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Working Paper:

Making the Connection: Broadband Access and Online Course Enrollment at Public Open Admissions Institutions

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Postsecondary students increasingly choose to take some or all of their courses online. While a number of studies have investigated student outcomes in online courses, past data limitations have hindered robust examination of a potential mechanism underlying their choice: access to high speed broadband. In this paper, I combine data from the National Broadband Map and IPEDS to investigate the relationship between access to high speed broadband and the number of students who attempt online courses at public open admissions four-year universities and community colleges in the lower 48 states. Fitting a number of Bayesian single-level and hierarchical regression models, I find that every tier increase in download speed is associated with a 41% to 56% average increase in the number of students who enroll in at least one online course. I do not find similar correlations between upload speeds and the number of providers. These results provide the first national-scale empirical evidence of a positive link between download speed and online course-taking among postsecondary students.

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1 Introduction

The number of students who enroll in online courses has increased dramatically since the early 2000s (Radford & Weko, 2011; Snyder, de Brey, & Dillow, 2016). Though the popular press has often focused more on massive open online courses, or MOOCs, (e.g., Pappano, 2012), relatively few college students take only distance education credits. Many instead split their time between face-to-face courses on campus and those offered online through their home institution (Snyder et al., 2016; Snyder & Dillow, 2015). As more people decide to pursue postsecondary education, it is likely that a significant portion of the higher education sector's expansion will occur online.

In the midst of this growth, those studying the outcomes of students who enroll in online course sections have found mixed results. Some studies that compare online students to those who enroll in face-to-face sections have found little to no average difference in end-of-course grades for online students (Bowen, Chingos, Lack, & Nygren, 2012; Figlio, Rush, & Yin, 2010; Joyce, Crockett, Jaeger, Altindag, & O'Connell, 2014). Other studies have shown the opposite, that some students who enroll in online courses, particularly those who attend open access institutions such as community colleges, may perform worse in terms of course persistence, grades, subsequent enrollment, and eventual degree attainment (Bettinger, Fox, Loeb, & Taylor, 2017; Hart, Friedmann, & Hill, in press; Huntington-Klein, Cowan, & Goldhaber, 2017; Xu & Jaggars, 2011, 2013).

Largely unexamined in this literature on outcomes, however, is a key mechanism through which most online students access their work: high speed broadband. Students who do not have access to quality broadband cannot take online courses. Existing disparities in broadband access (Federal Communications Commission, 2016a; Grubesic, 2008b; Grubesic & Murray, 2002; Prieger & Hu, 2008) are likely to lead to disparities in online education, which, as more courses become digital, could exacerbate inequities currently seen across the higher education sector as a whole. This especially may be true at public colleges and universities with open admissions policies that enroll greater numbers of first-generation and non-traditional students.

In this paper I investigate the relationship between access to high speed broadband and the number of students who attempt online courses at public universities and community colleges with open admissions policies in the lower 48 states during the period from 2012 to 2014. To do this I rely primarily on enrollment data from the Integrated Postsecondary Education Data System (Department of Education, 2015) and census block-level measures of broadband access from the National Broadband Map (National Telecommunications and Information Administration, 2011). I specifically operationalize broadband access using three key measures: download speed, upload speed, and the number of providers. In order to approximate the download/upload speeds and number of providers experienced by the average enrolled student at each institution, I assign each school broadband measures that are the population/inverse distance-weighted averages of those recorded in surrounding census block groups. Due to the nested nature of the data, with schools located in states that have different postsecondary policy contexts, I fit multilevel Bayesian regression models in addition to single level pooled models.

I find that for every tier increase in download speed, the percentage of an institution's students who enroll in some online courses increases an average of 41% to 56%. I do not find strong evidence of a similar association for upload speeds or the number of Internet service providers in the area. Multilevel models that allow broadband regression parameters to vary by state suggest that a few states—Tennessee, Alabama, and Oklahoma—may have very strong positive relationships between download speed and online course enrollments, with one state, Louisiana, having a very strong negative association. For the majority of states that show no strong positive or negative association (95% credible intervals cross zero), it could be the case that institutional and state-level higher education policies are stronger drivers of online enrollments than student access to faster broadband speeds. On the whole, this paper offers the first empirical evidence of a generally positive relationship between download speed and enrollment in online courses at public open admissions colleges and universities across the country. If the higher education sector continues its move toward increased digital offerings, these results suggest that student access to quality broadband should be taken into account lest the digital divide become a de facto educational divide.

2 Literature review

2.1 Rise of online education

Over time, a number of technologies have been used to make education at a distance possible. Correspondence courses that took advantage of the postal system in the 19th century mark a more formal start to higher education at a distance (Johnson, 2003). Moore and Kearsley (2011) note five generations of distance education: correspondence, broadcast radio and television, open universities (as seen in the United Kingdom and Australia, among other countries), teleconferencing, and the Internet/Web. With each new generation, improvements in technology meant potential improvements in the delivery of education. While radio and television broadcasts were faster and potentially more inclusive than direct mail, teleconferencing and the Internet once again "allowed a student to answer back," (Moore & Kearsley, 2011, p. 36).

The United States Armed Forces itself took advantage of distance education during the Second World War. Under the theory that better educated soldiers made better all-around soldiers, the federal government built a robust system of correspondence courses that troops could (and did) take during their downtime (Loss, 2012). Though these courses gave way to temporary place-based universities that soldiers attended before returning home at the end of the war, the idea that higher education was fit for many more than society's elite found its first application in these correspondence courses.

In the postwar period, a number of other countries similarly decided to make higher education available to new populations of students. The Open University of Great Britain, founded in the late 1960s, was new university model that used distance education technologies to enroll students from all over the country (Moore & Kearsley, 2011). Not a part of existing universities, it instead combined distance learning technologies, distributed brick-and-mortar locations around the country, and a "radical open admissions policy" (The Open University, 2015) to enroll a large number of students. Still operating today, the Open University has seen countries around the world borrow its name and model for their own similarly structured institutions (Keegan, 1996).

Aside from experiments among some state university systems such as the Articulated Instructional Media Project (AIM) at the University of Wisconsin (Moore & Kearsley, 2011), the United States has not attempted to develop an open national university along the same lines as Britain's Open University. This is in spite of the fact that the number of college-going students in the United States has steadily risen since the end of the Second World War. From the early 1960s to 2010, the number of postsecondary enrollments increased from fewer than 5 million students to over 20 million, a sizable proportion of which came from non-traditional, historically underserved populations (Snyder & Dillow, 2015). Enrollments at large public universities greatly increased to meet this new mass demand for higher education, as did the number of two-year institutions (Cohen & Brawer, 2003; Crookston & Hooks, 2012; Thelin, 2011).

One popular solution to the problem of rising enrollments of non-traditional students coupled with declining funding (Carlson, Ott, Armstrong, Zaback, & Auer, 2015; Tandberg, 2010) has been to expand online education offerings through existing colleges and universities[1] (Bowen, 2013; Deming, Goldin, Katz,

[1] *cf.* the Open University and its founding as an autonomous institution.

& Yuchtman, 2015; Goldrick-Rab, 2010). Online learning has been touted as a way to educate students in a flexible and cost-effective manner (Moloney & Oakley, 2010). Such a move is also in line with the equity mission found at open access public institutions (Cox, 2006).

While some researchers have held up massive open online courses, or MOOCs, as models for a new type of higher education (Bowen, 2013; Selingo, 2013), the newest digital revolution in higher education has not been limited to these unique courses. Public institutions in many states, especially those at the two-year level, have also steadily increased the number of online credit hours they offer in the past few years (Allen & Seaman, 2011; Allen, Seaman, Poulin, & Straut, 2016; Radford & Weko, 2011; Southern Region Educational Board, 2013, 2015). In the fall of 2012, 27% of all college students took at least one online course, with 13% completing all coursework through online classes (Snyder & Dillow, 2015). Two years later in the fall of 2014, those same numbers had increased to 28% and 14%, respectively (Snyder et al., 2016). Unlike MOOC students, many of whom take courses anonymously and for no credit, these data show that formally enrolled students often incorporate online courses into their degree pathways, taking them alongside more traditional face-to-face courses.

From correspondence classes meant to replace traditional higher education programs to online course sections as simply another option in the menu of higher education choices, distance education has remained one way to open higher education to a greater number of people than possible at traditional campuses. But as the technology of distance education has improved—from mail, radio and television to the Internet—so too have the requirements for participation increased. Where an address, paper, and pen had once sufficed, a computer and steady Internet connection are now required to take most distance education courses. Students who do not have these technological resources may find themselves effectively shut out. The open access rhetoric of online education, therefore, need first acknowledge the digital divide between those with access to the Internet and those without.

2.2 The digital divide: an overview

Scholars and policy-makers have long noted the divide between those who have access to communications technology and those who do not (R. H. Brown, Barram, & Irving, 1995; Irving et al., 1999; McConnaughey & Lader, 1998). Of recent concern is the digital divide between those with access to broadband and those without (Federal Communications Commission, 2016a). Because a large majority of persons in the United States have access to some form of broadband, researchers have transitioned from questions that ask *if* persons have access to questions that ask *what kind* of access (T. Brown et al., 2010). This represents an important shift as research has shown that local infrastructure, regardless of the relative affluence of the population, can have a major impact on the availability of service in a particular area (Grubesic & Murray, 2002). Even within a socioeconomically homogeneous local area, topological features can cause the quality of broadband connections to vary substantially across households and neighborhoods (Oyana, 2011).

Local variations notwithstanding, less affluent rural areas have generally had poorer access to broadband than wealthier and more urban areas (R. H. Brown et al., 1995; Copps, 2009; Federal Communications Commission, 2015). One reason for this disparity lies in prohibitive "last-mile" infrastructure costs that communications firms, local governments, and residents are reluctant to cover (Grubesic & Murray, 2004). In rural, suburban, and urban areas alike, those of lower socioeconomic status usually have the least access to broadband (Horrigan, 2010). Even the near ubiquity of cellular and satellite technology does not close the gap since wireless services still cannot compete with wired services in terms of speed and reliability (T. Brown et al., 2010) or coverage (Grubesic, 2012b).

Due to growing concern over these issues, Congress charged the Federal Communications Commission in 2009 with instituting the National Broadband Plan. This plan represents a concerted national attempt to close the digital divide by making sure that "every American 'has access to broadband capability' " (Federal Communications Commission, 2009, p. XI), a goal that is seen as worthwhile due its economic, civic, and educational benefits (Copps, 2009; Czernich, Falck, Kretschmer, & Woessmann, 2011). Since the inception of the plan, a number of government reports have been issued detailing the status of broadband in the country (latest: Federal Communications Commission, 2016b). Data collected from ISPs about broadband penetration has also been opened to the public in the form of the National Broadband Map (National Telecommunications and Information Administration, 2011). While these data come with their own limitations mostly owing to the size of the raw data (Grubesic, 2012a, 2012b), they nonetheless represent a vast improvement over previously available data on broadband (Grubesic, 2008a, 2008b, 2008c) and make possible new quantitative research on the effect that being on the wrong side of the digital divide may have on educational access and outcomes.

2.3 The digital divide in higher education

Regarding the effect of the digital divide on students, the National Broadband Plan's founding document notes that

> [t]oday, millions of students are unprepared for college because they lack access to the best books, the best teachers and the best courses. Broadband-enabled online learning has the power to provide high-quality educational opportunities to these students—opportunities to which their peers at the best public and private schools have long had access. (Federal Communications Commission, 2009, p. 5)

In concurrence, a number of studies have highlighted the negative effects of the digital divide for communities and students in postsecondary institutions. From the early days of the Internet, scholars have noted that white students were more likely than their African-American peers to have computers in their homes and to have used the Internet (Hoffman & Novak, 1998). Even in later years as more students gained access to the Internet, differential usage across gender and racial/ethnic groups in terms of communication and academic usage suggest a continued divide (Cotten & Jelenewicz, 2006; Jones, Johnson-Yale, Millermaier, & Pérez, 2009).

Two recent studies in particular reveal how infrastructural differences in broadband access among higher education students remain. Using GIS spatial data to examine the availability of broadband in the region around Southern Illinois University Carbondale, Oyana (2011) found that broadband quality was not uniform in the region and was generally inferior in poorer and more rural areas. Presenting data on the quality of signal as function of land topography, he showed a correlation between signal quality and median household income. Based on his analysis, Oyana concluded that without improvements to broadband infrastructures, much of the southern Illinois area under study could not support the large data requirements of the types of libraries and research labs that area students would need in order to have the same educational advantages as their peers who live in areas with better broadband access.

Hurst (2010) highlighted similar concerns for knowledge production in low broadband areas with a survey that asked students at Walters State Community College in eastern Tennessee to describe their home broadband access and how it related to and affected their coursework. He found that while 65% of his survey respondents ($N = 740$) said they felt having broadband access was very important for completing their schoolwork, 20% reported having no Internet access or only dial-up at home and 30% reported feeling dissatisfied with their broadband quality. He also found a statistically significant relationship between having faster internet speeds at home and the propensity for taking an online course.

Both of these studies provide suggestive evidence of a gap in broadband access that may make it more difficult for rural and low-income students to fully participate in courses that require online coursework. The authors' respective findings are echoed by others who suggest that some areas of the country lack access to the quality broadband, computers, and human capital required to successfully integrate online coursework into higher education (Cejda, 2007). These studies, nonetheless, have limitations. Singly, each considers only a small local area; together, they focus on the mid-southern region of the country. The generalizability of Hurst's findings are further limited by the fact that his analyses do not utilize metrics of broadband connectivity but instead rely exclusively on survey data.

