Need for Speed: Fiber and Student Achievement

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Abstract

This paper studies the broad effects of the introduction of fiber broadband, through the lens of student achievement. I link granular data on new fiber construction and advertised download speeds with administrative test score data and local labor market data. Exploiting variation in the introduction of fiber at the census block group level, I implement a difference-in-differences design and find a modest effect on educational outcomes, roughly on par with lowering class sizes by one student. In addition, I show fiber increases local employment and search intensity for supplementary educational materials (e.g., Khan Academy). Last, I show that increased competition from fiber providers drives quality improvements in other available technology.

Keywords: Education, Broadband, Fiber, Digital Divide.
JEL Classification: I2, O33, L86, J23

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1 Introduction

High-speed internet (broadband) is a crucial component of modern economies and a valuable input into the education production function. Broadband has affected the way educators teach students, assign homework, and more closely align with the needs of students and their parents. Likewise, students have adjusted to the emergence of this technology, making use of the wealth of resources available to complete assignments, study, and in the opposite extreme, cheat and plagiarize. Not only has access and adoption of broadband grown considerably over time (Dettling et al., 2018), the quality of these connections has as well.[1]

The rapid rise in broadband speeds has at least in part been driven by the diffusion of fiber broadband, in a bid to replace older technologies like cable and Digital Subscriber Line (DSL). Fiber's arrival brings not only speed, but reliability improvements, and has subsequently been hailed as "futureproof". Though access to the internet is clearly important on the extensive margin (Dettling et al., 2018; Vigdor et al., 2014), it is less clear whether high-quality fiber internet is expected to improve student outcomes relative to DSL or cable internet.

There are several reasons to expect that the introduction of fiber internet can affect student outcomes. First, while high-income households generally pay to ensure sufficient bandwidth for all members of their household at peak times, many households with DSL or cable internet report inconsistent access to sufficient bandwidth.[2] Second, though relatively few individuals take up fiber, fiber availability has the potential to affect all internet subscribers through competition among internet providers. Third, past work demonstrates that high-speed internet leads to employment growth, and the employment of parents can directly affect test scores. I provide evidence that these mechanisms are empirically relevant in my context as I show that the introduction of fiber internet increases average speeds of non-fiber internet, increases search intensity for Khan Academy, and increases employment.

To understand how the gradual diffusion of nascent fiber technology affects student achievement, I combine granular broadband availability data from the National Telecommunications and Information Administration (NTIA) and Federal Communications Commission (FCC) with administrative data from the North Carolina Education Research Data Center (NCERDC) to construct a precise accounting of how a student's access to broadband changes over time. The granularity of the data is a pronounced improvement over the existing literature and underpins my identification strategy.

[1] Average maximum download speeds rose from 270 Mbps in 2011 to 890 Mbps in 2018. Author's calculations from Form 477 and National Broadband Map data.

[2] See articles from HighSpeedInternet.com, Verizon, and WhistleOut. Furthermore, almost 60% of individuals that work from home report imperfect internet connections, and 80% of those individuals report they would be more productive with perfect internet (Barrero et al., 2021).

Identifying the effect of broadband is complicated by the endogenous construction of these networks. Household demand for fiber may induce providers to supply the technology, thus regressions of test scores on fiber suffer from omitted variables bias. To identify the causal effect of fiber broadband I use census block group variation in availability as well as variation in the timing that a student is exposed to fiber. Within these granular geographic areas, the average characteristics of treated and untreated students were balanced prior to the arrival of fiber, suggesting that the effects were unlikely to be driven by demand-related factors, and instead are related to supply factors. Given that I am able to observe the same students over time, my empirical strategy focuses on comparing students whose access to fiber changes to those that do not within the same census tract. Subsequently, the resulting identification assumption is that at fine geographies changes in fiber access are unrelated to growth rates.

As is common in scenarios where treatment is staggered, my empirical strategy consists of estimating difference-in-difference (DiD) and event-studies models. Using these strategies I identify the intent-to-treat effect of a student being exposed to fiber broadband on standardized math and reading scores. In addition, I compare the results from DiD and event-study models with estimates produced using a method proposed by de Chaisemartin and D'Haultfoeuille (2022) (DCDH). The estimates produced by OLS are similar to those from DCDH but suggest that OLS estimates are biased downward due to negative weighting (Goodman-Bacon, 2021). Accordingly, I rely on event-study and DCDH estimates in my preferred specifications.

The empirical results show that the introduction of fiber generates a substantial increase in the maximum download speed for treated census block groups. In particular, fiber becoming available increases the maximum download speed by 132 percent or roughly 313 Mbps.[3] This increase in download speeds translates to a marked increase in educational achievement. For my reduced form estimates, I find that the availability of fiber increases math test scores by 0.01 standard deviations, and reading test scores by 0.011 standard deviations. Event-study estimates suggest the effect of fiber is persistent and growing over time for both math and reading, such that the effect 6 years after their initial exposure was 0.023 standard deviations and 0.011 standard deviations respectively.

