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Time Poverty: A Hidden Factor Connecting Online Enrollment and College Outcomes?

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ABSTRACT

This study explored the relationships between voluntary online course enrollment (pre-pandemic), time poverty, and college outcomes. Results indicate that students who enrolled in at least one fully online course were significantly more time poor than other students; these differences were largely explained by age, parental status, and paid work. Yet, despite being more time poor, students who enrolled in online courses were more likely to successfully complete their courses, especially after controlling for time poverty. While students who took at least one online course were less likely to be retained in college and accumulated on average fewer credits, outcomes in online courses did not explain these differences; rather, other factors that make students both more likely to enroll online and to drop out or take fewer credits likely play a role. In particular, time poverty fully mediated the relationship between online enrollment and credit accumulation.

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Online learning; retention; academic momentum; time poverty; non-traditional students

Even before most colleges moved instruction online during the COVID-19 pandemic, online learning had become a fundamental aspect of postsecondary education, with enrollments increasing annually in contrast to declining enrollments in higher education overall (Allen et al., 2016). A defining feature of online learning pre-pandemic is that generally students would voluntarily enroll in this modality (Gelles et al., 2020). Historically, students who enroll in online courses have had significantly different characteristics than students who only take courses face-to-face (e.g., they are more likely to be employed FT, older, and to have children [e.g., Cavanaugh & Jacquemin, 2015; Faidley, 2018; Johnson & Mejia, 2014]). Prior studies have attempted to determine whether online course-taking impacts college outcomes. However, the research has produced mixed results; it is unclear whether enrolling in online courses has a positive, negative or no impact on college outcomes (e.g., Wladis et al., 2016; S. Jaggars, 2011; Shea & Bidjerano, 2014). Finding an answer to this

question is even more critical since the pandemic, as enrollment in online courses has been further outpacing higher education enrollment overall (NC-SARA, 2021); institutions are grappling with the implications of this, uncertain about whether to maintain increased online offerings or to revert back to prioritizing face-to-face courses.

In this study, we investigated a relatively unexplored factor that may differentiate students who choose to enroll in online courses versus those who do not: time poverty (i.e., the extent to which students have insufficient time for their studies). Research already indicates that students who take online courses do so because they need the flexibility that these courses offer (Jaggars & Bailey, 2010; Pontes et al., 2010). This suggests that time (or a lack thereof) may be a critical issue. Time poverty may be both a potential mediator of online course enrollment and outcomes, and a potential equity factor distinguishing students who enroll in online courses from those who do not. This study (conducted prior to the COVID-19 pandemic) explored these possibilities.

Conceptual framework: Time poverty

When conceptualizing time as a finite resource (e.g., Giurge et al., 2020), *time poverty* has traditionally been defined as having insufficient time to maintain physical and mental well-being (Vickery, 1977). Translating this to the higher education context, Wladis et al. (2018) define time poverty as insufficient time to devote to college work (i.e., lack of available time to maintain academic well-being). Thus we postulate that time poverty, a byproduct of demographic and environmental factors, reduces the quantity and quality of time that students have available for academic study, and that this lack of time simultaneously makes students more likely to enroll in online courses and to be at higher risk of poorer course and college outcomes (see, Figure 1).

Connections between demographics, environmental variables, online enrollment and course/college outcomes have been supported by prior research (e.g., Johnson & Mejia, 2014; McPartlan et al., 2021). Research has also established links between both demographic and environmental variables and time poverty, as well as between time poverty and college outcomes (Conway et al., 2021; Wladis et al., 2018, n.d.a, n.d.b). However, links between online course enrollment and course and college outcomes is mixed (e.g., Authors, 2016; S. Jaggars, 2011; Shea & Bidjerano, 2014); one reason is that students who choose to enroll online have significantly different characteristics (e.g., work and family responsibilities) than those who do not (e.g., Cavanaugh & Jacquemin, 2015; S. S. Jaggars, 2014). Thus, time poverty may be a critical missing variable which explains connections between student characteristics, online enrollment, and course/college outcomes. Figure 1 outlines the known

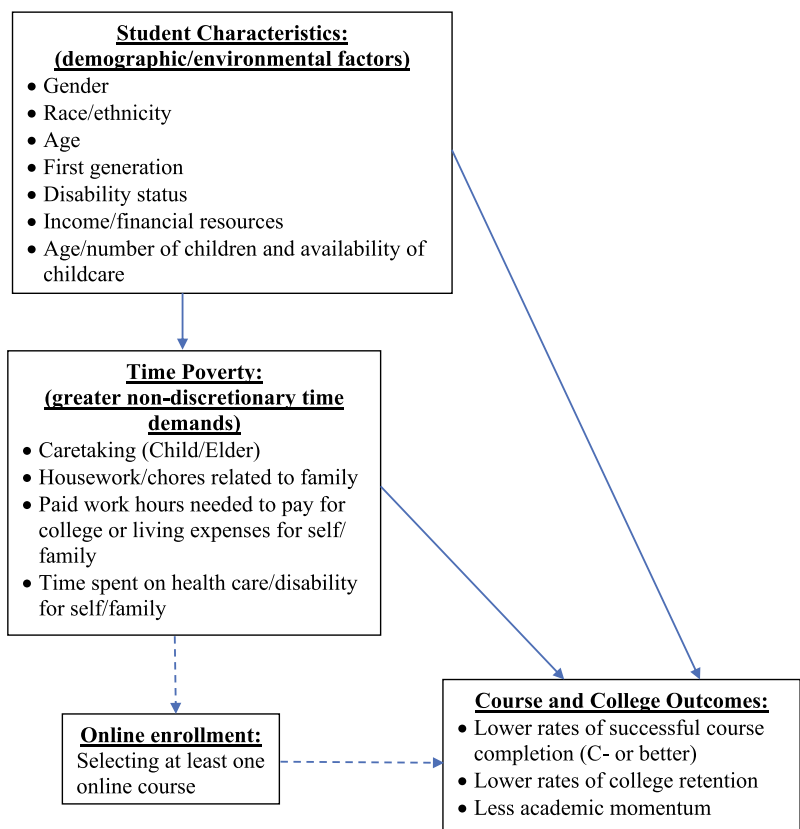


Figure 1. Conceptual framework: time poverty and online enrollment as they relate to outcomes in higher education. Solid lines represent relationships consistent with supporting evidence in the existing research literature. Dotted lines represent relationships with little-to-no evidence, or inconsistent evidence, in existing research literature. This study aims to explore the extent to which patterns in observational data are consistent or inconsistent with the relationships depicted by the dotted lines in this diagram.

relationships (solid arrows) and hypothesized relationships (dotted arrows) investigated in this study.