This paper adds to the literature on online higher education by rigorously investigating the connection between broadband access and the take up of online courses among students at open admissions colleges and universities across the country. With its national scope and novel data, this study further bridges the gap between research on the digital divide and online education. Though it may seem obvious that increased download speeds should be connected to increased online-based distance enrollment, the uncertainty surrounding the demands of online coursework may mean that students do not readily make the connection.

3 Theoretical framework

Under the human capital model of college enrollment, the enrollment decision requires a weighing of the potential gains of increased education against its costs (Becker, 2009; Turner, 2004). For many students, gains are realized as improved job prospects or increased wages (Eagan et al., 2014; Fishman, 2015). College costs generally include direct costs such as tuition, books, fees, room and board as well as indirect opportunity costs like forgone wages (Manski & Wise, 1983).

A key selling point of online courses is their potential to lower costs for both the institution and the student (Deming et al., 2015). For the institution, online students do not require physical plant space or the costs associated with using the space: desks, lights, chalk/whiteboards, paper handouts, electricity, support staff to maintain the space, *etc*. For this reason, the marginal cost of the course in terms of an additional student is close to zero. For courses in which grading may be largely automated (*e.g.,* those that rely on multiple choice tests rather than written assessments), the cost of an additional student in terms of instruction is also effectively zero. If most online courses are asynchronous, meaning that students are not required to view course materials at specific class meeting times but rather can do so when they choose, then schools can save money by reducing or eliminating off-hour course sections in which the student-instructor ratio may be comparatively lower and less cost-effective.

Students may also see online courses as personal cost reducers. Because online courses do not require travel to campus, a student can save on travel-related expenses such as gas or public transportation costs. Asynchronous courses do not demand a set block of time in which to work on them. Students in these types of online courses can self-pace and work at times with lower opportunity costs. The flexibility given by the online course may allow for a greater range of options in other areas—work, family—that themselves may not be as time flexible (Jaggars, 2014).

Online courses, however, may increase rather than decrease some educational costs. These additional costs may be difficult to measure due to informational asymmetry and uncertainty on the part of the student. When deciding whether to enroll in an online course, an important consideration is whether one has access to the quality of broadband required to successfully complete the course. Slow speeds, poor connections, and high connection prices may all reduce the likelihood of success by increasing the direct and indirect costs of enrollment. More money spent on improved broadband access/speeds is less money to spend on books or other supplies; more time spent completing and submitting online assignments due to low quality broadband is less time to complete other assignments, work, or spend with family.

At the time of enrollment, students may have difficulty connecting perceptions of their broadband connections as experienced through other devices and services (*e.g.,* cellular phone) to the demands of online coursework. Students who are older or who face socioeconomic barriers to their enrollment may have had little experience with broadband upon which to base their enrollment decision. It could be the case that broadband access is moot for students with constrained choice sets that effectively limit their options to online work. For these reasons, it is unclear whether broadband access should be correlated with the decision to enroll in online courses in the aggregate. For the student, this lack of information regarding their ability to take online courses may increase costs since uncertainty surrounding their ability to successfully complete the course may itself be a cost (Jaggars, 2014).

It is outside of the scope of this paper to fully investigate whether students perceive online courses as increasing or decreasing the costs associated with their enrollment decision. Instead, I focus on a single aspect—the association between broadband access and the decision to enroll in online courses. The limited prior literature suggests that students with better access to quality broadband connections are more likely to attempt and succeed in online coursework than their peers who lack access (Hurst, 2010). If individuals respond this way, it may also be true that institutions in areas with better broadband are more likely to offer course sections in an online format and/or encourage their faculty to move some work online into a hybrid setting. In either of these situations, I would expect measures of broadband access to be positively correlated with the number of students attempting online courses. If uncertainty surrounding online courses or broadband connectivity is high then students may perceive online courses to have higher costs. Or if schools have other prerogatives regarding online education that outweigh considerations of broadband access (*e.g.,* cost reductions), broadband access may be moot. In either scenario, I would not expect a strong connection between broadband measures and online enrollment.

To investigate the relationship between broadband and online enrollment, I rely on a number of assumptions. First, I assume that students attending public open access institutions who split their enrollments between online and face-to-face course sections are likely to live nearby. Both prior research (Mattern & Wyatt, 2009) and national survey data suggest that most students attend schools close to home (U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2012). Table 1 shows that in the years just before the study period, approximately three in four students attended college within 50 miles of their permanent address. Because the assumption of geographic proximity is less warranted for students who enroll only in online courses, I do not include institutions mostly likely to enroll this type of online education student—for-profit two-year colleges and selective public and private universities—in the data set.

To further support this assumption of proximity, I consider only the number of students who split their coursework between face-to-face and online courses. That these students must be on campus at least part of their time bolsters my assumption that they live nearby. Finally, I assume that the outcome of interest involves online coursework rather than other methods of distance education (*e.g.*, television, radio, CDs, mail-based correspondence). While the IPEDS variable allows for many types of distance learning technology, historical trends and the current technological landscape (Allen & Seaman, 2011; Allen et al., 2016; Moore & Kearsley, 2011) mean that online work makes up the vast majority, if not functionally all, of the distance coursework during the years under study.

4 Estimation strategy

I estimate the association between three measures of broadband access—download speed, upload speed, and the number of providers—and the number of students enrolling in some online courses using both Bayesian single and multilevel regression models. The Bayesian paradigm, as opposed to a frequentist paradigm, is warranted in this instance for two primary reasons.

First, the data I have represent the entire population of public open admissions postsecondary institutions that have students who enroll in online courses. Furthermore, these data are situated in their specific historical context, a time in which online-based online courses were growing in popularity and the technological means by which they were made possible were also developing and improving (Allen et al., 2016; Federal Communications Commission, 2016a; Snyder et al., 2016). A repeated sampling framework, on the other hand, is predicated on the belief that the analysis data represent a random sample of data from a population. The key assumption is that under repeated samples, which would realize different analysis data, fitted models would produce parameters that would converge to the true and fixed values. Were I to gather these institutional and broadband data again, however, I would not expect differences since the data represent the population of public open admissions institutions that had online enrollments at the time (Western & Jackman, 1994). A Bayesian approach, which instead views the data as fixed and the parameters as random, is more applicable (Jackman, 2009).

A second reason to employ a Bayesian framework is the nested nature of the data. Because schools are nested in states, hierarchical models that can account for correlation between units in groups may be preferred to single-level linear models (Gelman et al., 2014). The nature of the Bayesian framework is such that it is straightforward to move from single-level to multilevel models in terms of estimation and interpretation.

In the analysis, I first estimate a number of single-level Bayesian linear regression models that take the form

$$log(y_i) \sim N(\alpha + \beta Broadband_i + X\gamma, \sigma_y^2), \tag{1}$$

where y_i is the number of students who enroll in some online courses; α is a constant term; β is the parameter of interest for $Broadband_i$, the institution's measure of broadband; and X is a matrix of covariate data values with γ as its corresponding vector of parameters. Because the number of students who take some online courses is right skewed, I fit the log transformation of these values. This procedure normalizes the outcome, which allows me to use a normal likelihood function with a variance of σ_y^2. Using the natural log of the outcome has the added benefit of making β represent the percentage change in the number of students who take some online courses for each unit increase in the broadband measure of interest (Greene, 2012).

A key feature of Bayesian estimation is that one must set priors on all non-fixed parameters. These priors reflect the researcher's prior beliefs about what the parameters should be. One way of interpreting Bayesian analysis is that it is simply the use of new data to update prior beliefs. Broadly, priors may be strong or weak. The results of a Bayesian estimation, the posterior, are a compromise between the prior and data that weights each by the strength of its information. Strong priors in the face of weakly-informative data result in posterior beliefs that are not much changed. Weak priors estimated alongside strong data allow the data to "speak for themselves" (Gelman et al., 2014), giving results that are generally similar to those returned in a comparable frequentist analysis. In the single-level models, I utilize weakly-informative priors meaning that results are driven by the data and may be interpreted much as they would be were they generated using a frequentist estimation.[2]

To account for the nested structure of the data, in which institutions are located in states, I also fit two types of Bayesian multilevel models: one that allows state-varying intercepts and a second that allows both intercepts and slopes (β) to vary across the states. One particular advantage of multilevel models over single-level models is that they allow information to flow between observations within groups. To produce state-specific estimates, which may be warranted due to state-level differences in the higher education policy context, I could conduct separate estimations for each state. Due to small numbers of observations in some states, however, this procedure would produce noisy estimates. The multilevel model allows for partial pooling of the state-specific estimates across states. Institutions in states with few or no other observations can "borrow strength" (Jackman, 2009) from other similar institutions based on their group-level characteristics. With this "bias/variance" trade-off (Carlin & Louis, 2009; Gelman et al., 2014), I am be able to estimate the differential connection between broadband access and the number of students enrolled in online courses even in states with relatively few observations.

In the first multilevel model, each state is allowed to have its own intercept. It takes the form

$$\begin{aligned} log(y_i) &\sim N(\alpha_j + \beta Broadband_i + X\gamma, \sigma_y^2) \\ \alpha_j &\sim N(\delta_s Region_s + Z\psi, \sigma_s^2), \end{aligned} \tag{2}$$

[2]When coding the model, I technically use improper priors. Priors are improper when $\int p(\theta)\, d\theta \neq 1$, that is, the probabilities do not sum to one. All regression coefficients are drawn from a uniform distribution with support on $\theta \in (-\infty, \infty)$ and all variances from a positive uniform distribution: $\theta \in (0, \infty)$. Improper priors may combine with a likelihood function, however, to produce proper posterior distributions (Gelman et al., 2014).

in which X represent a vector of school and county level covariates, Z are state-level covariates, and unknown parameters $(\beta, \gamma, \psi, \sigma_y^2, \sigma_s^2)$ are again given diffuse priors. In the second specification of the multilevel model, the effect of the broadband measure is also allowed to vary across each state:

$$\begin{aligned} log(y_i) &\sim N(\alpha_j + \beta_j Broadband_i + X\gamma, \sigma_y^2) \\ \alpha_j &\sim N(\delta_s Region_s + Z\psi_s, \sigma_s^2) \\ \beta_j &\sim N(\delta_s Region_s + Z\psi_s, \sigma_s^2) \end{aligned} \tag{3}$$

I fit the three model types using each measure of broadband separately and together in a single equation. In each case, measures of broadband include both the level and squared value. For varying slope models, both the level and squared terms are allowed to have state-specific parameters. Both the full set of institutions and the subset of two-year institutions are used as data, producing eight sets of results for each of the three model types.[3]

5 Data

5.1 Institution data

Data on the number of students who enroll in online courses were taken from the Integrated Postsecondary Education Data System (Department of Education, 2015). Though the IPEDS survey has asked institutions if they are primarily distance learning schools for a number of years (a binary *yes* or *no* response), it has only asked institutions to break down the total number of students who attempt distance learning coursework since the fall of 2012.

IPEDS defines distance education as "Education that uses one or more technologies to deliver instruction to students who are separated from the instructor and to support regular and substantive interaction between the students and the instructor synchronously or asynchronously." (Department of Education, n.d.) The code book further defines the technologies that may fall under the heading of distance education as including "Internet; one-way and two-way transmissions through open broadcasts, closed circuit, cable, mi-

[3] In an alternative specification, I use the proportion of students as the outcome of interest. To properly model the proportion, which is bounded by [0,1], I use a beta likelihood function. The results for these models are qualitatively the same as those given by the log outcome/normal likelihood models, so I present the latter for ease of interpretation. More details about the beta likelihood specification as well results from the models are shown in Appendix A.

crowave, broadband lines, fiber optics, satellite or wireless communication devices; audio conferencing," (Department of Education, n.d.). While not all of these technologies are strictly broadband-based, it is likely that most distance education students at public open access institutions in the study period experienced distance education through online portals (Allen & Seaman, 2011; Allen et al., 2016; Moore & Kearsley, 2011). For this reason, I refer to these students as *online* students.

Specifically, I use the IPEDS variable that gives the number of students who took some of their courses online as the primary outcome. This number indicates the number of students who enrolled in both online and face-to-face courses. Because the data do not include the number of online courses that students took, the dosage of online course-taking within and between schools is unobserved. Sometimes-online students need only take one of each type of course to be labeled as such. This means that whereas some students represented in the data could have had balanced course loads, others were predominantly online students who took one face-to-face course or mostly in traditional courses with a single online course enrollment. Though it may be the case that broadband speeds are positively correlated with the number of online courses attempted, these data do not support this particular analysis.

Based on the theoretical framework, I include a number of school-level covariates in some model specifications. Online courses may reduce costs for students by increasing access or may increase costs by increasing uncertainty. Though the direction of the potential effect is unclear, it is possible that student populations will be differentially affected. To account for potential heterogeneity in response to online coursework, covariate models include, at the institutional level, proportions of students who receive Pell grants, non-white students, women, students who are 25 years old or older, and part-time attenders. Only undergraduate enrollments are considered. Models using all institutions include an indicator for status as a two-year college. As control measures, all models include the log transformation of the total number of students enrolled and indicators for the survey year of the observation.