Furthermore, I explore heterogeneity across race, gender, and other student statuses, as well as how the effects vary by the baseline technology. My results are consistent with a story where fiber widens some achievement gaps, similar to the prior literature. However, I also show positive returns for students with disabilities and economically disadvantaged students. Next, I classify students into low- or high-tech groups by their baseline speed the year before the arrival of fiber arrival. I find that students exposed to fiber with lower baseline technology experience similar gains to those with better technology. This

[3]This cuts down the time to download a 10 Gigabyte file from 14 minutes to 6 minutes, assuming a 100 Mbps connection and a 137 percent increase. Calculations based on Download Time Calculator.

suggests that lacking fiber could exacerbate existing achievement gaps between rural and urban students and subsequently have important implications for policymakers.

To better clarify how fiber affects student achievement, I first explore whether fiber access affects local employment using data from the Longitudinal Employment Household Dynamics (LEHD) program's Origin-Destination Employment Statistics (LODES). I find that fiber increases employment by 2.4 percentage points. Suggesting that income effects may drive the relationship between fiber availability and test scores. To contextualize these results I compare them to estimates of the effect of employment on test scores which indicate that the effect of fiber on test scores could be explained entirely by changes in income.

Next, I assess how competitive pressure from the arrival of fiber may impact the quality of other technologies, as well as the number of providers. First, I explore how the maximum download speeds of all other technologies change in response to fiber. I find that the arrival of fiber increases the speed of other technologies by roughly 22 percent, consistent with a story where incumbent providers compete with the firms that supply fiber by raising the speeds of their existing technology. Second, I estimate the effect of the arrival of fiber on the total number of providers. My results indicate that the number of providers increases by 0.392 on average. Together, these results suggest that part of the effect on test scores could be driven by firm competition that lowers prices or improves the available technology bundle. Lastly, I test whether interest in supplemental learning services such as Khan Academy is affected. Using data on search interest from Google Trends I follow Stephens-Davidowitz (2013) to assess the effect of fiber availability on Khan Academy search intensity. I find that fiber increases Khan Academy search intensity by roughly 0.45 standard deviations on average.

This paper contributes to several strands of the literature. First, I improve on the literature estimating the effect of broadband access on student achievement (Dettling et al., 2018; Vigdor et al., 2014; Sanchis-Guarner et al., 2022; Grimes and Townsend, 2018; Henriksen et al., 2022) using more precise geography and new methods accounting for staggered treatment. Second, this paper makes strides in distinguishing types of broadband, by both technology and speed. While other work has explicitly assessed high-speed broadband (Sanchis-Guarner et al., 2022; Grimes and Townsend, 2018), this paper shows both that fiber broadband produces achievement gains on top of existing technologies and finds evidence against diminishing returns to broadband speed.[4]

I also contribute to the literature that examines the effect of broadband on employment and earnings (Atasoy, 2013; Zuo, 2021; Dettling, 2017; Hjort and Poulsen, 2019; Beem, 2022). While identifying the impacts on labor market outcomes due to access, previous work similarly treats access as a monolith. Consistent with prior literature this

[4]Nearly all areas that gained access to fiber had some form of broadband available to them previously, consistent with a story where achievement is positively affected by improved speed/technology.

research finds a positive effect on employment. Yet, there appear to be additional gains in employment from changes in the available technology, as nearly every census block group has access to broadband of some form in my study. In addition, this paper adds to the industrial organization literature on internet service provider competition (Kearns, 2022; Molnar and Savage, 2017; Fister, 2019). Similar to Fister (2019) and Molnar and Savage (2017) I find evidence that competing firms' download speeds rise with competition. Finally, I add to the literature connecting educational software to student achievement (Murphy et al., 2014; Phillips and Cohen, 2015). While previous work has shown that Khan Academy (Murphy et al., 2014; Phillips and Cohen, 2015) is an effective tool to improve student outcomes there is no evidence that interest or usage responds to the geographic technological conditions of its potential users.

The rest of this paper is organized as follows. Section 2 lays out the conceptual framework and previous literature. Section 3 describes the data and discusses summary statistics. Section 4 explains each identification strategy and the accompanying assumptions required to identify the ITT. Section 5 discusses the results from the main analysis, heterogeneity, and robustness. Section 6 addresses the broader impacts of fiber access that affect student achievement, and Section 7 concludes.

2 Conceptual Framework

2.1 Fiber Broadband

A key feature of this paper is its focus on the rollout of fiber-optic broadband and the effects of increased internet speed more generally. While Digital Subscriber Line (DSL) and other broadband technologies have connected the U.S. digitally for years, fiber broadband's primary advantages are speed and quality. Fiber cables transmit information via light rather than electricity at speeds 70% of the speed of light. In contrast, DSL internet uses copper wires and telephone lines similar to dial-up, while cable internet uses the same lines as TV providers. Fiber's use of light rather than electricity subsequently boasts significantly higher symmetric upload and download speeds than either DSL or cable (though cable can compete for download speeds).