Many characteristics that have been identified as more likely in students who enroll in online courses (e.g., female, older, family responsibilities, paid work) have also been associated with time poverty. Previous research shows that parents (especially mothers) have higher rates of time poverty than comparable childless peers (e.g., Chatzitheochari & Arber, 2012; Kalenkoski et al., 2011). Specific to higher education, Wladis et al. (2018) report that student parents were significantly more time poor than comparable childless peers; this directly explained differences in academic momentum. Confirming with national data, Conway et al. (2021) found that having dependents correlated with greater time poverty and lower quality academic time, particularly for mothers. Recent work (Wladis et al., n.d.a) indicates that women, Black and Hispanic college students have significantly less time for their studies on

average than men, White and Asian students. These differences correlated with age and were largely explained by the number of children that students had and their access to childcare. Further, Wladis et al. (n.d.b) found that time poverty explained a significant proportion of differential college outcomes by gender and race/ethnicity. McPartlan et al. (2021) report that groups (i.e., women, older students, working students) that choose online learning due to competing responsibilities had outcomes that indicated that their course performance may have suffered because of greater engagement in non-academic activities (e.g., commuting, caring for dependents) and commensurately lower engagement in academic activities. From our conceptualization, this finding suggests that these online students were likely experiencing, and impacted by, time poverty.

Research questions

This study focuses on the following research questions:

- (1) To what extent is time poverty more prevalent among students who choose to enroll in online courses versus those who do not?
- (2) To what extent do differences in time poverty explain differences in course retention or successful course completion by online versus face-to-face enrollment?
- (3) To what extent do differences in time poverty explain or mediate differences in college retention (re-enrollment) and academic momentum (credit accumulation) by online versus face-to-face enrollment?
- (4) To what extent do differential outcomes in online versus face-to-face courses explain the relationship between online enrollment and college outcomes?

Literature review

Outcomes in online versus face-to-face courses

Many studies report that there are no positive or negative effects on course outcomes online versus face-to-face as measured by aggregate exams and course grades—supporting the “no significant difference” claim (e.g., Ashby et al., 2011; Cavanaugh & Jacquemin, 2015). Yet, research suggests that while aggregated data show no significant difference in outcomes between online and face-to-face courses, some studies have suggested that student characteristics moderate learning outcomes (gender, race/ethnicity, age and ability). Men, Latinx and Black students and those with lower GPAs have been found in a few studies to have poorer course outcomes online (lower grades/higher dropout) compared to face-to-face (Figlio et al., 2013; Xu & Jaggars, 2011b),

while older students and women have been found in some studies to withdraw less and have higher grades in courses online compared to face-to-face (Gregory, 2016; C. W. Wladis et al., 2015; Wagner et al., 2011). Some scholars have theorized that taking courses online causes worse course outcomes which in turn lead to worse college outcomes (e.g., Smith, 2016; Xu & Jaggars, 2011a, 2011b).

Online course-taking and college outcomes

Online course-taking and college retention

Retention is defined here as re-enrollment at the university in the subsequent semester. In large-scale studies, students who took one or more online classes in their first semester were 4–5 percentage points less likely to return for the subsequent semester and students who took higher proportions of online courses were less likely to graduate or transfer to a senior college (Jaggars & Xu, 2010; Xu & Jaggars, 2011a, 2011b). Smith (2016), using multi-institution data and controlling for student self-selection bias, also found an overall negative impact of online enrollment on course and college retention for four-year students.

However, other research that controlled for student characteristics has found opposite trends. Johnson and Mejia (2014), assessing the California community colleges and controlling for demographics and G.P.A., found that while online students did poorly short-term, those who took at least some online courses were more likely to earn their degree or to transfer to a senior college than those who did not. Shea and Bidjerano (2014), using national data and controlling for student characteristics, found that online course-taking helped students reach degree completion. James et al. (2016), using multi-institutional data, found that students taking courses in both modalities had slightly better odds of being retained than students taking either face-to-face or online courses exclusively. For students who are not retained, it is also unclear whether online enrollment is the cause. As suggested in Wladis et al. (2016) and James et al. (2016), there may be characteristics that increase *both* a student's likelihood of enrolling online and their odds of college dropout. Given the conflicting results in the literature, research is needed on factors that may correlate both with voluntary online enrollment and college retention.

Online course-taking and academic momentum

Academic momentum is the intensity with which students pursue their academic pathway; students who move through college at faster rates are more likely to complete their degrees than similar students who advance more slowly or have interrupted studies (Attewell et al., 2012; Jenkins & Bailey,

2017). Using nationally representative data, Attewell and Monaghan (2016) report that students who initially attempted 15 credits (versus 12) were significantly more likely to earn their degree. Similarly, an international comparison of eight U.S. and two Russian universities found that higher academic momentum was associated with lower attrition (Kondratjeva et al., 2017). Other studies have shown that students who initially have high academic momentum in their major are more likely to earn their credential (Denley, 2016; Jenkins & Cho, 2014). High academic momentum has been shown to have particularly large benefits for members of racial/ethnic minority groups (Belfield et al., 2016) and can impact the college outcomes of low-income students (Davidson & Blankenship, 2017). There is more limited research about the relationship between online course enrollment and academic momentum, but some research suggests that students who choose to enroll in at least one online course may have higher academic momentum or credit ratios in comparison to students who are not enrolled in an online course (Galbraith & Mondal, 2018; James et al., 2016).

Student characteristics: Students who take courses online vs. those who do not

One of the major difficulties of attempting to assess the impact of online enrollment is that students have traditionally (pre-pandemic) self-selected into online courses.¹ Students who voluntarily enroll in online courses are more likely to have non-traditional characteristics (Pao, 2016; Pontes et al., 2010), defined as: delayed enrollment (>age 24); no high school diploma; part-time enrollment; financially independent; have dependents; single parent status; or working full-time while enrolled (NCES, 2002). Using national data, Shea and Bidjerano (2014) found an overrepresentation of online students in six out of these seven categories. Further, many studies have found that those who take online courses are more likely to be older (>24), to have family responsibilities, and to be employed, in comparison to face-to-face students (Ashby et al., 2011; Cavanaugh & Jacquemin, 2015; Driscoll et al., 2012; Faidley, 2018; Jaggars & Xu, 2010; Johnson & Mejia, 2014; McPartlan et al., 2021; Pao, 2016; Smith, 2016; Wilson & Allen, 2011; Xu & Jaggars, 2011a, 2011b). For students who have commitments such as jobs and family, it is the anywhere/anytime nature of online courses that makes them more desirable (S. S. Jaggars, 2014).