Table 2 shows means and standard deviations of the numbers of students taking courses for credit, those taking some online courses, and other institutional covariates. Schools in Alaska and Hawaii are dropped due to their unique spatial situations—Alaska as a large, but sparsely populated state and Hawaii as an island group—that may bias the weights used to construct the broadband measures that I assign to each institution. Because data for all branches of Indiana's public two-year institution, Ivy Tech, were aggregated under a single identification code, these institutions were also dropped from the data set as broadband measures could not be accurately assigned to them. The final estimation data represent 1,018 unique public open admissions institutions observed across three years.

5.2 Broadband data

Broadband data were collected from the National Broadband Map website.[4] Gathered at the behest of the National Telecommunications and Information Administration in partnership with the Federal Communications Commission, these data were collected from Internet service providers (ISPs) within each state by appointed grantee agencies. Each service provider gave information about upload and download rates at the census block level as well as information on the number and types of community anchor institutions (typically libraries, K-12 schools, college, *etc*.) in the area (National Telecommunications and Information Administration, 2011). These data were corroborated against other sources of broadband information and released to the public. Data released in December 2012, 2013, and 2014 were used since they were collected around the same time period as the IPEDS data and represent the best estimates of broadband connectivity surrounding study institutions during the time period under study.[5]

Internet service providers reported measures of broadband speed in ordered categories that range from 1 (greater than 200 kB/sec and less than 768 kB/sec) to 11 (greater than 1 GB/sec). Past FCC guidelines suggested that the minimum required speed to watch university lectures was 4 MB/sec, which would fall under category 5.[6] Acknowledging the increasing "speeds required to use high-quality video, data, voice, and other broadband applications," (Federal Communications Commission, 2015, p. 3) as well as the demands placed on broadband connections by multiple users within the average household, the FCC recently updated these benchmarks, arguing that "having 'advanced telecommunications capability' requires access to actual download speeds of at least 25 Mbps and actual upload speeds of at least 3 Mbps," (Federal Communications Commission, 2015, p. 3). These new benchmark speeds fall under category 8. Figure 1 shows the variability in download speeds across the country as of December 2013. County-level values represent the population weighted average of all values within each respective county. The map makes clear the heterogeneity in average download speeds experienced by persons across the country. It also shows that while many counties have broadband-level Internet speeds under the old definition (roughly category 5), many fewer have broadband speeds under the new definition (category 8) (Federal Communications Commission,

[4] www.broadbandmap.gov

[5] Though subsequent years of student enrollment data have since been released, the National Broadband Map stopped being updated in June 2014. I have not incorporated the newest enrollment data for this reason.

[6] www.fcc.gov/guides/broadband-speed-guide

2015, 2016a).

A primary question for this analysis: how does one assign a broadband measure to each institution? Were the unit of analysis the student and home address known, I could simply assign each student the broadband measures of their home census block group. But because the unit of analysis is the school, I am unable to see where each student lives and must assign broadband measures to the institution that take into account those experienced by the average student who is enrolled there.

One solution would be to use the measures computed to produce Figure 1, assigning each school those of its county. Yet postsecondary students, especially those who are part-time, older, or attend non-residential schools, may not live in the same county as the one in which their institution is located. As shown in Table 1, a large portion of students may travel more than 20 miles to attend classes. To assign each institution the average download speed in its county, for example, may neglect the broadband experience of students who live in an adjacent county with very different download speeds. Aggregating the measures up to the county level would also mean losing the fine grain differences in broadband access within each county.

To better approximate the most likely distribution of students around institutions, I instead assign each school broadband measures using a weighting process that takes into account both (1) its distance to surrounding census block group-level measures and (2) the populations of those census block groups. The parts of the combined inverse-distance/population weight are discussed in turn below.

Inverse-distance weights were constructed by first computing the Great Circle distance, d_{sc}, from each institution, s, to all census block group centroids, c, in the lower 48 states, and producing an $N \times K$ matrix where $N = \#$ schools and $K = \#$ census block groups. For the year 2013, a $1,004 \times 217,290$ matrix of distances was the result. So that download speeds of nearby census block groups would count more than those of distant census block groups, these values were inverted and scaled to create inverse distances, id_{sc}:

$$id_{sc} = \frac{1}{(d_{sc})^r}. \tag{4}$$

Finally, weights were created by dividing each inverse distance over the row sums of the inverse distances (each row representing the distance between a single institution and all census block group centroids):

$$idw_{sc} = \frac{id_{sc}}{\sum_{c=1}^{C} id_{sc}}. \tag{5}$$

Were the data used in this study at the student level, the inverse distance weight would be sufficient to approximate the broadband measures experienced by each student (if I did not wish to simply assign them the values of their census block group). But because the data are aggregated to the institution level, I do not know exactly where the students live in relation to the school. Some may live very close whereas others commute from further away. It is also unlikely that students are evenly distributed around the school. It is more likely that students come from nearby population centers: towns, suburbs, and neighborhoods. The inverse distance-weighted average assigned to the school, therefore, is likely to be different from what would be assigned to the students were their addresses known.

To mitigate this potential bias, I employed a second weight that adjusted each school's inverse distance-weighted broadband measure average back toward values recorded in more highly populated areas. Accounting for population in spatial-weighting schemes has been shown to improve upon estimates in which only inverse distance weights are used (Hanigan, Hall, & Dear, 2006). Using census block group population estimates taken from the 2010 Census, I constructed a second $N \times K$ matrix (again, $N =$ # schools and $K =$ # census block groups) in which each column represents a census block group's population, pop_c, repeated in each row. The population weight, pw_c, is simply

$$pw_c = \frac{pop_c}{\sum_{c=1}^{C} pop_c}, \tag{6}$$

or the population in the matrix cell divided by the row sums.[7] In applying the second weight, I make the assumption that the likelihood a student lives in a particular census block group around the institution is proportional to that block group's population size. Lest major metropolitan centers unduly skew the average too far away from the institution (*e.g.,* census block groups in Charlotte, North Carolina, affecting averages of schools in the eastern part of the state), I use a quadratic decay ($r = 2$) in the inverse distance weight formula (Shepard, 1968). At this rate of decay, the effect of neighboring census block group broadband values on the institutional average quickly diminishes with distance, even when population sizes are taken into account. Thus the second population weight serves as a slight correction to the inverse distance weight, which dominates in the final computation of each broadband measure average at an institution.

The combined weights, $w_{sc} = pw_c \times idw_{sc}$, were then used to create weighted average broadband mea-

[7] Because the census block group population values are constant, it is not strictly necessary build an entire $N \times K$ matrix, which is simply a vector of values of length K repeated N times, or compute the row sums and weights N times. For purposes of computation, however, it is easier to build a full matrix that can be easily combined with the other weighting matrix when computing the final average.

sures for each school, $wbroadband_s$,

$$wbroadband_s = \sum_{c=1}^{C} \frac{w_{sc} \cdot broadband_c}{\sum_{c=1}^{C} w_{sc}}, \tag{7}$$

in which $broadband_c$ is the average broadband measure—download speed, upload speed, or number of providers—in the census block group. Each weighted average was computed using census block group broadband values reported in the December of the fall term in which the online course enrollment numbers were reported. Schools that appear more than once in the data set (the majority), therefore, have distinct broadband measure averages for each year.

Figure 2 offers a stylized visualization of this weighting process. Using Nashville State Community College (NSCC) as an example, dotted lines connect its location in Davidson County, Tennessee, shown by the gold diamond, to population centers in surrounding counties. (For clarity, the black dots represent county-level population centers rather than the census block group centers that were actually used.) The average download speed, for example, assigned to NSCC would be most influenced by the value recorded for the Davidson County center, the nearest black dot just the right of NSCC in the center of the map. Because the Davidson County value also represents the highest population density in the area, NSCC's average download value would be even further pulled in that direction.

The distribution of the weighted broadband measures across each year are shown in the second row of Table 3. Due to the asymmetric design of most residential broadband networks (Federal Communications Commission, 2016a), the average download speed is greater than that of the average upload speed. As might be expected due to continual demand for greater speeds, both download and upload averages increase in subsequent years, though the number of providers remains relatively stable (Federal Communications Commission, 2016a).

5.3 Geographic and demographic data

When estimating multilevel models, I use additional state level covariates to aid in fitting second level parameters. These include measures of statewide unemployment rates, which were taken from data provided by the Bureau of Labor Statistics (Bureau of Labor Statistics, 2012, 2013, 2014). To account for potential differences that funding structures could have on the availability of online courses, measures of state appropriations per full-time equivalent student in each year were gathered from a report produced by the State

Higher Education Executive Officers Association (SHEEO) (Carlson et al., 2015). I also include a measure of the proportion of two-year open admissions public institutions within each state that I computed using data from IPEDS. These variables were intended to account for potential differences across states in the number of students who might be likely to attend open admissions universities and/or attempt some online courses.

Because the likelihood of students enrolling in online courses (or an institution offering more sections) might be correlated with the average distance a student must travel to reach a postsecondary institution (Xu & Jaggars, 2013), I incorporate a measure of the average distance a person would have to travel to get to the nearest open admissions institution. To compute this measure, I first found the distance from each census block group centroid to the nearest public open access postsecondary school. I then averaged these distances to the state level, using the relative population in each block group as the weight. Though a rough measure, it does give an indication of the spread of institutions around each state in terms of its population centers and is variable across the states. I include the log transformation of this measure alongside other state-level measures.

Finally, to account for potential differences between students living in rural and urban areas (Cejda, 2007), I include both a self-constructed measure of population density for each school and an array of indicators for degree of urbanicity/rurality. I computed the first measure by summing the averages of census tract density (tract population divided by land area) to the county level and assigning each institution the value of its county. Indicator variables for degree of urbanicity come from the United States Department of Agriculture, which assigns all counties one of nine rural-urban continuum codes (United States Department of Agriculture Economic Research Service, 2013). As with the population density, I assign each school the value of its county. Unlike the measures above, I incorporate both of these measures into the vector of first-level covariates in all models.

6 Results

To generate the results, I utilized a computationally-based Markov chain Monte Carlo algorithm that fit each Bayesian model a repeated number of times. While simple Bayesian models may be solved analytically, non-trivial equations are often too complex or have no closed-form solution (Gelman et al., 2014). To solve these problems, a computer program uses an iterative process to propose, compare, and either accept or reject parameter values. With enough iterations, parameters produced by the process will come from the true posterior distribution (Brooks, Gelman, Jones, & Meng, 2011). Though no tests exist that can determine whether enough samples have been drawn so that the true posterior is effectively summarized by their distribution, there are a number of best practices that support such a conclusion.

First, the algorithm is generally run multiple times to generate multiple chains of results. If these independent chains converge, that is, give distributions of results that are the same, this supports a conclusion that the draws summarize the posterior density distribution. For this analysis, I ran four independent chains with different starting values that appear to converge based on visual inspection of density plots and Rubin-Gelman statistics, which compare within-chain variance to between-chain variance, close to 1 (no significant difference) (Gelman et al., 2014).

Second, each chain should have a large number of draws. Because each chain starts with different values that are unlikely to come from the posterior, a large number of iterations is needed so that chains have time to reach the posterior. To prevent the initial and likely improbable starting values from biasing the results, it is common practice to discard some number of initial draws (Gelman et al., 2014). For all models, each of the four chains was run for 2,000 iterations and the first 1,000 of these values discarded. Combining these chains means that results for each model are a function of 4,000 draws.[8]

6.1 Single-level models

Table 4 shows the results for the single-level linear models. The Bayesian point estimates represent the mean of the posterior distribution with the accompanying numbers in the square brackets showing the 95% credible interval.[9] Models 1-3 use each broadband measure—download speed, upload speed, and the number of providers—in turn along with its quadratic. Model 4 uses all broadband measures and their quadratics in the same equation. All models include indicators for two-year institutions, year, and USDA urban/rural continuum code (not reported); the natural log of the institution's total of student enrollment as well as its proportions of non-white students, women, Pell grant recipients, part-time attendees, and students 25 years and older; and the county-level measure population density, logged. In all models, the dependent

[8]All models were estimated using command line version of Stan's No-U-Turn Sampler (NUTS), a variant of the Hamiltonian Monte Carlo sampler that may more efficiently explore the parameter space. To reduce the amount of lagged auto-correlation between successive draws in the chains and improve convergence, all models were estimated using centered data (Lunn, Jackson, Best, Thomas, & Spiegelhalter, 2013) and a QR reparameterization.

[9]All reported 95% credible intervals represent the middle 95% of the posterior distribution, meaning that the lower and upper bound values are the 2.5% and 97.5% quantile values, respectively.

variable is the natural log of the number of students who took some online courses. The parameter posterior distributions therefore represent the percent change in the number of sometimes online students for a one unit change in the covariate.

I first consider model (1), which uses download speed as the measure of broadband access. Because all right-hand-side variables were centered, the intercept, α, may be interpreted as the expected log number of students who take some online courses for average institution.[10] At $\alpha = 6.729$, this translates to about 836 students (95% credible range: [817, 856]). Though this number is lower than that shown in Table 2 (1391 students), it accounts for different enrollment sizes across institutions as well as changes over time that skew the unconditional average. Indeed, the mean values for the year indicators, $\beta_{2013} = 0.103$ and $\beta_{2014} = 0.157$, show positive growth in the number of students taking online courses on the order of 10 to 15% over that seen in 2012. This aligns with general trends described elsewhere in the literature (Allen et al., 2016; Snyder et al., 2016).