While there is considerable variation in download speeds across technologies, fiber is easily the fastest and most reliable. To download a 6.5 Gigabyte file would take 1-14 hours using DSL, 1 minute to 14 hours with cable, but just 1 minute with a fiber connection.[5] Furthermore, fiber is less susceptible to outages due to extreme weather since light transmission is relatively unaffected by weather conditions, while electricity transmission used by other technologies can easily be damaged due to adverse weather

[5]Figures come from Century Link.

conditions. Naturally, given the prevailing infrastructure, both DSL and cable are cheap to provide, and thus take-up of these technologies largely dwarfs fiber.

With symmetric and fast download and upload speeds, multiple individuals and devices can all connect to a home network seamlessly. Even among cable subscribers with comparably fast plans, users must often compete for bandwidth with individuals outside of their household during "peak hours". Subsequently, individuals often do not actually get the download speeds they pay for. Moreover, while cable may offer comparable download speeds to fiber, upload speeds are often substantially less and as such, make high upload speed intensive activities like Zoom calls difficult.

Fiber's pronounced speed and quality advantage over other technologies make for an interesting setting to study the impact of broadband on outcomes for a few reasons. First, while previous work has looked at broadband broadly, there is little work that differentiates between various broadband technologies or speeds.[6] Second, access to broadband at speeds of 10 Mbps download speed is nearly universal (Zuo, 2021), such that there is considerably less variation in access to other common broadband technologies such as DSL or cable over the time period where granular data on access is available. By comparison, fiber coverage is significantly less ubiquitous. Yet, the cost to providers has fallen considerably in recent years, fueling the subsequent rollout of fiber which is the focus of this paper. Third, corresponding fiber construction generally increases the number of providers in a given market. Thus, areas fiber becomes available experience changes in provider competition where providers may compete on price or quality.

2.2 Background and Theory

The role that the internet plays in achievement has increasingly become a topic of interest due to the COVID-19 pandemic. While access to the internet in schools is nearly universal,[7] persistent disparities in home access remain. Ensuring access to resources such as broadband is essential to preserving equitable education guarantees enumerated in many state constitutions. If the lack of reliable internet translates to losses in academic achievement, without robust policy initiatives, disparities in access are likely to exacerbate existing gaps. Subsequently, policymakers have increasingly begun targeting areas that lack broadband access or fail to adopt through the introduction of programs such as the Emergency Broadband Benefit,[8] as well as, the Connect America Fund.

Despite the growing importance of broadband, persistent differences in access and

[6] Grimes and Townsend (2018) is the only study the author is aware of that explicitly discusses extremely high-speed broadband. However, the discussion of the technology is limited. Sanchis-Guarner et al. (2022) assess changes in the intensive margin for DSL, but these changes in speeds are dwarfed in comparison to my setting.

[7] See Snyder and Dillow (2013).

[8] See the FCC's website for more information on the Emergency Broadband Benefit.

quality affect students' ability to participate in digital academic activities relative to their peers. In North Carolina, a study by the North Carolina Department of Information Technology (NCDIT) found that 10% of surveyed households had no internet access at home.[9] Similarly, Pew Research Center found that 15% of households with school-aged children did not have a high-speed internet subscription (Anderson and Perrin, 2018). These results mask large disparities in access between income groups, where 35% of low-income households did not have a connection versus just 6% for high-income households.[10]

Theoretically, the effect of fiber on achievement is ambiguous. Achievement may be positively related to fiber internet if students use technology for productive activities such as studying or completing homework. Survey results from both teachers and students support this narrative. An analysis by Pew Research Center finds almost 60% of 8th grade students report relying on the internet to finish their homework (Auxier and Anderson, 2020).[11] On the teacher side, results from the 2018 Teacher Working Conditions survey administered by the North Carolina Department of Public Instruction indicate that 70 percent of high school teachers, 60 percent of middle school teachers, and 43 percent of elementary school teachers in North Carolina regularly assign homework that requires internet access to complete (NC Teacher Working Condition Survey Results, 2018).

In addition, given the rise of devoted online learning platforms like Khan Academy, and spaces like Youtube where creators can post educational content, we might expect achievement gains as supplemental resources become available.[12] Fiber could afford students speed or reliability in their internet connection that was not previously present. Apart from the direct effects of broadband on school activities, using high-speed internet might passively affect a student's written test scores if increased exposure to reading and writing translates experience into output (Penuel, 2006; Underwood et al., 1994; Warschauer et al., 2010).

An alternate channel through which fiber broadband access could affect achievement is through the labor market outcomes of a student's parents. If fiber access has a causal effect on local earnings and employment the associated income gains could affect achievement. Household income is an important input into the achievement production function, where more well-off parents can afford tutors or other resources that improve student out-

[9]See the NCDIT's report on the Homework Gap here.

[10]Among households without access in North Carolina, the NCDIT found that cost was the most significantly cited factor. This is consistent with work on willingness to pay that formally estimates the elasticity of demand for broadband (Carare et al., 2015).

[11]The same study reports that roughly 35% of teenagers need their phone to complete homework.