There is also strong evidence that a larger proportion of female students self-select into online courses (Ashby et al., 2011; Cavanaugh & Jacquemin, 2015; Faidley, 2018; Pao, 2016; Wilson & Allen, 2011). Jaggars and Xu (2010), Johnson and Mejia (2014), and Smith (2016) and Xu and Jaggars (2011a, 2011b), all using different multi-institution datasets, report that students in online courses are significantly more likely be female, which Shea and

Bidjerano (2014) confirmed using national data. McPartlan et al. (2021) found that women were more likely than men to select online courses due to employment conflicts. We also note that student parents are more likely to be women, particularly women of color, and to be single mothers (Institute for Women's Policy Research, 2019), which may in part explain the higher rates of online enrollment among women vs. men. McPartlan et al. (2021) contends that demographic differences (e.g., age or gender) should not be considered as the cause of differential outcomes, rather the relationship between demographics and outcomes is likely mediated by other factors consequential for course performance. As posited in this study, one such mediator may be time poverty.

Method

Sample and data source

This study was conducted at the City University New York (CUNY), the third largest university system in the U. S. (Yale Daily News, 2013). More than three-quarters of CUNY's 275,000 undergraduates identify as nonwhite; 42% are non-native English speakers; 45% are first generation college students; and 40% have household incomes under \$20,000. CUNY is not nationally-representative; yet, its diverse student body and large online course portfolio make it a sound choice for exploring the relationship between online course taking, time poverty, and college outcomes, particularly among “non-traditional” college students.

The sample frame contained all students enrolled in any course at CUNY which had at least one fully online and one face-to-face section during a fall or spring term between fall 2015 to spring 2017; these courses came from two- and four-year campuses and were broadly representative of levels/disciplines. Students were invited to take part in an online survey during the term. Institutional records were combined with 41,574 student surveys, representing 34,081 unique students (some students took the survey in multiple terms). The response rate was 18%, more than double those of other official CUNY surveys (CUNY Student Experience Survey, 2014). Sample analysis indicates that it is roughly representative of the larger population (see, Table 1). Because of the extremely large sample frame ($n = 580,048$), almost all minor differences were statistically significant: overall, students who completed the survey were comparable to those who did not, however, women were more likely to complete the survey (75% of respondents vs. 64% of non-respondents). Because there was adequate representation of both men and women and we controlled for gender throughout much of the analysis that follows, we do not consider this to be a major limitation.

Table 1. 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
disability	42.2%	
first generation	58.0%	
non-discretionary hrs/wk	37.8	
total non-disc. + academic hrs/wk	63.9	
housework hrs/wk	10.1	
paid work hrs/wk	18.5	
childcare hrs/wk	9.7	

Researchers have increasingly called for more attention to be paid to survey representativeness, and less to response rates, as a growing body of research has found that response rates alone are poor measures of survey quality, and further, that large surveys with much lower response rates than the one used in this study can be just as representative as surveys with higher response rates. Fosnacht et al. (2017) found that simulated response rates of 15–20% for sample frames of 1,000 students or more generated sample means whose correlation with those of a full survey sample with a larger response rate was 0.98–0.99.

Furthermore, weighting and multiple imputation were used to adjust for non-response bias at the student and survey question level, respectively. Weights for survey responses were based on the 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 as independent variables.² Multivariate multiple imputation by chained equations imputed values for survey questions with missing responses, using all independent variables. Depending on variable type, logit models or predictive mean matching using three nearest neighbors³ (Schenker & Taylor, 1996) 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 reported here used the final imputed and weighted dataset.

Measures

Online courses were defined as all courses for which 80% of instruction was conducted online. In practice, almost all of these courses were 100% online. All other courses are classified as “not online,” but for ease of reading, we call these courses *face-to-face*. We also note that in this sample, almost all online courses are asynchronous. Thus, this study is comparing students who enrolled in at least one fully online (typically asynchronous) course to those who did not.

Both course and college outcomes were measured in this study. The main course-level outcome of interest is *successful course completion*, or whether the student completed the course with a C- grade or better, which is the criteria typically used to determine if a student will receive transfer credit or credit in their major for the course.⁴

College outcomes measured in this study were *college retention* (re-enrollment at CUNY in the subsequent regular semester, spring or fall) and *academic momentum* (number of credits earned in the regular session that term). We chose these measures because they are temporally close to the student’s reported time use (which may vary by term), and because they are also a significant predictor of long-term academic outcomes [e.g., transfer, degree completion] (DesJardins et al., 2006).

Time poverty was the primary independent variable in this study; this was operationalized as total reported non-discretionary time, or time spent on “necessary” life activities. Activities classified as “necessary” varies in the literature; we followed a model that classifies non-discretionary time as 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). Our results describe the linear relationship between non-discretionary time and outcomes; models which included quadratic relationships were also investigated, but linear models fit the data better.

The survey asked students to report the number of hours they spent on different activities during a typical week that semester to record time use. Categories and descriptions in the survey were modeled after those found in the American Time Use Survey (ATUS; U.S. Bureau of Labor Statistics, 2020), but streamlined since that survey collects a much wider set of variables. Inputs for questions were restricted to numerical values that prevented students from inputting invalid values (such as negative values or more than 168 hours per week).

Control variables were included in the analyses to account for factors that may correlate strongly with online enrollment, time poverty, and educational outcomes. They included: gender, race/ethnicity, age, G.P.A., median household income of the student’s zip code, first-generation college student status, disability status, and whether the student was a first-time freshman. We present two types of models: base models (including only the independent

and dependent variables of interest) and full models (containing other covariates). The base models best describe patterns for groups (e.g., online students) as they currently are, and are therefore particularly relevant to the design of policies and interventions; whereas full models may give insight into how other factors correlate with both online enrollment and academic outcomes, although they may be more difficult to interpret because of complex confounding relationships (see, Foster, 2010). Formal mediation analysis also allowed us to explore some of these relationships more formally.

Equations and software packages used for analytical models

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

For logit models (e.g., survey completion, retention as dependent variables), the equation was:

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

For linear regression (non-discretionary time, credits as dependent variables) the equation was:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon$$

For both equations, $x_1, \dots, x_n$ represent the independent variables (e.g., age, ethnicity), and ε represents the difference between actual versus predicted probability (e.g., of retention) or between actual versus predicted values (e.g., non-discretionary hours) of the dependent variable for each student.

We also use mediation analysis to explore the extent to which the relationship between two variables (e.g., online enrollment and academic outcomes) can be explained by their joint relationship with a third mediator (M) variable (e.g., time poverty). This uses statistical methods to break up patterns of correlation between the independent variable (IV) (e.g., online enrollment) and the dependent variable (DV) (e.g., college outcomes) into two components: the direct “effect,” measuring the proportion of the relationship between the IV and the DV which cannot be explained by the mediator, and the indirect “effect,” measuring the proportion of the relationship between the IV and the DV which can be explained by the mediator (see Buis, 2010, for more details on mediation). We recognize that the language of mediation is often associated with causation, and this is an observational study for which causal inferences are not appropriate. Attempts to reword this study using other terminology seemed too inaccessible to non-methodologists, so we use the language of mediation but put the word “effect” (e.g., direct or indirect

“effect”) into quotes. We also remind the reader throughout that these data do not support causal inferences; our goal with this approach is to strike a reasonable balance between rigor of terminology and accessibility.

