KSQ