[12]Khan Academy has conducted a number of studies on the efficacy of its platform, which show meaningful improvements to students' math test scores (Murphy et al., 2014; Phillips and Cohen, 2015). Murphy et al. (2014), show that use of Khan Academy's platform was positively associated with higher math scores, lower math anxiety, and increased confidence in doing math. Phillips and Cohen show students experienced growth on the mathematics portion of the Northwest Evaluation Association (NWEA) Measures of Academic Progress (MAP) Growth Assessment that exceeded their expected growth (Phillips and Cohen, 2015).

comes. A growing literature has connected broadband to labor market outcomes (Zuo, 2021; Hjort and Poulsen, 2019; Beem, 2022; Dettling, 2017), but does not distinguish between different qualities of broadband.[13]

Conversely, access to fiber could potentially adversely affect student achievement if students substitute time away from school work towards non-productive entertainment activities. Students with access to the internet are likely to play video games, interact with peers on social networking apps, talk with friends, and consume other media, such as video and music (Kaiser Family Foundation, 2010; Bulman and Fairlie, 2016). Given the growing uses for the internet, it is unsurprising Pew Research found 45% of teens say they are almost constantly using the internet, which suggests broadband could significantly divert time use towards non-productive uses (Anderson and Perrin, 2018). Despite the theoretical reasons for students to divert time away from productive uses, there is mixed evidence that this is the case (Junco, 2012; Kirschner and Karpinski, 2010; Bauernschuster et al., 2014).[14] Lastly, broadband could facilitate cheating and plagiarism (Rainie, 2005).

While there is a large body of work examining the effect of computers and other technology in schools, less work has been done estimating the effect of technology use at home.[15] Among studies that do attempt to answer this question, the majority of the literature focuses on computer use and finds no effect or modest positive improvements in student outcomes (Fairlie and Robinson, 2013; Fairlie and London, 2012). Of prior work that does attempt to answer how broadband affects outcomes (Dettling et al., 2018; Vigdor et al., 2014), even fewer have studied the effect of high-speed internet, comparable to fiber, on student outcomes (Grimes and Townsend, 2018; Sanchis-Guarner et al., 2022).

This literature has not reached a consensus on the sign of the effect of broadband on student performance, nor whether broadband is likely to exacerbate achievement gaps. Dettling et al. (2018) finds that exposure to broadband generally improved students' SAT scores as well as the basket of post-secondary schools they applied to, however, the effects were concentrated among more well-off students. Conversely, Vigdor et al. (2014) find modest, but significant negative effects on both math and reading standardized test scores using within-student estimators. Despite the conflicting results, both studies conclude that access to the internet is likely to broaden differences in achievement as gains (or losses) accrue to more advantaged (less advantaged) students. Importantly, these prior studies link student addresses to postal code level data on broadband availability; this study improves on this work by merging addresses with broadband availability data at

[13]broadband reduces labor market frictions by improving labor market matching and job search (Kuhn and Mansour, 2014; Kroft and Pope, 2014; Bhuller et al., 2020).

[14]Observed trends suggest broadband is strongly associated with lower GPA but less predictive of time use (Junco, 2012; Kirschner and Karpinski, 2010). Bauernschuster et al. (2014) examine the effect of broadband on student time spent on extracurricular activities and find no evidence that broadband crowds out other activities.

[15]See Bulman and Fairlie (2016) for a comprehensive review of the literature.

the block group level.

Studies that assess the effect of comparably faster broadband generally find positive results. Sanchis-Guarner et al. (2022) estimate the effect of faster home internet on test scores using a regression-discontinuity design (RDD). They find medium-sized effects, where a 1 Mbps increase in internet speeds increases test scores by 7% of a standard deviation.[16] Their results are driven by more advantaged students, consistent with Dettling et al. (2018). Difference-in-differences estimates of school access suggest that fiber improves standardized test pass rates (Grimes and Townsend, 2018).[17] Furthermore, in contrast with the rest of the literature, they conclude that schools with more low-socioeconomic students benefit more, perhaps narrowing existing gaps. While the authors find benefits that accrue from a national program to provide "ultra-fast" internet to schools, home access is more likely to directly affect students as it affords students flexibility and autonomy (DiMaggio and Hargittai, 2001).

Overall, while current research has attempted to describe the impact of broadband on achievement, more work is needed. his paper stands to update our current understanding of the impact of high-speed internet and clarify the mechanisms through which fiber availability affects students.

3 Data

3.1 Broadband availability

Data on fiber broadband availability comes from the Federal Communications Commission's (FCC) Form 477 data, as well as the National Telecommunications and Information Association's National Broadband Map (NBM). Form 477 data date back to 2014 and extend through 2018. NBM data ranges from 2010-2013, such that my broadband availability dataset covers the entire period from 2011-2018. Form 477 data is the most comprehensive dataset on internet availability in the United States available to researchers today. Internet Service Providers are required by law to submit to the FCC a list of census blocks where they can provide access to the internet in one direction at least 200 kilobits-per-second (Kbps). The dataset provides the maximum advertised download/upload speeds, and importantly, the technological medium for the given speed.