For mediation analysis, we used the KHB decomposition method (Buis, 2010), which is a general decomposition method based on the traditional SEM framework. This model is preferable to others because it generates an indirect effect that is not distorted by the rescaling that occurs when a potential mediator variable that is correlated with the dependent variable is added to a nonlinear model, such as in logistic regression. In the KHB method (in linear regression) if Y represents the dependent variable, X the independent variable, and M is the potential mediator, then we consider the two equations:

$$Y = \alpha_D + \beta_D X + \Gamma_D M + \varepsilon_D \quad (1)$$

$$Y = \alpha_T + \beta_T X + \varepsilon_T \quad (2)$$

Here β_D represents the direct “effect” of X on Y , β_T represents the total “effect” of X on Y , and $\beta_I = \beta_T - \beta_D$ is the indirect “effect” of X on Y . In the KHB method, residuals of a linear regression of M on X are calculated:

$$R = M - (a + bX) \quad (3)$$

And then R is used in place of M in Equation (1) that estimates the direct “effect” of X on Y :

$$Y = \tilde{\alpha}_T + \tilde{\beta}_T X + \tilde{T}_T R + \tilde{\varepsilon}_T \quad (4)$$

Because the addition of R to the model adds only the component of M that is uncorrelated with X , the residuals have the same standard deviation in Equations (1) and (4), but the coefficient of X in Equation (1) is the direct “effect,” whereas the coefficient of X in Equation (4) is the total “effect.” While other methods have also been developed to address the problems of rescaling that occur during mediation analysis with logistic regression, 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 rescaling (see, Kohler et al., 2011).

Results

Time poverty by online enrollment

Students were classified as “no fully online” if none of the courses they enrolled in were fully online and as “some fully online” if they enrolled in *at least one* fully online course during the study period. The mean non-discretionary time commitments (in hours/week) by students’ course enrollment status is shown in Figure 2.

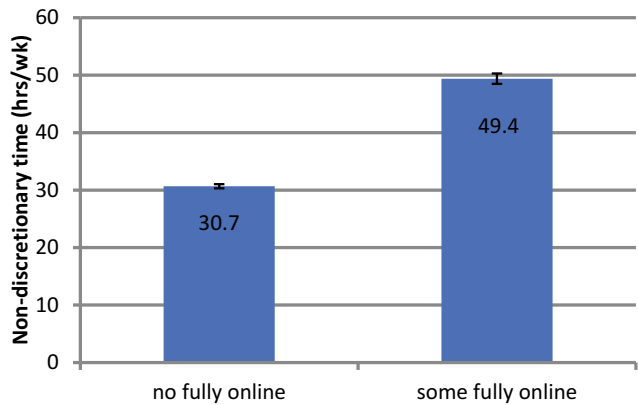


Figure 2. Total non-discretionary time (Hours/Week) by course enrollment status (From weighted, imputed linear regression model; Error bars indicate 95% confidence interval).

There are both significant and substantial differences in the time that students have available for college when we compared students who enrolled in at least one fully online course versus those who did not. To generate [Figure 2](#), linear regression was used to model total non-discretionary time (hours/week) as the dependent variable, and enrollment in at least one fully online course as the independent variable (see, [Table 2](#)). Students who enrolled in at least one fully online course were significantly more time poor, with 18.7 more hours/week of non-discretionary time commitments on average than those who did not ($p < .001$). After including control variables, this difference

Table 2. Regression analysis of the relationship between online course enrollment and total non-discretionary time.

non-disc. Time (hrs/wk)	base		full	
	Coef.	SE	Coef.	SE
online enrollment (ref. gp. not online)				
some online	18.7***	0.46	11.8***	0.65
female			8.0***	0.51
ethnicity				
White			6.8***	0.72
Black			10.0***	0.74
Hispanic			10.7***	0.65
AI/NA			−1.3	3.32
age			1.3***	0.04
disability			1.1	0.67
GPA				
<2.0			5.9***	1.39
2–2.49			2.2*	1.09
2.5–2.99			0.8	0.96
3–3.49			−0.8	0.88
3.5–4.0			−1.3	0.86
median income of zip (per \$1000)			−0.02	0.01
first generation			2.1***	0.53
constant	30.7***	0.18	−17.0*	0.3

*** $p < .001$; ** $p < .01$; * $p < .05$.

was smaller but still substantial and significant at 11.8 hours/week ($p < .001$), indicating that controlling for or matching on many standard institutional research variables is likely *not* sufficient to fully account for differences in time poverty among online-vs.-face-to-face students. This suggests that prior studies that have compared students across mediums without controlling for time poverty have significant limitations, particularly given research which has shown that time poverty is strongly related to college outcomes for some groups such as student parents (Wladis et al., 2018). This relationship is explored in more depth later.

Exploring some potential explanations for differential rates of time poverty

One possible explanation for why students who voluntarily enroll in online courses may be more time poor (than those who do not) is that they are more likely to work, to have families, and to be older (Ashby et al., 2011; Cavanaugh & Jacquemin, 2015; Faidley, 2018; Johnson & Mejia, 2014; Pao, 2016; Wilson & Allen, 2011). Thus, to better understand the patterns from Figure 2 and Table 2, we break up non-discretionary time into three key categories: time spent on housework, paid work, and childcare, and compare differences in these subcategories between online and non-online students. Figure 3 was generated by separate weighted linear regression models which were used to predict the mean time spent separately on each category by enrollment status; we report p -values from those models here but have not included the models themselves because of space constraints.

Students who enrolled in at least one online course spent significantly more time on each of these activities than those who did not ($p < .001$), although the

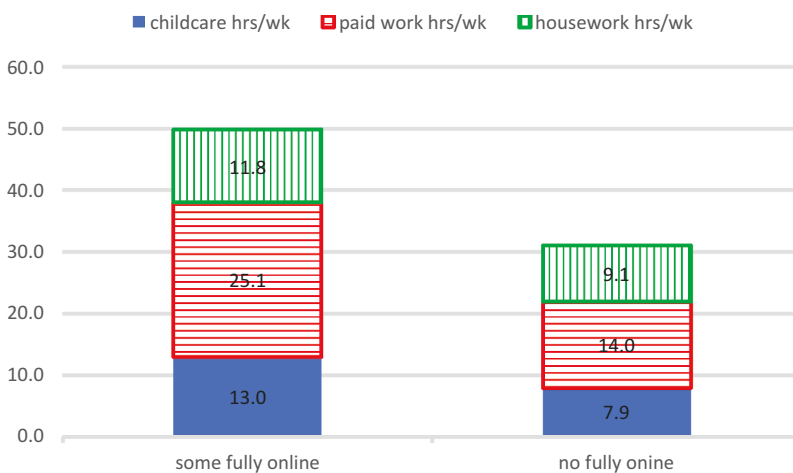


Figure 3. Mean hours/week spent on childcare, paid work, and housework by enrollment status (From separate, weighted, imputed linear regression models).

relative magnitude of these differences varied. Work was the biggest difference, with students enrolled in at least one fully online course spending 80% more time compared to those who took no fully online courses during the study period. Childcare was the second biggest difference, with students in at least one fully online course spending 63% more time than those who only enrolled face-to-face. Housework showed the least difference, with students in at least one fully online course spending 39% more time than those who were not enrolled online.