All else equal, two-year institutions are likely to have around 7% more ($\beta_{two-year} = 0.068$) of their students take some online courses than four-year institutions. Though all schools in this analysis utilize open admissions practices, this finding may reflect the two-year sector's particular focus on access (Cox, 2006). Concerning characteristics of the student body, the results are mixed. On one hand, institutions with greater proportions of Pell grant recipients and students over 25 years old show increases in the percentage of students taking some online courses. These findings are in line with arguments of online courses as means to increase access (Bowen, 2013; Selingo, 2013). On the other hand, schools with greater proportions of women, non-white students, and those attending part time are associated with lower percentages of students taking some online courses, which runs counter to the same arguments. One potential explanation may be that the high correlation between some of these student body characteristics, many of which fall under the "non-traditional student" designation (Snyder et al., 2016), produces counter-intuitive marginal results.

Two other institution-specific characteristics are of interest. First, schools located in areas with higher population density have fewer students who take some online courses. For a 10% increase in the population density surrounding an institution, 0.7% fewer students choose to enroll in some online courses ($\beta_{log(population density)} = -0.074$). Though the relationship is weak (keeping in mind that the degree of urbanicity is also accounted for in the model by the USDA urban continuum codes), it does support arguments

[10]Throughout the rest of the paper, I will generally use the Bayesian point estimates when referring to the mean of parameter's posterior distribution. They should be understood, therefore, in their proper context as useful summaries of full probability distributions.

that online courses may be particularly appropriate in less populated areas that are less likely to have strong transportation networks (Copps, 2009). Second, the model shows that as the total number of enrolled students increases, proportionally greater numbers of them take online courses, with every 1% increase in the former associated with a 1.154% increase in the latter ($\beta_{log(enrollment)} = 1.154$). The positive elasticity of this relationship provides evidence that recent growth in enrollments may be due in part to increases in the number of students taking online courses, which, once prepared, benefit from economies of scale (Deming et al., 2015).

Turning to the parameter of interest in model (1), $\beta_{download}$, Table 4 shows a positive association between tiers of download speed and the number of students enrolling in some online courses. For a single-tier increase in speed, akin to roughly a 2 to 3X increase in megabytes/sec (Mbps) download rate, approximately 32% more of an institution's students enroll in some online courses ($\beta_{download} = 0.324$). The credible intervals show much variance in the probable marginal effect, however, ranging from a high point of a 69% increase to a low point that is negative, -5%. Though Bayesian analyses do not utilize null hypothesis significance tests in the way that frequentist analyses do, it nonetheless may be useful to consider the 95% credible intervals as boundaries of interest. Because the lower bound of the credible interval on $\beta_{download}$ is negative, it suggests some uncertainty about the parameter.[11] Yet since fully 96% of the sample draws are greater than zero, $Pr(\beta_{download} > 0 = 0.961)$, a more properly Bayesian interpretation is that the model indicates that there is a greater than 95% probability that the association between download speed and online course enrollment is positive.

Results for models (2) and (3), which operationalize broadband access using upload speed and the number of providers, respectively, are reported in the next two columns of Table 4. The posterior distributions of the covariate parameters in each remain much as they were in the first model. But unlike download speed, neither upload speed nor provider count are strongly predictive of online course enrollment numbers. Though both β_{upload} and $\beta_{provider}$ posterior distributions have negative mean values—$\beta_{upload} = -0.075$ and $\beta_{provider} = -0.003$—each has large portions of its distribution above zero: $Pr(\beta_{upload} > 0 = 0.202)$ and $Pr(\beta_{provider} > 0 = 0.480)$.

In the fully specified model (4), download speed once again is the most strongly predictive of the broadband measures. On average, a single tier increase in download speed is associated with a 41% increase

[11] If the mean value presented in the table represented a frequentist point estimate, one could not reject the null that $\beta = 0$ under a two-tailed test of significance at conventional levels of significance ($\alpha = 0.05$). This is not to say, however, that it would not be jointly significant with its quadratic term.

($\beta_{download} = 0.41$) in the number of students who attempt some online courses. The large spread between the 95% credible interval suggests a wide range of possible marginal effects, from 8% to 82% increases in online course takers. In this model, however, the lower bound does not cross zero, which provides stronger evidence that the marginal effect is positive. The credible intervals for both upload speed and provider coefficients once again cross zero and are therefore comparatively uninformative.

In second set of models, I limit the data set to two-year institutions. Results from these models, which are shown in Table 5, generally follow the same pattern as those found when four-year institutions are included. None of the broadband parameters of interest, however, are as informative. In all models, the 95% credible intervals indicate greater variance in the posterior distributions as well as cross zero. There are two possible explanations for this finding.

First, it could be that broadband measures are more salient for online course enrollment at four-year institutions (or, alternately, less salient at two-year institutions). If the average student at a four-year institution is less constrained when choosing course sections than the average student at a two-year institution, then broadband speed and/or access may become more important in terms of online course enrollment. Alternatively, students at two-year institutions, who are more likely to be non-traditional (Snyder et al., 2016), may have other factors that limit their effective choice set and make broadband speeds less important (Jaggars, 2014).

Second, it may be the case that the reduced data set simply has less information about a potential connection. Four-year institutions make up approximately 12% of all observations in the data set and contain about 13% of the undergraduate student population represented by the schools. Yet 18.9% of students at four-years took some courses online (an average of 1,524 students per school), while 17.6% of students at two-year institutions did so (1,372 average per school). Dropping four-year institution observations from the analysis may remove enough information that wider, less informative posterior distributions are the result.

6.2 Hierarchical models

To account for the nested nature of the data and estimate potentially heterogeneous effects across states, I fit two sets of multilevel models (Gelman et al., 2014). In the first set, I allow the intercept to vary by state. As with the single-level linear regression models, the dependent variable is the log transformation of the number of students who attempt online courses. In addition to the covariates used in the single-level equations, I include a number of second-level covariates to help predict each state's unique intercept. These include the state average unemployment rate, statewide average appropriations per full time equivalent student, the proportion of open admissions public two-year institutions within the state, and the population-weighted average distance to the nearest public open admissions institution. In interest of space, coefficients for these parameters and the varying intercepts are not reported.

Table 6 shows the posterior means for these models. Again, I fit four separate equations in which each broadband parameter was included singly and alongside the others. Broadly the results from the varying intercept multilevel models are similar to those found in the single level models. In models (1), (2), and (3), all of the broadband parameters of interest measures have 95% credible intervals that include zero. In the fully specified model (4), however, the marginal effect of download speed is once again positive ($\beta_{download} = 0.556$) and with a 95% credible interval that does not cover zero [0.166, 0.957]. For each tier increase in download speed, institutions show a 56% average increase in the percentage of students who attempt some online courses, with a 95% probable association between 17% and 96%.

Though the number of providers, as in the single-level models, remains less informative, the marginal effect of upload speed in model (4) becomes more informative. For each tier increase in upload speed, 22% fewer students are expected to take some online courses. This result appears counter-intuitive. Why should improved upload speeds be associated with reductions in online course take-up? One possibility lies in the asymmetric nature of most residential broadband connections. Downloaded and uploaded data travel the same line, so ISPs must decide how to balance the load. Because most Internet services are structured to send audio, video, text, and other files to the end-user who in turn needs only send small files of instructions regarding what to download, most residential broadband connections are asymmetric, meaning they allow download rates to be much higher than upload rates (Federal Communications Commission, 2014, 2016a). If increased upload rates come at the expense of download rates and download rates are more salient for online students, then it is reasonable that the average marginal effect of upload speed be negative (see in particular model (2) in Table 6).

Another reason for this counter-intuitive finding may lie in the technologies used to serve broadband. Though some people have access to broadband served through fiber optic lines, which use glass fibers and light to send digital signals, many users with wired connections have their broadband delivered through copper wires that also transmit their telephone or cable television signals (National Telecommunications and Information Administration, 2011). Broadband data transmitted over these lines more quickly degrades with distance, making it more difficult for ISPs to separate signal from noise as well as separate the data requests of users who share the line (reduce "crosstalk") (Grubesic & Murray, 2002). Holding download speeds and the number of providers constant as in model (4), it may be that increases in upload speed allow for more traffic on wired lines that degrades the average signal quality for users along the line. The negative sign, therefore, could reflect a decrease in the proportion of students who attempt some online courses due to a less robust broadband connection, not necessarily faster upload speeds. I note, however, that because the marginal increase for download speed in model (4) is larger than the decrease for upload speed, even concomitant increases in both measures (+1 tier increase in both download and upload speeds) is associated with a 33% average increase in the number of students taking some of their courses online.

Table 7 shows the results from the varying intercept models fit to the subset of two-year institutions. The posterior means generally follow the pattern set by those found for the full data set. As before the 95% credible intervals become wider and in many cases cross zero. Though the indicator for status as a two-year institution remains positively associated with students taking some online courses when four-year institutions are included (Table 6), once again the evidence points to students at four-year institutions being an important part of the overall estimated effect.

In a final set of models, I allowed parameters on broadband measures to vary by state in addition to the intercepts. As with the single-level and varying intercept models, I include each broadband parameter and its quadratic independently (models 1-3) and together (model 4). Rather than report a large table of unique intercepts for each state, I instead show the differences in marginal effect in two figures. In Figure 3, only download speed is included in the model (model 1). In each plot, the blue central dot represents the median posterior value. The red and gray error bars show the 68% and 95% (1σ and 2σ) of the distributions. A black vertical line is set where $\beta_j = 0$. The plot on the left shows the results produced for the full set of institutions; the plot on the right shows those for the subset of two-year institutions.

Focusing first on the left plot in Figure 3, four states—Tennessee, Colorado, Alabama, and Oklahoma—show positive associations between download speed and enrollment in some online courses and have 95% credible intervals that do not include zero. At the other end of the plot, both Texas and Louisiana show strong negative associations and similarly have credible intervals that do not include zero. The rest of states all have credible intervals that cover zero, with median marginal effects that fall on either side of zero. Looking at only two-year institutions in the right plot, students at two-year institutions in Texas and Louisiana continue to show strong negative reactions to increased broadband speeds whereas only Colorado and Alabama show significant positive marginal effects. Figure 4 shows state-level differences in the marginal effect of download speed on online course enrollment in models that also contained varying slopes for upload speed and the number of providers (model 4). In these models, Tennessee, North Dakota, Alabama, and Oklahoma show positive associations credibly above zero in the full data set; only Alabama also shows a similar association in the two-year subset. No states in either the full set or two-year subset show a credible negative association.

Together, Figures 3 and 4 suggest that students in some states more than others may be driving the results found in the single level and varying intercept models. Though states such as Tennessee and Oklahoma have many rural students who may be more inclined to take some online courses, other equally rural states do not show such a strong association. In fact, Louisiana, a Southern state like Tennessee and Alabama shows credibly negative association between download speeds and online course enrollment. These varying slope estimates should be interpreted with caution, however, due to the reduced number of observations within each state that increase credible intervals in low population states (*e.g.*, Wyoming), making state-specific estimates less certain.

7 Conclusion

This paper offers empirical evidence of a positive association between broadband access and student enrollment in online courses at open admissions public colleges and universities in the United States. In preferred model specifications, I find that single tier increases in download speeds in the area surrounding an institution correspond to 41% to 56% average increases in the number students who take some online courses. Because the majority of these parameter posterior densities lie to the right of zero, the marginal effect of increased download speeds is almost certainly positive. The precise marginal effect is unclear, however, as the 95% credible intervals across the models indicate a wide range of possible values—as much as 17% to 96% in the varying intercept hierarchical model. Among the subset of two-year institutions, I find similar but less precise results.

I do not find similar correlations for upload speed. Generally, upload speeds appear to be negatively correlated with online enrollment numbers. With the exception of a single model, however, these estimates are less certain than those estimated for download speeds. The negative marginal effect for upload speeds is curious, but as I note above, the asymmetric design of most broadband connections may mean that increases in upload speed come at the expense of download speed. If online courses for most students consist of streaming audiovisual materials and submitting papers or taking online tests, then download speeds should be comparatively more important than upload speeds. My results support this hypothesis.

The average number of providers in an area, on the other hand, generally has no clear association with the number of students taking some online courses. In all models, the parameter on this measure have 95% credible intervals that cross zero. In many models, the average marginal effect is close to zero. In theory, increases in the number of providers should foster competition that lowers prices and/or improves speeds. That students do not appear to respond to a greater number of providers suggests a market failure due to a lack of real competition. Despite nominal access to the services offered by ISPs, geographic restrictions and costs may prevent some users from actually accessing those services (Grubesic & Murray, 2002; Oyana, 2011). The lack of clear association between the number of providers and the take-up of online courses may reflect this difference between the nominal number of ISPs, which I can observe in the data, and actual number of ISPs reasonably available to users, which I do not.

Finally, I find evidence of heterogeneous effects of broadband access across the states. Schools in some states show strong positive associations between download speed and the number of sometimes online students. Schools in most other states show little connection, and, in a couple of states, credibly negative correlations. The high variability in state-level estimates could occur for a number of reasons. If download speed measures are measured with error, any relationship between broadband and online education should be expected to attenuate. Similarly, the aggregated broadband measures that I construct may smooth over differences and reduce the variation required to untangle clear effects. My study, through its reliance on the assumed proximity of online students to their institutions and many aggregated measures, may suffer from such attenuation. Policy contexts within each state may also drive differences between them. Those with strong positive associations between download speed and online enrollments may have higher education policy contexts conducive to institutions offering online courses. States with little or negative associations, on the other hand, may lack the capacity or interest in expanding online offerings.