Previous researchers have too used FCC data on broadband availability. However, prior to 2010, the finest level of geography available was the postal code. By defining

[16] It is difficult to compare these results to this paper since the average download speed in their context was 5 Mbps.

[17] The authors estimate a staggered adoption TWFE model, which suggests that their estimates could be biased due to negative weighting. In addition, Grimes and Townsend (2018) provide evidence for the parallel trends assumption by estimating the effect of broadband on passing rates for the year before broadband became available. By doing this in a TWFE framework the regression makes improper comparisons of later and earlier treated units which could bias this result.

access at the postal code level researchers risk overstating the availability of broadband (Dettling et al., 2018). Dettling et al. (2018) address this concern by creating an alternative definition of access that trends closely with Pew Research usage rates and predicts teen usage rates from the Current Population Survey. This measure is attractive, yet newer iterations of FCC data are less susceptible to this issue due to their granularity. Nevertheless, there is a consensus that newer data from the FCC and NBM data face the same challenge since providers need not be able to provide access to the entire census block (Grubesic, 2012; Busby and Tanberk, 2020; Ford, 2021).

Cautioning against widespread use, Ford (2011) has offered a more scathing review of the NBM data and suggests that it not be used for causal analysis due to measurement error, as well as, selection bias due to non-compliance from some firms providing data. While measurement error could cause attenuation, selection bias could be concerning if there was selection into reporting fiber. If selection bias was a concern we would see some inappropriately labeled untreated students experience changes in their outcomes relative to treated students which would attenuate my estimates. While I cannot test whether a non-compliant firm could have provided fiber but did not report, just 6 of 104 total providers in North Carolina did not submit data for the NBM in 2011.[18] Furthermore, of the non-compliant firms, the majority offer either wireless broadband or cable. This suggests that if there is bias arising from non-compliance it is likely small. Furthermore, since there is significantly more cost investment associated with fiber it's plausible that firms do not over-report fiber availability at the same rate as other technologies.

A related concern is that the composition of these datasets reflects different collection methods; it is reasonable to think that the earlier data may not be comparable to the latter. Whitacre and Gallardo (2020) discuss the issues associated with combining the two datasets, and while there is a clear survey break for certain technologies, there does not appear to be severe measurement error in fiber. They similarly combine both datasets to assess the effect of broadband access at the county level on economic outcomes and note that well-documented issues with the data could bias their results, however, they conclude these issues are likely to attenuate their results. Given known issues that arise with existing broadband data, measurement error is similarly likely to attenuate my estimates.[19]

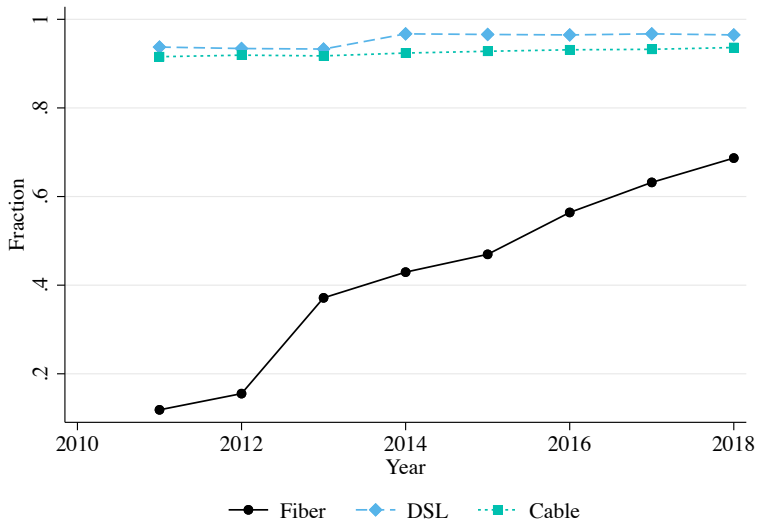
I opt to define a census block group as having access to fiber if at least one provider offers access to fiber broadband at any speed. This definition is somewhat more restrictive

[18]See North Carolina's progress report for Q4.

[19]While measurement error in the extensive margin of fiber access is less of a concern, measurement error in the maximum download speeds across other technologies may be for estimates of the first-stage. My subsequent results demonstrate that these concerns are similarly unfounded since fiber almost always produces changes in speeds that exceed existing technologies. Nevertheless in Appendix A.1, I how descriptive evidence of the first-stage for later years that shows smoother estimates but comparably large shocks. If anything these figures further motivate my identification strategy.

than Dettling et al. (2018) for urban and rural zip codes. They define an urban zip code as treated if there is at least one provider for every 2,700 people and if there is one provider per 12 square miles for rural zip codes. For comparison, while my measure varies by the size of the block group, the corresponding penetration rate is about one fiber provider for every 1,338 people.[20]