Two major factors contributing to these differences are age and parental status. According to weighted linear regression models, for every additional year of age, a student's non-discretionary time commitments went up by 1.5 hours/week, and this correlation is highly significant ($p < .001$).⁵ This is likely due to a complex host of factors, including needing to work and family care responsibilities. Using the same weighted linear regression models to predict differences in age by online enrollment, results indicate that students who enrolled in at least one fully online class were on average 4.4 years older than those who did not, which was significant ($p < .001$).

Likely one of the reasons that older students have more time poverty is that they are more likely to be parents. In this sample, students who enrolled in at least one fully online course had roughly twice as many children as those who did not ($p < .001$). To briefly test whether number of children mediates the differences in time poverty by online enrollment, the KHB method was used (see, Table 3).

In Table 3, the total, direct, and indirect "effects" are all significant ($p < .001$) and controlling for number of children reduced the gap in non-discretionary time by online enrollment by 20.4%, from 18.7 to 14.9 hours/week (in full models, there is a similar pattern, but the number of children explains an even greater proportion of the gap). It makes sense that the number of children does not entirely explain the time poverty gap. For example, students enrolled in online courses are 7.5 percentage points more likely to be women, and even when women and men have the same number of children, women on average spend more time on childcare and housework (Chatzitheochari & Arber, 2012;

Table 3. Mediation analysis (KHB method) of the extent to which number of children mediates the relationship between voluntary online enrollment and time poverty, linear regression coefficients reported.

non-disc. Time (hrs/wk)	base		full	
	Coef.	SE	Coef.	SE
online enrollment (ref. gp. not online)				
total "effect"	18.7***	0.3	14.5***	0.5
direct "effect"	14.9***	0.3	13.7***	0.5
indirect "effect"	3.8***	0.2	0.8*	0.3

Full model includes control variables: gender, race/ethnicity, age, disability status, GPA, median income of zipcode, first generation status.

*** $p < .001$; ** $p < .01$; * $p < .05$.

Kalenkoski et al., 2011; Wladis et al., 2018). However, this does show that the number of children that a student had explains a substantial proportion of the differences in time available for college. There are likely also other explanations that contribute to differences in the time poverty of students who enroll in online courses versus those who do not; for example, students who elect to enroll in online courses are more likely to work full-time (Driscoll et al., 2012; Xu & Jaggars, 2011a), and often also have other complex life situations such as serious health issues of their own or an immediate family member (Wladis et al., 2020).

Course outcomes and time poverty

We next considered the relationship between enrollment in a fully online course, course outcomes, and time poverty (see, Figure 4).

This relationship was explored using KHB mediation models (see, Table 4 and Figure 5). In Table 4, the total, indirect, and direct “effects” are all significant, both in base and full models. In both cases, the direct “effect” was positive (i.e., online enrollment was correlated with higher rates of successful course completion; the size of this “effect” was smaller but still significant in full models, suggesting that some of this difference is explained by student characteristics such as GPA, gender,

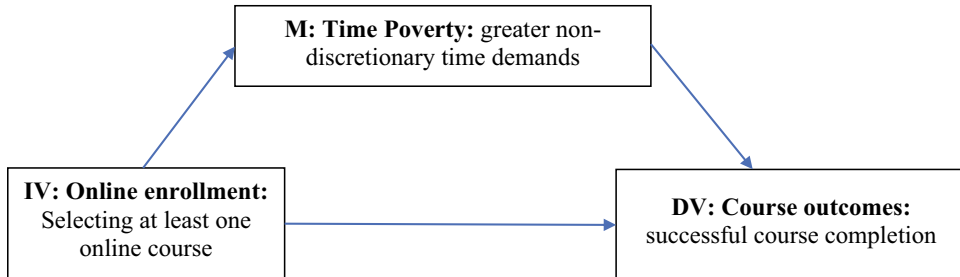


Figure 4. Time poverty as a potential mediator between online course enrollment and course outcomes.

Table 4. Mediation analysis (KHB method) of the extent to which time poverty mediates the relationship between voluntary online enrollment and course outcomes, average partial effects reported.

Successful course completion	base		full	
	APE	SE	APE	SE
online enrollment (ref. gp. not online)				
total “effect”	2.8pp***	0.2pp	1.1pp***	0.2pp
direct “effect”	2.9pp***	0.2pp	1.2pp***	0.2pp
indirect “effect”	–0.1pp*		–0.2pp***	

Full model includes control variables: gender, race/ethnicity, age, disability status, GPA, median income of zipcode, first generation status.

pp denotes percentage points.

*** $p < .001$; ** $p < .01$; * $p < .05$.

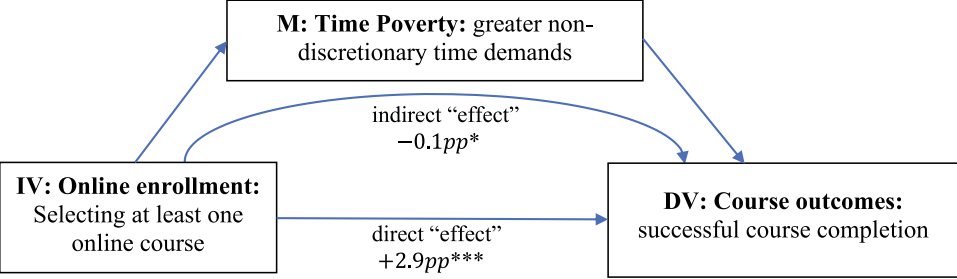


Figure 5. Positive correlation between online course enrollment and course outcomes, suppression “effect” of time poverty as a mediator.

race/ethnicity, or median household income), but in both the base and full models, the indirect “effect” (i.e., the part of this relationship correlated with measures time poverty) was negative. Thus, the significantly higher rates of successful course completion among students enrolled in fully online courses may be lower than they would be if both students in fully online courses and those in courses that are not fully online had the same amount of time poverty, although the difference in these models is not very large.

College outcomes and time poverty

The relationship between fully online course enrollment, college outcomes, and time poverty was then considered (see, Figure 6).