As a limitation, I note that the dependent variable I utilize does not measure course completion, only the number of students who enrolled in some online courses. Student persistence within the course is an important outcome to measure since students may make the rational decision to withdraw rather than persist and earn low grade or fail the course (Xu & Jaggars, 2011, 2013). Because the course enrollment decision typically comes in the months prior to the start of the course, it may be that some students only realize broadband access barriers after enrolling. As I note in section 3, students may not have a clear idea about the quality of their area broadband or, if they do, how it corresponds to the demands of an online course. Thus while my results speak to the possible effect that broadband access has on students' decisions regarding whether to enroll in online courses (or for institutions to offer them), they do not extend to student performance in online courses.

A final limitation of this paper is that I cannot differentiate between student demand for online courses and institutional supply. Increases in broadband speeds may induce students to demand more online course options. Conversely, postsecondary institutions situated in areas with better broadband access may choose to offer more online course options. Under this second scenario, students only respond to increases in broadband quality insofar as their schools do by offering more online courses (or comparatively fewer face-to-face courses). Findings, therefore, should not be interpreted causally, but instead as regression-adjusted measures of the association between broadband speed and online course enrollment.

These potential limitations notwithstanding, this paper offers support for the conclusion that access to quality broadband, particularly in the form of faster download speeds, is an important component of the choice to enroll in some online courses. Schools, however, may choose to offer online courses regardless of area broadband speeds based on their institutional needs and goals (Allen & Seaman, 2011; Allen et al., 2016; Moore & Kearsley, 2011). If students are effectively limited in their choice set to these courses, they may be forced to register for them regardless of their broadband connectivity. State-level higher education policies may also support online education to varying degrees based on financial and political rather than technological considerations (Johnstone, 2006; Kinser, 1999). Though these results speak only to enrollments and not completions, it is logical to think that improved broadband would also be associated with improved student outcomes in online courses.

A scenario of infrastructure-irrelevant policy-making, therefore, has important ramifications for the future of online higher education policy. As recent trajectories suggest, distance education delivered through online technology will almost certainly play an important part in the future of higher education (Allen et al., 2016; Bowen, 2013; Selingo, 2013; Snyder et al., 2016). Insofar as it has the potential to be less expensive on the margins and reach more non-traditional students due to its flexibility, online education will be appealing to higher education institutions, especially those without deep endowments that mostly serve non-traditional student populations. But if these populations are also most at risk for lacking access to quality broadband (Cejda, 2007; Hurst, 2010), then the move to online coursework may have negative effects on their educational outcomes.

Should it be true that students respond positively to broadband speeds, public open admissions institutions that desire to increase the number of online learning opportunities may first wish to consider speeds in their service area. They may also find partners with those in other sectors who wish to improve broadband infrastructure for economic reasons. If, conditional on equitable access, students at these institutions realize equal or better educational outcomes, improving broadband infrastructure around public postsecondary institutions may pay triple dividends in the form of improved student outcomes, lower costs, and improved infrastructure that can be shared with all members of the community.

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Table 1: Distance from student's home (in miles) to NPSAS institution by dependency status

	< 21	21–50	51–100	101–500	> 500
Total	59.9	13.6	7.2	11.8	7.6
Dependency status					
Dep.	54.8	14.1	9.8	16.3	5.1
Ind.	64.7	13.2	4.7	7.4	10.0

Notes. Data come from the U.S. Department of Education, National Center for Education Statistics, 2011-12 National Postsecondary Student Aid Study (NPSAS:12). All numbers are percentages. Computation by NCES PowerStats.

Table 2: Descriptive statistics of institution sample

	Mean/(SD)
Total enrollment	7838
	(8406)
Some online enrollment	1391
	(1717)
Two year institution	0.88
	(0.33)
Non-white student enrollment	0.42
	(0.24)
Women enrollment	0.42
	(0.07)
Pell grant recipients	0.42
	(0.15)
Part-time enrollment	0.57
	(0.15)
Aged 25 years and older	0.37
	(0.11)
2013	0.4
	(0.49)
2014	0.3
	(0.46)
N (2012)	751
N (2013)	1004
N (2014)	742

Notes. Total enrollment and some online enrollment represent the average number of students rounded to nearest student. Other rows are proportions. Standard deviations are shown in parentheses. Schools included in the sample are public, open admissions postsecondary institutions that report at least one student who took some distance education courses.

Table 3: Descriptive statistics of broadband measures

	2012	2013	2014
Download tier	6.96	7.27	7.42
	(0.72)	(0.73)	(0.74)
Upload tier	4.43	4.66	4.95
	(0.81)	(0.89)	(0.94)
Number of providers	3.26	3.43	3.45
	(0.93)	(1.06)	(1.01)

Notes. Values are the average of broadband measures assigned across all schools in the sample in a given year. Each school is given a value that is the population-distance-weighted average of surrounding measures (at the census block level). Download and upload speeds are reported in ordered categorical tiers from 1 to 11. Broadband data come from the National Broadband Map. Standard deviations are shown in parentheses.

Table 4: Single level Bayesian regressions of log number of students who enrolled in some distance education courses on broadband measures

	(1)	(2)	(3)	(4)
Download speed	0.324			0.41
	[-0.046,0.687]			[0.008,0.821]
Download speed^2	-0.024			-0.027
	[-0.049,0.002]			[-0.056,0.001]
Upload speed		-0.075		-0.206
		[-0.256,0.103]		[-0.432,0.017]
Upload speed^2		0.003		0.015
		[-0.014,0.021]		[-0.006,0.038]
# Providers			-0.003	0.019
			[-0.11,0.1]	[-0.097,0.131]
# Providers^2			-0.002	-0.003
			[-0.014,0.011]	[-0.016,0.011]
Two year institution	0.068	0.078	0.076	0.068
	[-0.005,0.14]	[0.004,0.151]	[0.001,0.149]	[-0.004,0.139]
log(Total enrollment)	1.154	1.155	1.155	1.157
	[1.119,1.189]	[1.119,1.192]	[1.119,1.19]	[1.121,1.193]
Prop. non-white	-0.64	-0.641	-0.646	-0.626
	[-0.756,-0.524]	[-0.756,-0.523]	[-0.758,-0.533]	[-0.747,-0.507]
Prop. women	-2.205	-2.197	-2.226	-2.199
	[-2.628,-1.782]	[-2.602,-1.804]	[-2.63,-1.817]	[-2.599,-1.798]
Prop. Pell grant	0.658	0.62	0.65	0.627
	[0.457,0.866]	[0.417,0.829]	[0.445,0.854]	[0.414,0.84]
Prop. part-time	-0.461	-0.463	-0.459	-0.463
	[-0.67,-0.247]	[-0.676,-0.243]	[-0.682,-0.236]	[-0.677,-0.252]
Prop. 25 years and older	0.379	0.399	0.396	0.414
	[0.118,0.636]	[0.153,0.645]	[0.151,0.652]	[0.169,0.657]
log(Pop. density)	-0.074	-0.065	-0.069	-0.069
	[-0.099,-0.048]	[-0.091,-0.039]	[-0.095,-0.044]	[-0.093,-0.044]
2013	0.103	0.11	0.101	0.105
	[0.048,0.159]	[0.054,0.166]	[0.044,0.158]	[0.05,0.161]
2014	0.157	0.171	0.15	0.167
	[0.097,0.218]	[0.109,0.234]	[0.089,0.211]	[0.105,0.228]
(Intercept)	6.729	6.729	6.729	6.729
	[6.706,6.752]	[6.707,6.752]	[6.707,6.752]	[6.706,6.752]
Unique institutions	1018	1018	1018	1018
N	2497	2497	2497	2497

Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Covariates not reported include indicators for USDA urban/rural community codes. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a normal likelihood sampling statement. The outcome measure in all models is the log number of students at each institution who enrolled in some distance education courses.

Table 5: Single level Bayesian regressions of log number of students who enrolled in some distance education courses on broadband measures: two year institutions

	(1)	(2)	(3)	(4)
Download speed	0.188			0.231
	[-0.308,0.697]			[-0.369,0.829]
Download speed^2	-0.016			-0.016
	[-0.051,0.019]			[-0.057,0.026]
Upload speed		-0.111		-0.207
		[-0.329,0.109]		[-0.451,0.041]
Upload speed^2		0.005		0.015
		[-0.017,0.027]		[-0.009,0.04]
# Providers			0.049	0.075
			[-0.07,0.168]	[-0.053,0.202]
# Providers^2			-0.011	-0.012
			[-0.025,0.004]	[-0.028,0.003]
log(Total enrollment)	1.14	1.138	1.143	1.141
	[1.1,1.181]	[1.097,1.178]	[1.103,1.183]	[1.101,1.182]
Prop. non-white	-0.758	-0.746	-0.758	-0.751
	[-0.882,-0.633]	[-0.871,-0.623]	[-0.882,-0.634]	[-0.882,-0.625]
Prop. women	-2.216	-2.205	-2.231	-2.2
	[-2.65,-1.792]	[-2.646,-1.78]	[-2.674,-1.801]	[-2.621,-1.772]
Prop. Pell grant	0.699	0.652	0.708	0.668
	[0.473,0.934]	[0.425,0.873]	[0.477,0.935]	[0.428,0.895]
Prop. part-time	-0.335	-0.357	-0.321	-0.352
	[-0.584,-0.098]	[-0.604,-0.109]	[-0.561,-0.077]	[-0.597,-0.106]
Prop. 25 years and older	0.366	0.391	0.395	0.417
	[0.107,0.63]	[0.121,0.661]	[0.128,0.661]	[0.15,0.685]
log(Pop. density)	-0.064	-0.055	-0.063	-0.058
	[-0.09,-0.037]	[-0.082,-0.028]	[-0.09,-0.036]	[-0.086,-0.031]
2013	0.099	0.104	0.094	0.104
	[0.037,0.16]	[0.043,0.163]	[0.035,0.153]	[0.045,0.162]
2014	0.161	0.176	0.149	0.174
	[0.096,0.225]	[0.11,0.242]	[0.086,0.214]	[0.109,0.239]
(Intercept)	6.746	6.746	6.746	6.746
	[6.722,6.77]	[6.722,6.769]	[6.722,6.77]	[6.723,6.769]
Unique institutions	899	899	899	899
N	2186	2186	2186	2186

Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Covariates not reported include indicators for USDA urban/rural community codes. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a normal likelihood sampling statement. The outcome measure in all models is the log number of students at each institution who enrolled in some distance education courses.

Table 6: Varying intercept Bayesian regressions of log number of students who enrolled in some distance education courses on broadband measures

	(1)	(2)	(3)	(4)
Download speed	0.32			0.556
	[-0.017,0.649]			[0.166,0.957]
Download speed^2	-0.024			-0.04
	[-0.047,-0.001]			[-0.068,-0.013]
Upload speed		-0.122		-0.224
		[-0.314,0.072]		[-0.459,-0.003]
Upload speed^2		0.009		0.022
		[-0.01,0.028]		[0,0.045]
# Providers			-0.068	-0.081
			[-0.173,0.042]	[-0.193,0.03]
# Providers^2			0.006	0.007
			[-0.008,0.018]	[-0.006,0.02]
Two year institution	0.087	0.099	0.1	0.093
	[0.003,0.172]	[0.016,0.186]	[0.014,0.184]	[0.006,0.179]
log(Total enrollment)	1.134	1.133	1.134	1.135
	[1.098,1.17]	[1.097,1.17]	[1.099,1.17]	[1.099,1.171]
Prop. non-white	-0.795	-0.792	-0.787	-0.801
	[-0.946,-0.641]	[-0.948,-0.637]	[-0.938,-0.628]	[-0.954,-0.647]
Prop. women	-2.089	-2.092	-2.1	-2.115
	[-2.476,-1.701]	[-2.501,-1.694]	[-2.509,-1.698]	[-2.526,-1.706]
Prop. Pell grant	0.525	0.505	0.495	0.506
	[0.279,0.772]	[0.268,0.752]	[0.243,0.745]	[0.262,0.75]
Prop. part-time	-0.847	-0.827	-0.846	-0.844
	[-1.095,-0.597]	[-1.078,-0.588]	[-1.099,-0.605]	[-1.092,-0.598]
Prop. 25 years and older	0.221	0.221	0.236	0.237
	[-0.042,0.496]	[-0.04,0.479]	[-0.021,0.499]	[-0.028,0.503]
log(Pop. density)	-0.048	-0.041	-0.041	-0.041
	[-0.076,-0.02]	[-0.069,-0.011]	[-0.07,-0.013]	[-0.07,-0.011]
2013	0.101	0.102	0.097	0.108
	[0.045,0.155]	[0.047,0.157]	[0.043,0.15]	[0.054,0.161]
2014	0.168	0.171	0.159	0.178
	[0.109,0.226]	[0.112,0.231]	[0.099,0.219]	[0.118,0.235]
Unique institutions	1018	1018	1018	1018
N	2497	2497	2497	2497