Figure 1: Fraction of Students with Access to Broadband by Technology



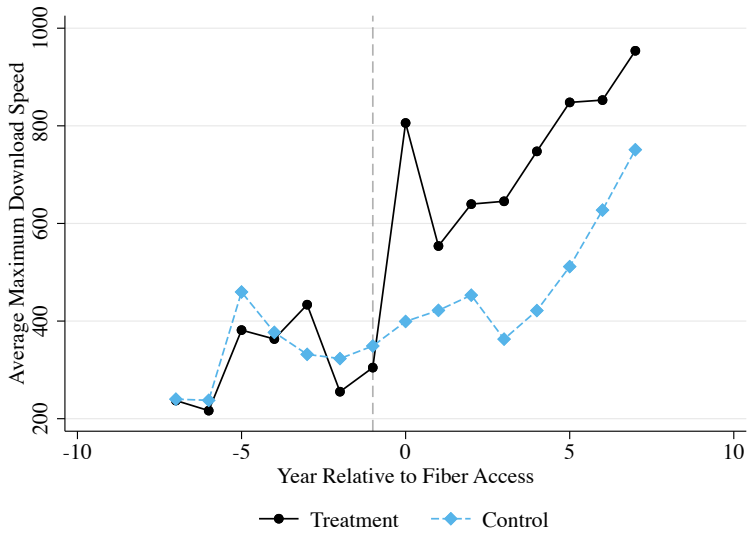
Notes: Graph plots the fraction of block groups for which broadband was available for DSL, cable, and fiber technologies. Source: Author's tabulations based on National Broadband Map and FCC Form 477 data.

Figure 1 shows how access to fiber, DSL, and cable has changed over the course of my sample period. From the figure, it is clear that access to fiber has climbed considerably, where the percentage of block groups covered rose from 11.9% in 2011, to 68.7% in 2018. While there has been very little movement in the fraction of block groups covered by DSL or cable, the arrival of fiber represents a significant change in the available technology. How this change in technology affects individuals is evident in Figure 2, which describes how the average maximum download speed changes just after the arrival of fiber. The figure compares treated block groups for which fiber became available to control blocks that never got access. Fiber radically increases the maximum speed available and persists afterward.[21]

[20]Figure based on the median number of people in a block group using the 2010 Census.

[21]Figure A.1 shows the same relationship using only the FCC Form 477 data which has considerably less measurement error.

Figure 2: Average Maximum Broadband Speeds Relative to When Fiber Became Available

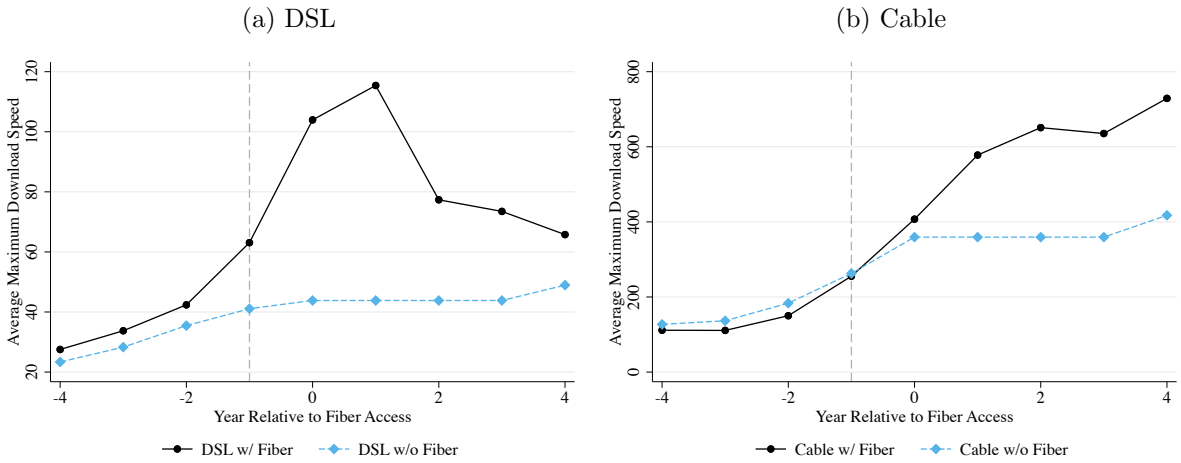


Notes: Graph plots the average maximum download speed by year, relative to when fiber became available for areas that had access to fiber versus those that did not. Source: Author's tabulations based on National Broadband Map and FCC Form 477 data.

Figure 3 conducts a similar exercise but separates out this relationship for DSL and cable technologies. Similarly, there is a clear decoupling of the average maximum download speeds between areas that gain fiber and those that did not which is present for both DSL and cable. If fiber did not induce competition on quality we would expect the trends in DSL and cable speeds to evolve similarly between areas that gained fiber and those that did not. Subsequently, it would appear incumbent providers facing competition from fiber improve the quality of their service following the introduction of fiber.[22]

[22]This is consistent with a story where providers compete on download speeds, but cannot on upload speeds due to technological constraints. I present similar descriptive figures in A.2.