First, college retention (re-enrollment in the subsequent semester within CUNY) was explored: In Table 5, using KHB analysis, the total, direct, and indirect “effects” are all highly significant ($p < .001$).

A student who enrolled in a fully online course was roughly 6.2 percentage points less likely to re-enroll in college in the subsequent semester and roughly 7.9% of this difference was explained by the greater time poverty of students who enrolled in fully online courses (Figure 7). Thus, time poverty explains a significant portion of the differences in college retention, but this is only

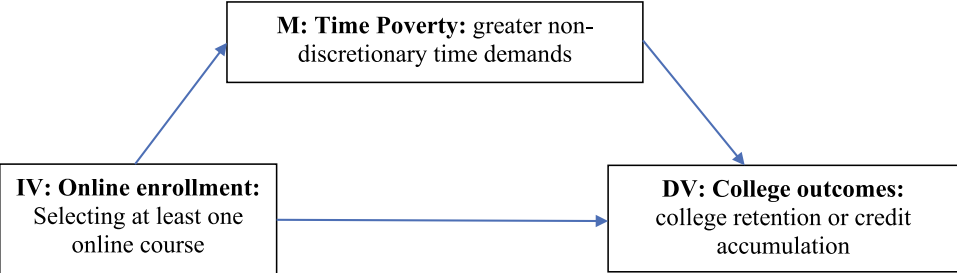


Figure 6. Time poverty as a potential mediator between online course enrollment and course outcomes.

Table 5. Mediation analysis (KHB method) of the extent to which time poverty mediates the relationship between voluntary online enrollment and college outcomes, linear regression coefficients and average partial effects reported.

	base		full	
College retention	APE	SE	APE	SE
online enrollment (ref. gp. not online)				
total "effect"	−6.2pp***	0.2pp	−5.2pp***	0.2pp
direct "effect"	−5.7pp***	0.2pp	−5.0pp***	0.2pp
indirect "effect"	−0.5pp***		−0.2pp***	
Credit accumulation	Coef.	SE	Coef.	SE
online enrollment (ref. gp. not online)				
total "effect"	−0.487***	0.029	−0.357***	0.03
direct "effect"	−0.009	0.03	−0.111***	0.03
indirect "effect"	−0.477***	0.009	−0.245***	0.009

Full model includes control variables: gender, race/ethnicity, age, disability status, GPA, median income of zipcode, first generation status.

pp denotes percentage points.

*** $p < .001$; ** $p < .01$; * $p < .05$.

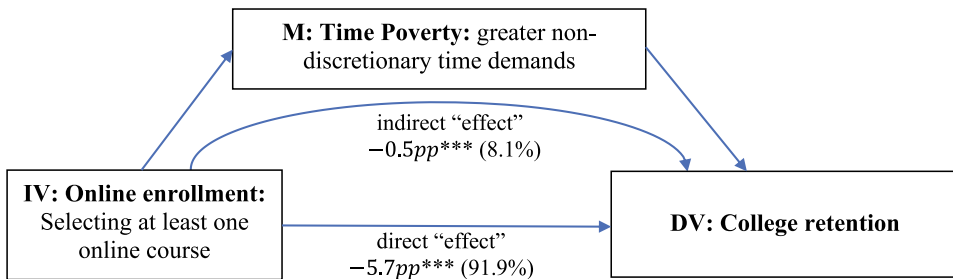


Figure 7. Time poverty as a significant partial mediator of the negative correlation between online course enrollment and college retention.

a partial mediation and other factors also contribute to this retention gap (e.g., quality of time; measures of time not included in our measure of non-discretionary time such as eldercare or health care; stressors; etc.).

Second, the relationship between fully online course enrollment, academic momentum (credit accumulation), and time poverty was explored. In Figure 8

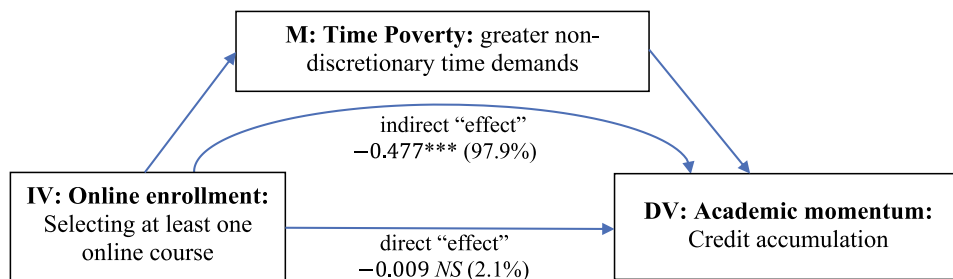


Figure 8. Time poverty as a significant complete mediator of the negative correlation between online course enrollment and academic momentum (Credit accumulation).

and Table 5, using KHB analysis, the total and indirect “effects” are highly significant ($p < .001$), but the direct “effect” is not significant in base models. Thus, in base models, enrolling online itself was not a predictor of earning fewer credits; rather any significant increased time poverty of students who voluntarily enrolled online entirely explained this difference. A student who enrolled in a fully online course earned on average about one half credit less than students who did not enroll in fully online courses, but this difference was 98.1% explained by their higher time poverty (i.e., non-discretionary time commitments). While this may not seem like a large difference, it could impact time-to-degree: for example, at the mean enrollment intensity observed in this study, students who enrolled in only face-to-face courses would be less than one credit shy of finishing in 11 semesters; students who enrolled in at least one online course would need 12 semesters. Time poverty appears to explain almost all of the differences in credit accumulation for students who took fully online courses versus those who did not.

In the full models, unlike in base models, the direct correlation between online course enrollment with credit accumulation was significant; the reader may wonder whether the outcomes of the courses in which students enrolled online may explain this lower credit accumulation. We note that this is not the only possible explanation. If there are other characteristics that simultaneously correlate with voluntary online course enrollment and lower credit accumulation, but which were not included in our model (e.g., stress, personal health, eldercare, lower time quality for college, etc.), this could also explain this difference. Interpreting more complex models with covariates can be particularly difficult with observational data (Foster, 2010). To investigate this further, we next explored whether our data are consistent with a hypothetical mediation model in which poorer outcomes in online courses might explain differences in college outcomes.

Do course outcomes explain differences in college outcomes?

Some scholars have theorized that students enrolled in fully online courses have worse college outcomes because of negative outcomes in fully online courses (Smith, 2016; Xu & Jaggars, 2011a, 2011b; see, Figure 9).