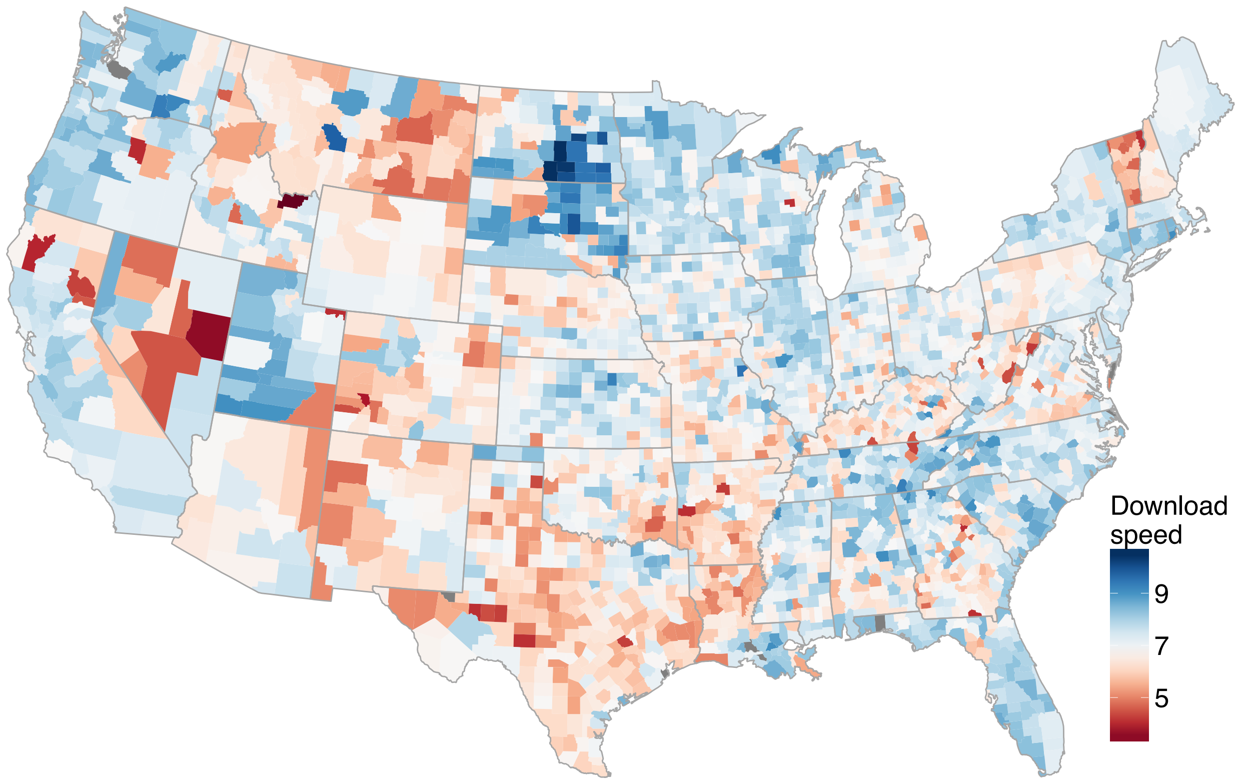
Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Intercepts (not reported) were allowed to vary at the state level. First level covariates not reported are indicators for USDA urban/rural community codes. Second level covariates include state unemployment rate, statewide average appropriations per FTE student, the proportion of public open admissions institutions in the state that are two-year institutions, and a population-weighted measure of the average distance to the nearest open admissions institution in the state. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a normal likelihood sampling statement. The outcome measure in all models is the log number of students at each institution who enrolled in some distance education courses.

Table 7: Varying intercept Bayesian regressions of log number of students who enrolled in some distance education courses on broadband measures: two year institutions

	(1)	(2)	(3)	(4)
Download speed	-0.002			0.216
	[-0.514,0.508]			[-0.365,0.798]
Download speed^2	-0.004			-0.019
	[-0.039,0.031]			[-0.059,0.022]
Upload speed		-0.222		-0.201
		[-0.438,0.01]		[-0.463,0.059]
Upload speed^2		0.018		0.02
		[-0.005,0.04]		[-0.005,0.047]
# Providers			-0.036	-0.04
			[-0.158,0.086]	[-0.158,0.08]
# Providers^2			-0.002	-0.002
			[-0.016,0.013]	[-0.016,0.013]
log(Total enrollment)	1.133	1.134	1.136	1.138
	[1.091,1.174]	[1.093,1.174]	[1.096,1.176]	[1.099,1.178]
Prop. non-white	-0.859	-0.847	-0.838	-0.866
	[-1.024,-0.691]	[-1.016,-0.682]	[-0.997,-0.678]	[-1.027,-0.705]
Prop. women	-2.022	-2.043	-2.051	-2.053
	[-2.442,-1.603]	[-2.48,-1.618]	[-2.487,-1.623]	[-2.46,-1.628]
Prop. Pell grant	0.532	0.52	0.494	0.497
	[0.277,0.786]	[0.262,0.768]	[0.243,0.746]	[0.242,0.752]
Prop. part-time	-0.752	-0.747	-0.769	-0.774
	[-1.033,-0.468]	[-1.032,-0.467]	[-1.048,-0.492]	[-1.059,-0.501]
Prop. 25 years and older	0.098	0.096	0.129	0.134
	[-0.189,0.384]	[-0.19,0.373]	[-0.152,0.418]	[-0.151,0.422]
log(Pop. density)	-0.048	-0.04	-0.041	-0.039
	[-0.078,-0.017]	[-0.07,-0.009]	[-0.072,-0.009]	[-0.071,-0.009]
2013	0.097	0.094	0.088	0.106
	[0.04,0.152]	[0.04,0.15]	[0.033,0.143]	[0.049,0.162]
2014	0.17	0.17	0.155	0.183
	[0.109,0.233]	[0.11,0.23]	[0.093,0.214]	[0.123,0.244]
Unique institutions	899	899	899	899
N	2186	2186	2186	2186

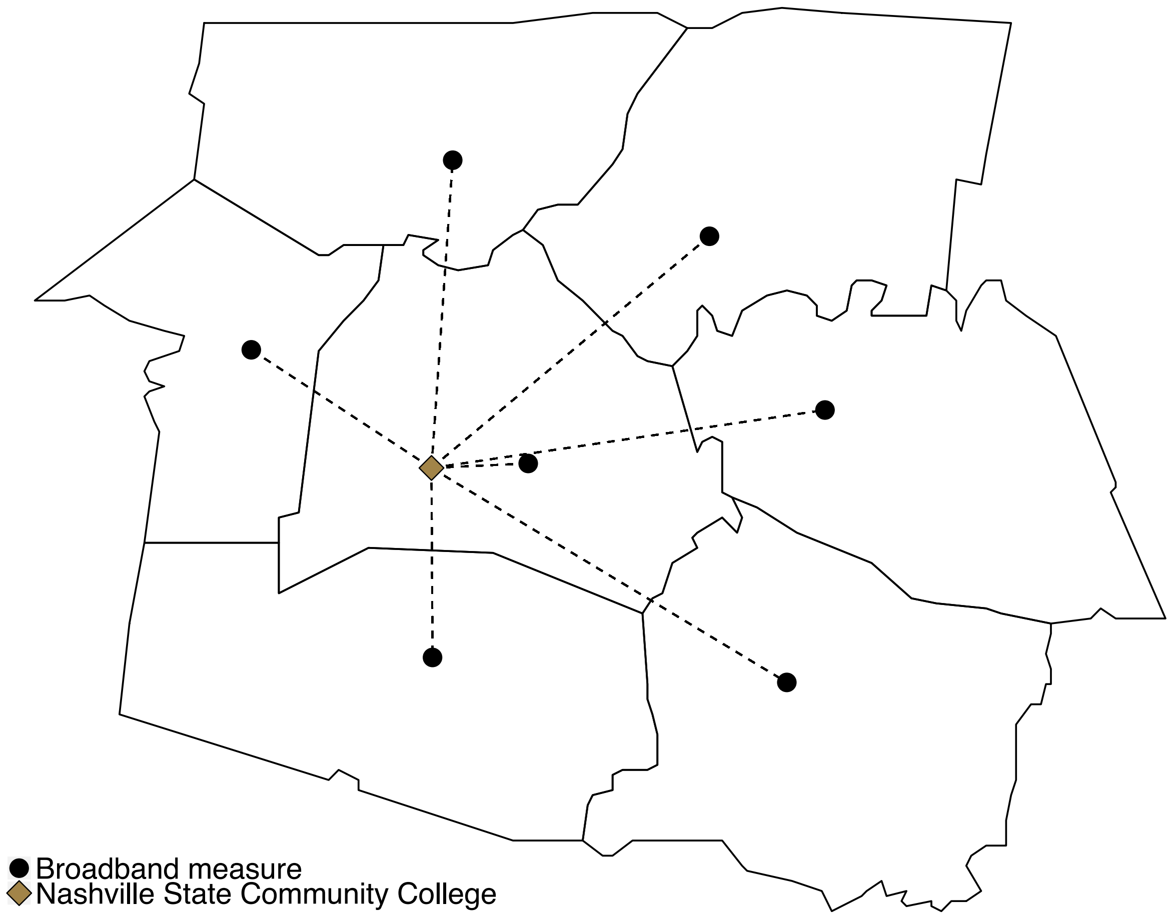
Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Intercepts (not reported) were allowed to vary at the state level. First level covariates not reported are indicators for USDA urban/rural community codes. Second level covariates include state unemployment rate, statewide average appropriations per FTE student, the proportion of public open admissions institutions in the state that are two-year institutions, and a population-weighted measure of the average distance to the nearest open admissions institution in the state. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a normal likelihood sampling statement. The outcome measure in all models is the log number of students at each institution who enrolled in some distance education courses.

Figure 1: Average county-level broadband download speed, December 2013



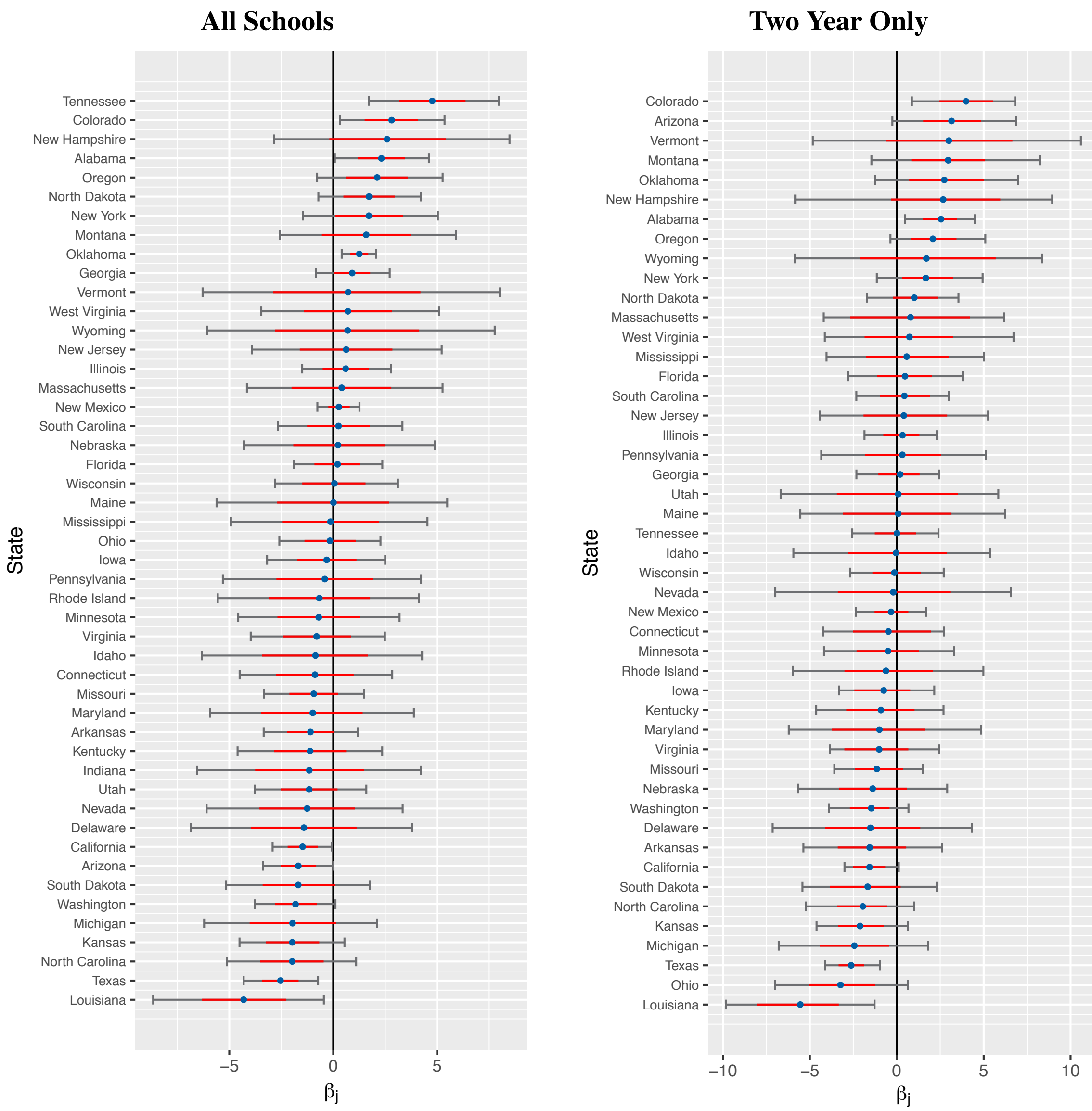
Raw broadband download speeds come from the National Broadband Map (NBM) and are reported at the census block level. For this map and the analysis, these values have been aggregated to the county level using census block group populations as weights. The NBM reports ordinal categories of speeds. Category 5 speeds (approximately 4 megabytes/sec, light red on the map), are what the FCC has historically recommended for watching lectures online. Recently, the FCC upgraded the definition of broadband to download speeds of at least 25 megabytes/sec, which would fall under category 8 (dark blue on the map).