Figure 3: Average DSL and Cable Speeds Relative to When Fiber was Available



Notes: The figure plots the average maximum download speeds by DSL and cable respectively, in the event years before and after the arrival of fiber. To avoid measurement error in download speeds from the NBM data I restrict to the years after 2013 and keep only the untreated blocks and those whose treatment occurs in 2014 or later.

3.2 Student Achievement

Longitudinal administrative data on student achievement comes from the North Carolina Education Research Data Center (NCERDC). North Carolina students are required to take end-of-year standardized tests in reading and math, which are then linked to additional demographic and other information by the NCERDC. I then further standardize the test scores to have a mean of zero and a standard deviation of one for each grade-year. Subsequently, the main outcomes of this paper are standardized math and reading scores for students in grades 3-8. In addition, the data contains basic demographic information such as sex, ethnicity, and whether the student is economically disadvantaged. Additional information on whether the student is an English Language Learner (ELL), or has a documented disability provides further margins that I use for heterogeneity analyses in this paper. Importantly, NCERDC geocodes student addresses and matches them to census block groups.[23] The inclusion of student addresses enables me to student-level variation in fiber broadband availability.

My final sample is comprised of 5,158,485 observations of 3rd through 8th grade students from 2011-2019. Demographically the students in my sample are 50% female, 50% white, 25% black, 16% Hispanic, and 3% Asian.[24] Furthermore, 6% have ever been classified as an English Language Learner (ELL), 3% have ever repeated a grade, 8% have ever had a disability, and 52% are economically disadvantaged. I classify students as

[23]Some student addresses are at the census tract level if there are not enough students in a block group to meet anonymity standards. This covers just 1,047 students or 0.02% of all students in my sample.

[24]I refer to students that are two or more races, or are Native or Pacific Islander as "Other".

having a disability if they are deaf, hearing impaired, have a mild intellectual disability, are specific learning disabled, or have a speech-language impairment. I drop all other students with documented disabilities; this includes autistic students, deaf-blind students, and those with moderate or severe intellectual disabilities.[25]

Table 1: Summary Statistics by Future Fiber Access

	No Fiber		*Fiber*		
	Mean	SD	Mean	SD	p-value
		Broadband Variables			
Max Speed	200.65	67.83	202.44	29.44	0.170
Low-Tech	0.00	0.00	0.13	0.24	0.000
High-Tech	0.00	0.00	0.14	0.24	0.000
Number of Providers	7.40	0.51	7.43	0.40	0.041
		Student Variables			
Math Score	0.01	0.72	0.02	0.72	0.004
Reading Score	0.04	0.73	0.05	0.72	0.004
Ever Repeated Grade	0.03	0.19	0.03	0.17	0.172
Female	0.50	0.50	0.50	0.50	0.654
White	0.52	0.41	0.52	0.41	0.234
Black	0.26	0.36	0.25	0.37	0.514
Asian	0.02	0.11	0.03	0.17	0.150
Hispanic	0.14	0.31	0.14	0.33	0.227
Other Race	0.05	0.22	0.05	0.21	0.832
ELL	0.06	0.21	0.06	0.23	0.303
Economically Disadvantaged	0.55	0.45	0.54	0.42	0.002
Disability	0.06	0.25	0.06	0.23	0.852
		Cost Variable			
Cost	30.08	6.74	29.82	3.32	0.066

Notes: The table presents summary statistics for the year 2013 separately by future fiber access. For each variable, I partial out census tract fixed effects and add back the mean. Column (5) reports the p-values from a regression of each row-wise variable on future access with standard errors clustered at the block group level. Low-tech and high-tech refer to students that live in areas that fell below and above the 50th percentile of download speeds the year before fiber arrived, there are no untreated units in this group by construction.

4 Empirical Strategy

4.1 Estimation

To identify the effect of broadband on outcomes we need plausibly exogenous variation in fiber availability. A naive regression of test scores on fiber is biased as fiber availability

[25]These include dyslexia, dysgraphia, and dyscalculia (Wachala, 2020).

is correlated with other unobserved determinants of student outcomes. More affluent, urban households are more likely to both gain access to fiber and take up the service, biasing our estimates upwards. Similarly, we might expect bias if household demand induces providers to supply fiber. Lastly, bias will arise if households endogenously sort into areas in response to fiber.