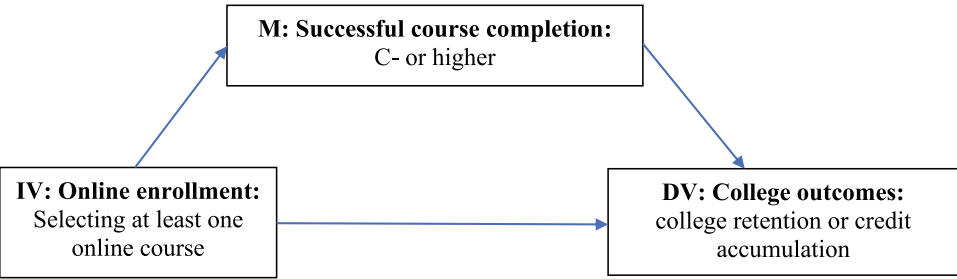


Figure 9. Successful course completion as a potential mediator between online course enrollment and college outcomes.

To investigate whether patterns in the data are consistent with this hypothesis, we analyzed the extent to which rates of successful course completion mediate the relationship between fully online course enrollment and college retention, using the KHB method (see Table 6).

First, we consider college retention: In Table 6 and Figure 10 the total, direct, and indirect “effects” are all significant in both the base and full models ($p < .001$); however, the indirect “effect” (of course outcomes on college retention) is positive while the direct “effect” (of online enrollment on college retention) is negative. Thus, while students who enroll in fully online courses were significantly less likely to re-enroll in college in the subsequent semester, this appears not to be the result of their completing online courses less successfully but rather the result of some other factors not included in our models.

Second, we investigated the extent to which rates of successful course completion mediate the relationship between fully online course enrollment

Table 6. Mediation analysis (KHB Method) of the extent to which successful course completion mediates the relationship between voluntary online enrollment and college outcomes, linear regression coefficients and average partial effects reported.

College retention	base		full	
	APE	SE	APE	SE
online enrollment (ref. gp. not online)				
total “effect”	−6.2pp***	0.1pp	−5.2pp***	0.2pp
direct “effect”	−6.3pp***	0.1pp	−5.2pp***	0.2pp
indirect “effect”	0.1pp***		0.0pp***	
Credit accumulation	Coef.	SE	Coef.	SE
online enrollment (ref. gp. not online)				
total “effect”	−0.467***	0.029	−0.348***	−0.41
direct “effect”	−0.591***	0.029	−0.390***	−0.534
indirect “effect”	0.124***	0.006	0.042***	0.136

Full model includes control variables: gender, race/ethnicity, age, disability status, GPA, median income of zipcode, first generation status.

pp denotes percentage points.

*** $p < .001$; ** $p < .01$; * $p < .05$.

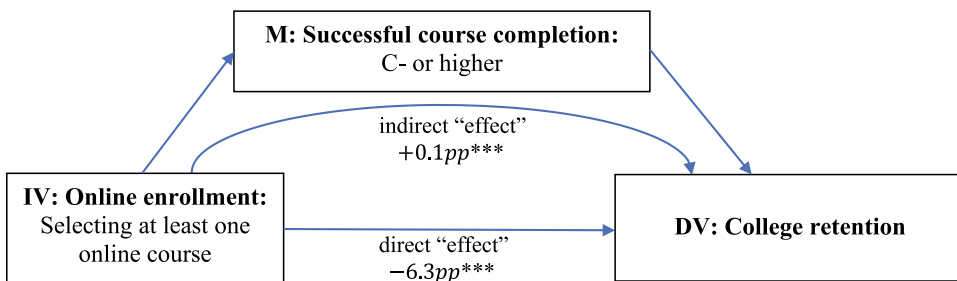


Figure 10. A negative correlation between online course enrollment and college retention which is not explained by course outcomes as a mediator (Significant suppression “effect”).

and academic momentum: In Table 6 and Figure 11 the total, direct, and indirect “effects” are all significant in both the base and full models ($p < .001$); but again, the indirect “effect” (of course outcomes on credit accumulation) is positive while the direct “effect” (of online enrollment on credit accumulation) is negative. Thus, while students who enroll in fully online courses earn on average fewer credits, this appears not to be the result of their completing online courses less successfully; rather, it again appears to be the result of some other factors not included in our models. Perhaps other life stressors or priorities that are not included in actual hours spent on non-discretionary tasks are the reason for these differences. For example, health problems, issues with quality or flexibility of time that are not reflected in quantity of available time, or mental health/stress levels, could all be correlated both with fully online course enrollment and college retention or academic momentum (Eisenberg et al., 2009; Suhrcke & De Paz Nieves, 2011), yet not necessarily be well-correlated with other variables routinely collected by institutional research.

Limitations

There is a possibility that the time measures in this study were impacted by desirability bias or students’ inaccurate recollections of time use because they were retrospective and self-reported. Hence, future studies seeking to replicate this work may seek to use alternate measures of time use (i.e., other approaches, such as the experience sampling method (e.g., Sonnenberg et al., 2012), may result in more accurate time use data). We also note that our measure of time poverty is incomplete. Our measures of non-discretionary time did not include time that students might have spent on eldercare or healthcare, and because of this, findings may actually *underestimate* the time poverty of some groups, and the relationship between time poverty and course

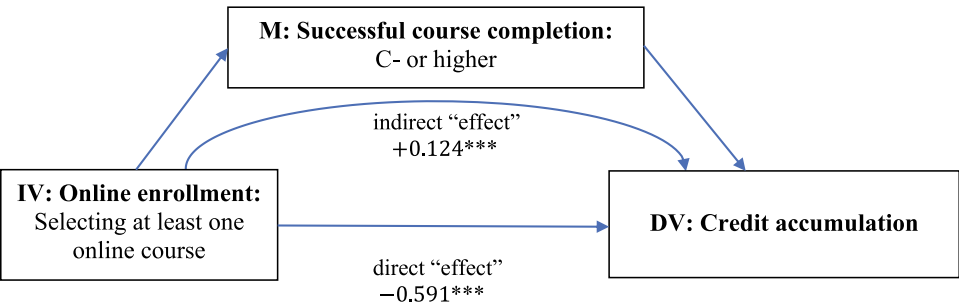


Figure 11. A negative correlation between online course enrollment and academic momentum (credit accumulation) which is not explained by course outcomes as a mediator (Significant suppression “effect”).

or college outcomes. Future research is currently underway to address this limitation.

We note also that the CUNY student population includes a higher proportion of foreign-born students and ethnic/racial minorities, lower SES students, first-generation students, and students requiring developmental coursework, which may affect the sample's national representativeness. However, this also makes it a particularly good sample for investigating trends for various traditionally underrepresented and understudied groups in higher education.

New York City has universal pre-kindergarten, which may have reduced the strength of the relationship between parental status, time poverty, and college outcomes for parents with children in this age range. Furthermore, New York City spends more on public benefits than any other U.S. municipality, and New York state provides a higher proportion of on-campus childcare than 47 other U.S. states (Eckerson et al., 2016). Thus, we note it is possible that regional policy factors could have influenced the results, and that the time poverty relationships in this study may *underestimate* national trends.