Figure 2: Example weighting scheme for download speed at institution



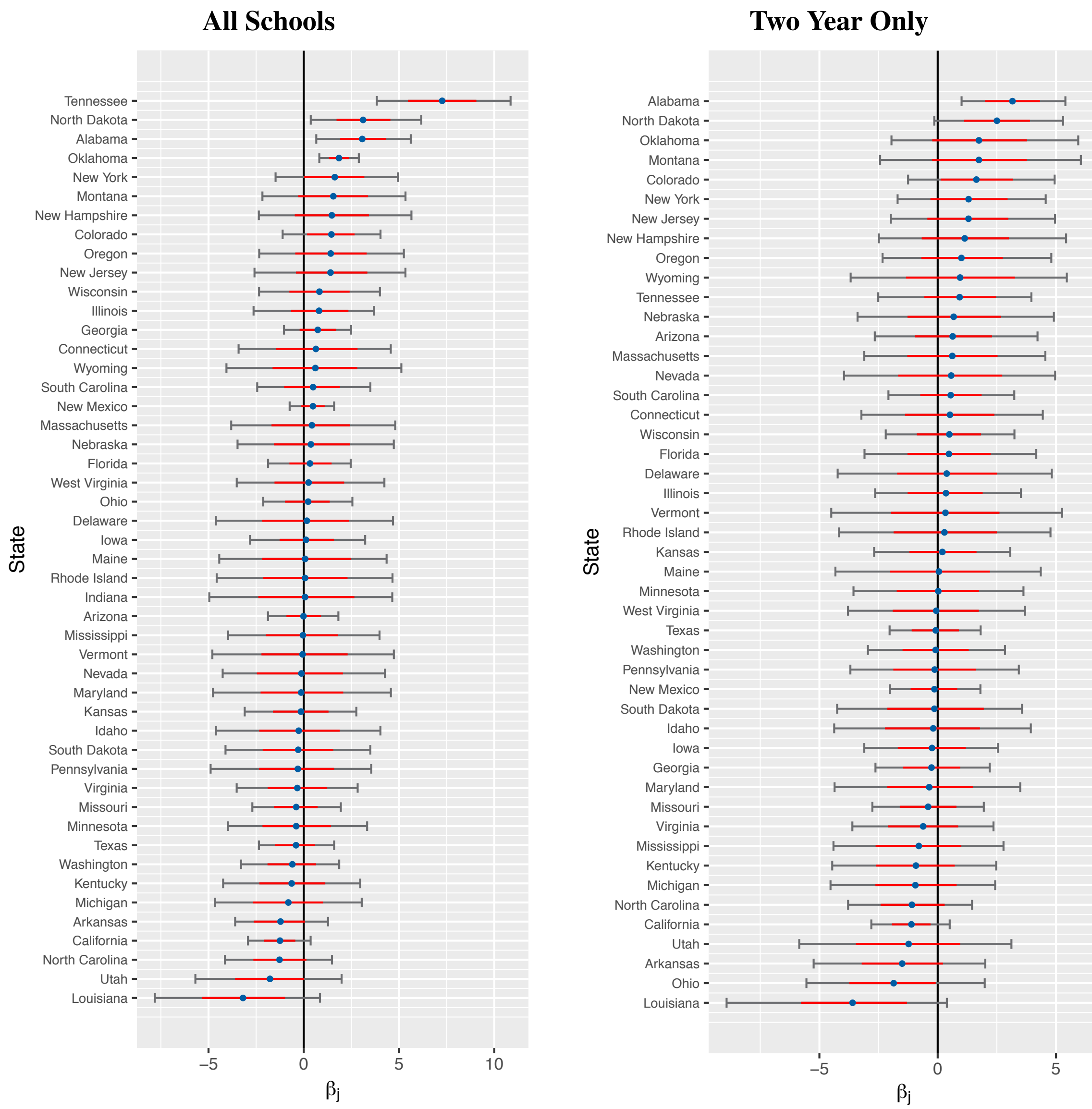
Each postsecondary institution is assigned a download speed that is a weighted version of those calculated for the surrounding areas. Raw broadband download speeds from the National Broadband Map, which are recorded at the census block level, are first aggregated to the census block group level. The distances between each institution and all census block group centers are then computed (represented by the dotted lines). These distances are used as inverse weights in a formula that assigns each institution the weighted average of its surrounding county values, with an adjustment for the population recorded for the census block group. In the example above, Nashville State Community College's broadband measures are most heavily influenced by those computed in Davidson County, center, but is also a function of those computed for surrounding block groups (including all those not shown).

Figure 3: State-level differences in the marginal effect of download speed on the number of students taking some online courses



The figure above shows state-level heterogeneity across β_j parameters, the marginal effect of download speed on the number of students who take some online courses. Dots represent the median β_j value. The red bars show the 68% credible intervals; the light gray bars show the 95% credible intervals.

Figure 4: State-level differences in the marginal effect of download speed on the number of students taking some online courses in fully specified model



The figure above shows state-level heterogeneity across β_j parameters, the marginal effect of download speed on the number of students who take some online courses. Upload speed and number of providers were also included in both models and allowed to vary at the state level. Dots represent the median β_j value. The red bars show the 68% credible intervals; the light gray bars show the 95% credible intervals.

A Alternative specifications

In an alternative specification, I fit equations using the proportion of students who took some online courses as the outcome. To model this outcome, I use a beta likelihood function with dispersion parameter that accurately accounts for the [0,1] bounds of the dependent variable (Gelman et al., 2014):

$$\frac{online}{total} \sim beta(a,b)$$
$$a = \mu \times \phi$$
$$b = (1-\mu) \times \phi$$
$$\mu = \frac{exp(X\beta)}{1+exp(X\beta)}$$

As with the primarily analysis models, I fit single level as well as hierarchical models in which the intercepts and parameters on broadband measures are allowed to vary at the state level. Results from these models show the marginal effect of broadband on the logged-odds of a percentage increase in the number of students who took some online courses. The results from these models are qualitatively the same as those reported in the main text of the paper.

Table A1: Single level Bayesian beta regressions of percentage of students who enrolled in some distance education courses on broadband measures

	(1)	(2)	(3)	(4)
Download speed	0.205			0.224
	[-0.136,0.561]			[-0.182,0.642]
Download speed^2	-0.015			-0.012
	[-0.04,0.009]			[-0.041,0.016]
Upload speed		-0.077		-0.201
		[-0.257,0.106]		[-0.413,0.019]
Upload speed^2		0.002		0.012
		[-0.016,0.02]		[-0.01,0.033]
# Providers			0.004	0.041
			[-0.099,0.111]	[-0.073,0.154]
# Providers^2			-0.003	-0.005
			[-0.016,0.009]	[-0.018,0.008]
Two year institution	0.092	0.101	0.098	0.094
	[0.019,0.162]	[0.027,0.178]	[0.025,0.173]	[0.021,0.168]
log(Total enrollment)	0.149	0.15	0.151	0.151
	[0.112,0.184]	[0.115,0.187]	[0.115,0.187]	[0.114,0.19]
Prop. non-white	-0.609	-0.611	-0.617	-0.58
	[-0.73,-0.493]	[-0.724,-0.496]	[-0.735,-0.501]	[-0.697,-0.46]
Prop. women	-2.36	-2.308	-2.377	-2.313
	[-2.805,-1.925]	[-2.746,-1.872]	[-2.811,-1.958]	[-2.729,-1.896]
Prop. Pell grant	0.696	0.66	0.692	0.648
	[0.492,0.909]	[0.453,0.862]	[0.482,0.897]	[0.44,0.861]
Prop. part-time	-0.474	-0.476	-0.475	-0.47
	[-0.68,-0.267]	[-0.687,-0.261]	[-0.688,-0.257]	[-0.679,-0.26]
Prop. 25 years and older	0.438	0.469	0.462	0.481
	[0.2,0.673]	[0.225,0.714]	[0.219,0.702]	[0.232,0.728]
log(Pop. density)	-0.063	-0.054	-0.059	-0.056
	[-0.088,-0.037]	[-0.079,-0.029]	[-0.086,-0.034]	[-0.083,-0.029]
2013	0.112	0.124	0.113	0.116
	[0.055,0.17]	[0.068,0.181]	[0.057,0.17]	[0.06,0.174]
2014	0.151	0.173	0.149	0.164
	[0.089,0.214]	[0.11,0.235]	[0.091,0.209]	[0.1,0.228]
(Intercept)	-1.436	-1.437	-1.436	-1.437
	[-1.461,-1.41]	[-1.461,-1.412]	[-1.46,-1.412]	[-1.461,-1.413]
Unique institutions	1018	1018	1018	1018
N	2497	2497	2497	2497

Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Covariates not reported include indicators for USDA urban/rural community codes. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a reparameterized beta likelihood sampling statement. The outcome measure in all models is the percentage of students at each institution who enrolled in some distance education courses.

Table A2: Single level Bayesian beta regressions of percentage of students who enrolled in some distance education courses on broadband measures: two year institutions

	(1)	(2)	(3)	(4)
Download speed	0.08			0.034
	[-0.461,0.606]			[-0.537,0.603]
Download speed^2	-0.008			0
	[-0.044,0.029]			[-0.04,0.04]
Upload speed		-0.113		-0.203
		[-0.329,0.104]		[-0.458,0.056]
Upload speed^2		0.004		0.012
		[-0.018,0.025]		[-0.014,0.037]
# Providers			0.05	0.088
			[-0.069,0.174]	[-0.039,0.216]
# Providers^2			-0.011	-0.013
			[-0.027,0.003]	[-0.029,0.002]
log(Total enrollment)	0.136	0.134	0.14	0.136
	[0.096,0.177]	[0.094,0.175]	[0.1,0.18]	[0.096,0.176]
Prop. non-white	-0.739	-0.727	-0.744	-0.718
	[-0.866,-0.612]	[-0.849,-0.606]	[-0.876,-0.612]	[-0.849,-0.588]
Prop. women	-2.451	-2.397	-2.474	-2.398
	[-2.921,-1.988]	[-2.853,-1.94]	[-2.917,-2.04]	[-2.852,-1.95]
Prop. Pell grant	0.752	0.708	0.755	0.704
	[0.529,0.982]	[0.481,0.937]	[0.531,0.982]	[0.474,0.93]
Prop. part-time	-0.364	-0.395	-0.363	-0.375
	[-0.611,-0.123]	[-0.631,-0.154]	[-0.606,-0.114]	[-0.616,-0.138]
Prop. 25 years and older	0.443	0.488	0.494	0.506
	[0.177,0.705]	[0.23,0.754]	[0.232,0.761]	[0.241,0.768]
log(Pop. density)	-0.052	-0.043	-0.052	-0.045
	[-0.079,-0.025]	[-0.07,-0.016]	[-0.08,-0.025]	[-0.072,-0.018]
2013	0.11	0.122	0.109	0.118
	[0.051,0.171]	[0.064,0.18]	[0.05,0.167]	[0.056,0.179]
2014	0.153	0.179	0.146	0.171
	[0.086,0.219]	[0.114,0.245]	[0.081,0.21]	[0.103,0.24]
(Intercept)	-1.441	-1.442	-1.442	-1.443
	[-1.468,-1.414]	[-1.467,-1.417]	[-1.468,-1.416]	[-1.468,-1.418]
Unique institutions	899	899	899	899
N	2186	2186	2186	2186

Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Covariates not reported include indicators for USDA urban/rural community codes. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a reparameterized beta likelihood sampling statement. The outcome measure in all models is the percentage of students at each institution who enrolled in some distance education courses.