We also note that there is a complex but important relationship between income and time poverty that we have not investigated in depth here. Income poverty may have both a positive (the more hours one works, the less discretionary time one has) and a negative (the more money one has, the more one can afford childcare or other time-saving help that increases one's discretionary time) relationship with time poverty. While in this study we have used some measures of income as controls in some models, this is insufficient to draw clear conclusions about whether the time poverty of a particular student is voluntary or the result of significant financial need. Some students may be time poor through choice (i.e., opting to enroll part-time because they have other priorities) and other students may be time poor because they lack the resources to pay for childcare or to work fewer hours. Traditional models of student need have often been insufficient in measuring the true financial need of students for college, particularly for more "nontraditional" groups (see Goldrick-Rab, 2016). Thus, better measures of financial need are necessary to properly investigate the complex relationship between time and income poverty; we aim to address this in future research.

Discussion

This study demonstrates for the first time using quantitative data on a large-scale dataset that students who voluntarily enroll online are on average significantly more time poor than those who do not, reinforcing and expanding on trends shown in prior qualitative research (Fox, 2017; McPartlan et al., 2021; S. S. Jaggars, 2014; Wladis et al., 2018). The time poverty of students in this study who enrolled in at least one online course was particularly striking: the mean amount of time spent on paid work, childcare, housework, and

college work altogether totaled 79.6 hrs/wk, or the equivalent of roughly two full-time jobs.

Data from this study indicate that these differences in time poverty for online-versus-not-online students were largely explained by age and parental status, and also to related measures of time spent on both childcare and paid work. Students who enrolled in at least one online course were significantly older than those who did not, corroborating previous research (Driscoll et al., 2012; McPartlan et al., 2021; Smith, 2016; Wilson & Allen, 2011); and age was strongly correlated with time poverty. Additionally, students who enrolled in at least one fully online course had roughly twice as many children; spent 63% more time on childcare; and spent 80% more time working, compared to those who took no fully online courses; the number of children that a student had significantly mediated the relationship between online enrollment and time poverty. This confirms previous research that online learners are more likely to be parents and tend to be employed for more hours than their face-to-face counterparts (e.g., Driscoll et al., 2012; Xu & Jaggars, 2011a, 2011b). However, this study gives precise measures of the costs that online students face in terms of time available for college related to childcare and paid work, by quantifying their non-discretionary time commitments.

Despite being more time poor, students were more likely to successfully complete online courses, especially after controlling for time poverty. This supports Ashby et al. (2011), who report better completion online. However, while course outcomes were positive, students who enrolled in at least one online course had lower academic momentum and were retained in college at lower rates than those who did not. Mediation models revealed that lower rates of retention and credit accumulation among online students could not be explained by outcomes in online courses. This suggests that differences in college outcomes cannot be explained by students completing online courses less successfully; rather other factors (e.g., time poverty, health issues, stressors, quality of time for college) that may make students simultaneously more likely to opt for online courses and also more likely to drop out or accumulate fewer credits likely play a role. Critically, time poverty mediated the relationship between online enrollment and college outcomes in our findings, explaining a significant but partial portion of the difference in retention and all of the significant difference in academic momentum.

Implications for research and practice

The COVID-19 pandemic necessitated a radical shift in higher education, accelerating the systematic adoption of online courses that had slowly been happening in the last decade, and now requiring institutions to re-think how they will offer courses in the “new normal” (Garcia-Morales et al., 2021). As institutions debate whether to keep increased online offerings or revert to pre-

pandemic levels, a better understanding of who enrolls online and what impacts their success is critical. This study suggests that any such discussion, and future research and interventions, may need to consider student time poverty as a factor. For example, given the time poverty of many online students, and the time costs to attending class face-to-face (e.g., commute, lower flexibility of time; Gherhes et al., 2021), there might be unrecognized risks to policies that require or pressure students to enroll in face-to-face sections even when they would prefer to enroll online.

This study also revealed a major limitation in current supports for online students. While interventions to help retain online students often include technological or academic support, we know of no widespread interventions that aim to reduce the unequal time poverty of those who voluntarily enroll online versus those who do not. Yet, results from this study strongly suggest that any intervention aimed to improve the college outcomes of online students would do well to consider ways to measure and address time poverty. For example, supports which aim to reduce students' paid work hours (e.g., providing more financial aid to cover living expenses), as well as affordable or free childcare for student parents, are promising candidates for future interventions to be tested through causal studies. Also, voluntary enrollment in at least one fully online course is a readily available variable in institutional datasets that could help institutions to identify students who are particularly time poor. Students in online courses are not the only ones who are time poor; however, this is one variable that could help with targeting interventions to provide the resource of time for those students in college who may need it the most.

Pre-pandemic, students who enrolled in at least one online course had 20 hrs/wk less time for college than other students yet spent only 4.9 hrs/wk less on their education. This may have mitigated some of the potential negative impacts of time poverty on course and college outcomes for these students, but the result is that online students had 15 hrs/wk less free time compared to other students, because they dedicated more time to their studies. This increased work may have other hidden negative consequences for time-poor students (e.g., less time for health care, eldercare, sleep, exercise or leisure, which has been associated with higher levels of stress/burnout Mathuews, 2018); this raises equity concerns. Future research should focus on measuring some of these potential hidden negative consequences of time poverty.

In higher education, time is often seen as an individual good free from constraint (Bennett & Burke, 2017); however, this view may not reflect the lived realities for students who have work and family commitments. Only 20% of student parents in this study said that the childcare available to them allowed them sufficient time for their studies, and just over three quarters of the students in this population who work do so in order to pay for living expenses (CUNY, 2018), so increased childcare and work hours among this

population may largely be involuntary (i.e., many of these students might opt to spend more time on their studies if they could afford to do so). This suggests that there may be critical equity implications for any interventions aimed at improving the time poverty of online students, or other time-poor students in higher education.

Notes

1. During the COVID-19 pandemic, many students were forced online; however, this study focuses on *voluntary* online enrollment, the standard for decades prior to the pandemic, and likely the model that most colleges return to after the pandemic.
2. Propensity scores for the likelihood of survey completion were computed using logistic regression based on: age, gender, ethnicity, ESL status, college re-enrollment, remedial course placement, G.P.A, credits earned, online course-taking, and college level (community college, baccalaureate, graduate), and weights were normed to reflect the sample frame size.
3. For $n \geq 100$, Schenker and Taylor (1996) found only small differences between $k = 3$ and $k = 10$. Increasing the donor pool increases the risk of biased parameter estimates; thus we have chosen $k = 3$.
4. We also explored patterns for course retention, but they were substantially similar to those for successful course completion, so because of space limitations we do not report them here.
5. We also considered non-linear representations of age, but a linear model fit the data better.

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