Table A3: Varying intercept Bayesian beta regressions of percentage of students who enrolled in some distance education courses on broadband measures

	(1)	(2)	(3)	(4)
Download speed	0.261			0.369
	[-0.069,0.605]			[0,0.759]
Download speed^2	-0.02			-0.027
	[-0.044,0.003]			[-0.054,-0.001]
Upload speed		-0.052		-0.123
		[-0.248,0.139]		[-0.346,0.105]
Upload speed^2		0.001		0.01
		[-0.018,0.02]		[-0.012,0.032]
# Providers			-0.05	-0.062
			[-0.157,0.054]	[-0.177,0.052]
# Providers^2			0.002	0.004
			[-0.01,0.015]	[-0.009,0.017]
Two year institution	0.09	0.1	0.104	0.097
	[0.007,0.173]	[0.015,0.186]	[0.019,0.188]	[0.013,0.183]
log(Total enrollment)	0.122	0.122	0.123	0.125
	[0.085,0.158]	[0.086,0.16]	[0.087,0.158]	[0.089,0.162]
Prop. non-white	-0.746	-0.735	-0.732	-0.74
	[-0.896,-0.595]	[-0.894,-0.58]	[-0.886,-0.579]	[-0.895,-0.585]
Prop. women	-2.291	-2.287	-2.304	-2.301
	[-2.74,-1.875]	[-2.718,-1.844]	[-2.726,-1.878]	[-2.719,-1.873]
Prop. Pell grant	0.472	0.455	0.443	0.456
	[0.225,0.718]	[0.214,0.702]	[0.205,0.692]	[0.216,0.699]
Prop. part-time	-0.922	-0.904	-0.924	-0.918
	[-1.166,-0.672]	[-1.152,-0.664]	[-1.166,-0.686]	[-1.157,-0.683]
Prop. 25 years and older	0.348	0.348	0.37	0.365
	[0.088,0.606]	[0.088,0.62]	[0.119,0.623]	[0.106,0.618]
log(Pop. density)	-0.041	-0.034	-0.035	-0.034
	[-0.071,-0.013]	[-0.064,-0.004]	[-0.065,-0.004]	[-0.064,-0.004]
2013	0.109	0.113	0.107	0.119
	[0.056,0.163]	[0.061,0.167]	[0.053,0.161]	[0.065,0.172]
2014	0.164	0.171	0.157	0.179
	[0.105,0.221]	[0.111,0.228]	[0.098,0.212]	[0.12,0.239]
Unique institutions	1018	1018	1018	1018
N	2497	2497	2497	2497

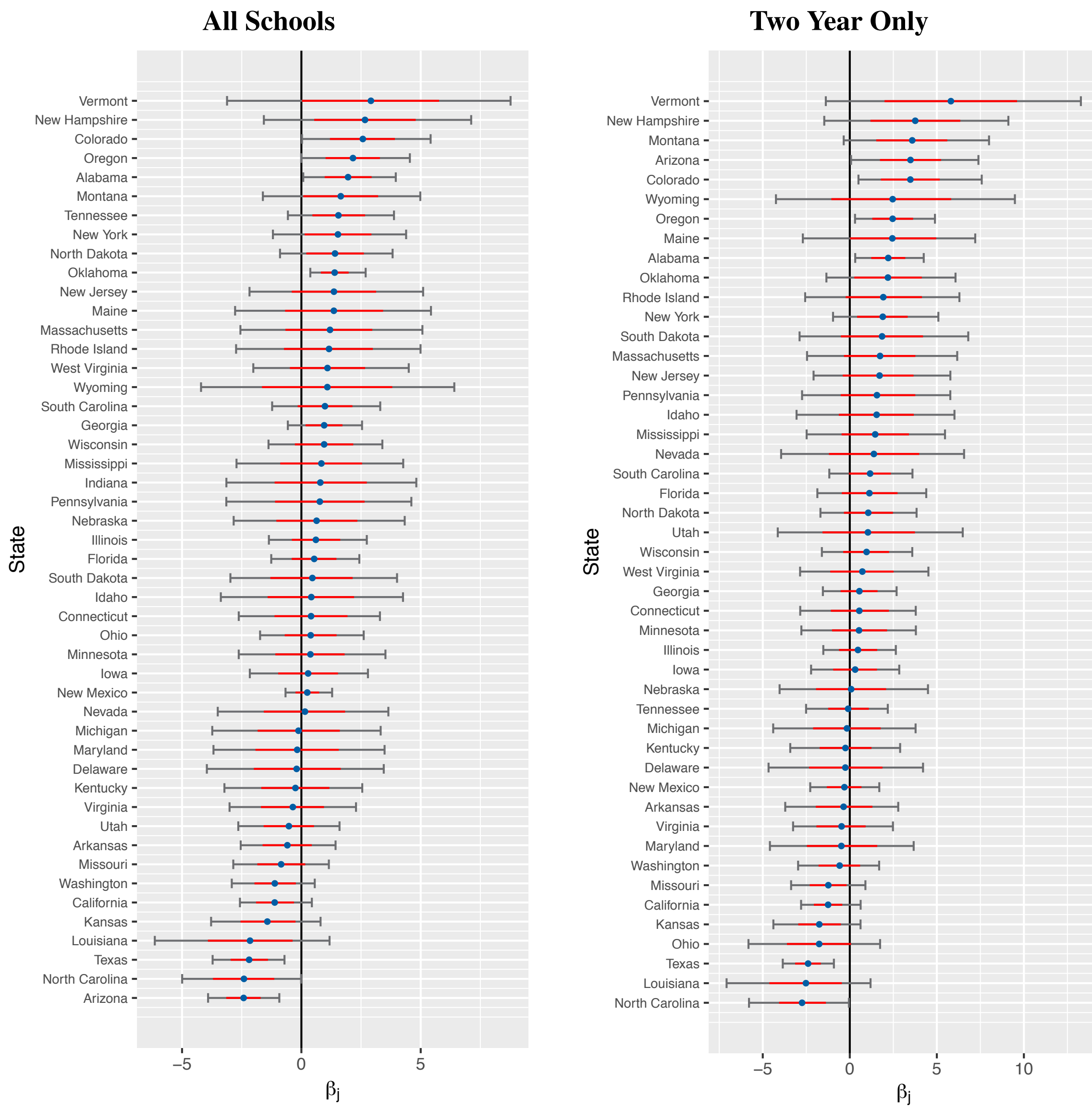
Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Intercepts (not reported) were allowed to vary at the state level. First level covariates not reported are indicators for USDA urban/rural community codes. Second level covariates include state unemployment rate, statewide average appropriations per FTE student, the proportion of public open admissions institutions in the state that are two-year institutions, and a population-weighted measure of the average distance to the nearest open admissions institution in the state. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a reparameterized beta likelihood sampling statement. The outcome measure in all models is the percentage of students at each institution who enrolled in some distance education courses.

Table A4: Varying intercept Bayesian beta regressions of percentage of students who enrolled in some distance education courses on broadband measures: two year institutions

	(1)	(2)	(3)	(4)
Download speed	-0.06			-0.044
	[-0.565,0.449]			[-0.604,0.532]
Download speed^2	0.001			0
	[-0.034,0.036]			[-0.039,0.038]
Upload speed		-0.126		-0.086
		[-0.351,0.1]		[-0.337,0.17]
Upload speed^2		0.007		0.007
		[-0.016,0.029]		[-0.019,0.031]
# Providers			-0.021	-0.025
			[-0.144,0.098]	[-0.157,0.104]
# Providers^2			-0.005	-0.004
			[-0.019,0.01]	[-0.02,0.011]
log(Total enrollment)	0.132	0.134	0.135	0.135
	[0.09,0.173]	[0.093,0.173]	[0.094,0.175]	[0.095,0.174]
Prop. non-white	-0.811	-0.791	-0.786	-0.8
	[-0.964,-0.651]	[-0.956,-0.628]	[-0.955,-0.623]	[-0.961,-0.637]
Prop. women	-2.273	-2.286	-2.323	-2.285
	[-2.728,-1.827]	[-2.745,-1.808]	[-2.778,-1.866]	[-2.762,-1.833]
Prop. Pell grant	0.505	0.488	0.451	0.456
	[0.249,0.753]	[0.225,0.757]	[0.189,0.705]	[0.195,0.719]
Prop. part-time	-0.877	-0.87	-0.904	-0.897
	[-1.174,-0.593]	[-1.157,-0.575]	[-1.197,-0.619]	[-1.188,-0.607]
Prop. 25 years and older	0.178	0.183	0.225	0.223
	[-0.131,0.472]	[-0.105,0.474]	[-0.082,0.526]	[-0.068,0.525]
log(Pop. density)	-0.045	-0.038	-0.038	-0.035
	[-0.076,-0.014]	[-0.07,-0.007]	[-0.069,-0.007]	[-0.067,-0.004]
2013	0.105	0.106	0.1	0.119
	[0.047,0.161]	[0.051,0.161]	[0.043,0.155]	[0.064,0.176]
2014	0.16	0.168	0.149	0.18
	[0.097,0.223]	[0.105,0.232]	[0.09,0.209]	[0.116,0.244]
Unique institutions	899	899	899	899
N	2186	2186	2186	2186

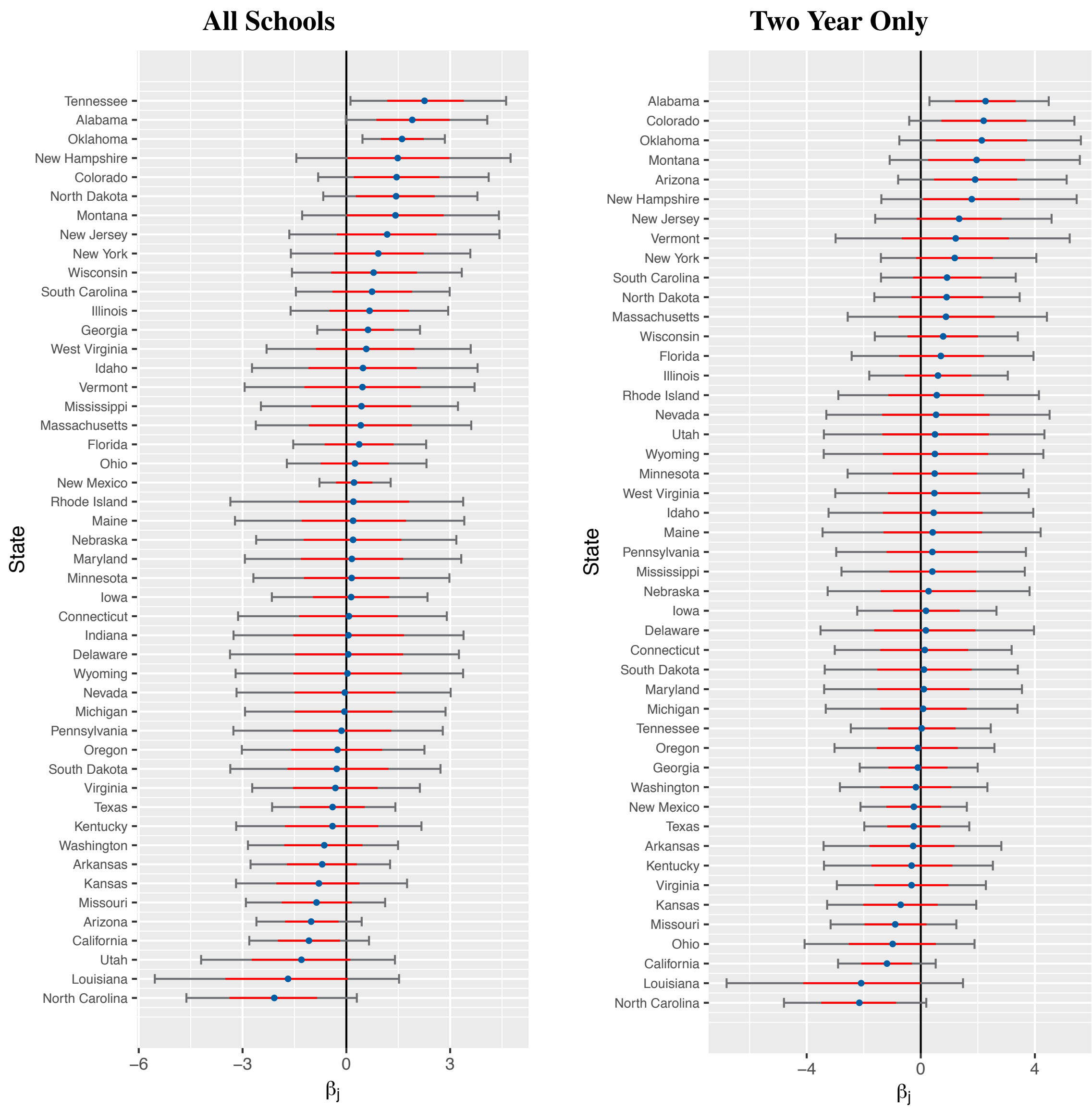
Notes. Bayesian point estimates represent posterior mean values. Values in the square brackets are 95% credible intervals. Intercepts (not reported) were allowed to vary at the state level. First level covariates not reported are indicators for USDA urban/rural community codes. Second level covariates include state unemployment rate, statewide average appropriations per FTE student, the proportion of public open admissions institutions in the state that are two-year institutions, and a population-weighted measure of the average distance to the nearest open admissions institution in the state. Parameter distributions in each model are the combination of four independent MCMC chains of 1000 draws each (with 1000 initial draws discarded as burn-in) for a total of 4000 total draws. All models were estimated using the Stan NUTS sampler with a reparameterized beta likelihood sampling statement. The outcome measure in all models is the percentage of students at each institution who enrolled in some distance education courses.

Figure 5: State-level differences in the marginal effect of download speed on the proportion of students taking some online courses



The figure above shows state-level heterogeneity across β_j parameters, the marginal effect of download speed on the proportion of students who take some online courses. Dots represent the median β_j value. The red bars show the 68% credible intervals; the light gray bars show the 95% credible intervals.

Figure 6: State-level differences in the marginal effect of download speed on the proportion of students taking some online courses in fully specified model



The figure above shows state-level heterogeneity across β_j parameters, the marginal effect of download speed on the proportion of students who take some online courses. Upload speed and number of providers were also included in both models and allowed to vary at the state level. Dots represent the median β_j value. The red bars show the 68% credible intervals; the light gray bars show the 95% credible intervals.