Motivated by these concerns the goal of my identification strategy is to isolate suitably exogenous variation such that differences in fiber access are driven by idiosyncratic factors unrelated to student outcomes. I rely on quasi-random variation in the timing of the availability of fiber that arises from the staggered rollout of fiber over my sample period. In addition, I leverage the panel nature of my student test score data, as well as, the granularity of broadband data to compare within-student changes in outcomes for students in the same census tract. I define a student as treated if fiber, at any speed, was available in her census block group, in a given year. To account for endogenous sorting to areas with fiber I fix each student's block group to be the block group of their first observation in the data. Subsequently, I first estimate the effect of fiber broadband availability on student outcomes by OLS using the following model:

$$y_{i,t} = \alpha_i + \gamma_{k(i),t} + \sum_{\tau=-5}^{-2} \beta_\tau D_{i,t}^\tau + \sum_{\tau=0}^{5} \beta_\tau D_{i,t}^\tau + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the outcome for student i, at time t. α_i is a vector of student fixed effects, $\gamma_{k(i),t}$ is a vector of census tract-by-year fixed effects, $D_{i,t}^\tau$ are indicators that take a value of 1 if student i is τ years away from their initial exposure to fiber broadband. For all regressions, I omit the interaction term for the year before a student's initial treatment. Student fixed effects constrain identification to come from within-student changes in fiber access and account for time-invariant differences across students and locations. Census tract-by-year fixed effects account for time-varying determinants of test scores at the census tract level. Importantly, the coefficients of interest, β_τ, capture the causal intent-to-treat (ITT) effects of fiber on student outcomes τ periods before/after broadband becomes available. I estimate the ITT rather than the average treatment effect on the treated because I do not observe broadband adoption. For the figures in the following sections, I plot the estimates of β_τ in event-time and cluster my standard errors at the census block group level.[26]

Embedded in my identification strategy is the assumption that within a sufficiently fine geographic area differences in access to fiber are driven entirely by quasi-random factors that affect supply. Given this empirical framework, I would fail to capture the causal effect of interest if the timing of fiber availability (entry of firms) was correlated

[26]Given that treatment occurs at the block group level, I cluster my standard errors at the block group level to allow for autocorrelation within a block group over time.

with other time-varying determinants of student outcomes not captured by the model. Similar to the setting in Dettling et al. (2018), the assumptions of this research design might be violated if student demand drove the entry of firms providing fiber access. This is unlikely given a body of evidence that broadband access was significantly lagged due to supply-side constraints (Dettling et al., 2018; Greenstein and Prince, 2006; Faulhaber and Hogendorn, 2003). In addition, infrastructure costs to provide access are intrinsically related to time-invariant location-specific factors, so the inclusion of student fixed effects should capture these unobserved factors.

Table 1 presents basic summary statistics at baseline by fiber access for both the relevant variables on access, as well as those at the student level broken down by future access. For each variable I partial out the census tract fixed effects. In the final column, I regress each row-wise variable on future access and report the corresponding p-value. For broadband variables, I find areas that are eventually treated have slightly more providers. Furthermore, eventually treated students have marginally higher math and reading test scores and are less likely to be economically disadvantaged. Lastly, I use data from CostQuest Associates on the per unit cost to expand access to broadband used for determining the Connect America Phase II model-based support.[27] The final row of Table 1 suggests the cost to build-out broadband was balanced between treated and untreated areas.

For table estimates, I estimate the following equation:

$$y_{i,t} = \alpha_i + \gamma_{k(i),t} + \beta Fiber_{i,t} + \epsilon_{i,t} \tag{2}$$

where $Fiber_{i,t}$ takes a value of one if student i lived in a block group where fiber was available in time t. Subsequently, if conditional on the student fixed effects and tract-by-year fixed effects, outcomes would have evolved similarly for students for which fiber becomes available, and for those that did not, β captures the causal ITT effect of fiber on outcomes. In some specifications, I include school fixed effects to account for school-specific factors that affect test scores, or school-by-year fixed effects to capture school-year-specific shocks.

Subject to the parallel trends assumption stated above, the estimates from Equations 1 and 2 will capture the causal ITT effect of fiber. However, even in the case where parallel trends hold the TWFE estimates from Equation 2 could still be biased by issues that arise in differences-in-differences designs with staggered treatment (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021). In particular, bias in my setting might arise from improper comparisons of students who gained access

[27] See the Connect America Fund Phase II webpage for an overview of the program. Estimates of the cost are based on a forward-looking model intended to estimate the cost for a price cap carrier to provide broadband to an area at 10 Mbps down/1 Mbps up.

to fiber earlier to those who gained access to fiber later. Negative weights placed on some units will bias the regression coefficient away from the true sign (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020). Furthermore, the leads and lags in Equation 1 could be biased from contamination if there is treatment effect heterogeneity across different treatment groups (Sun and Abraham, 2021).

To address the possibility of bias that arises from staggered treatment designs I compare the OLS estimates to the estimator proposed by de Chaisemartin and D'Haultfoeuille (2022) (DCDH hereafter) by plotting the coefficients and their confidence intervals in event-time. For all figures, I include tract-by-year fixed effects akin to the OLS estimates, and for tables, I vary the fixed effects. DCDH's estimation strategy uses not-yet-switchers with the same treatment as the switching group at the start of the panel as controls for the group treated in year t. The DCDH estimator is conditionally unbiased and identifies a weighted average of cohort-specific average treatment effects (cohort-specific ITTs in my setting) robust to treatment effect heterogeneity. Unlike OLS, the DCDH estimator relies on comparing outcomes of treated and untreated groups for each period after a group's initial treatment to its outcomes the period before, whereas OLS uses all units and all time periods as controls.

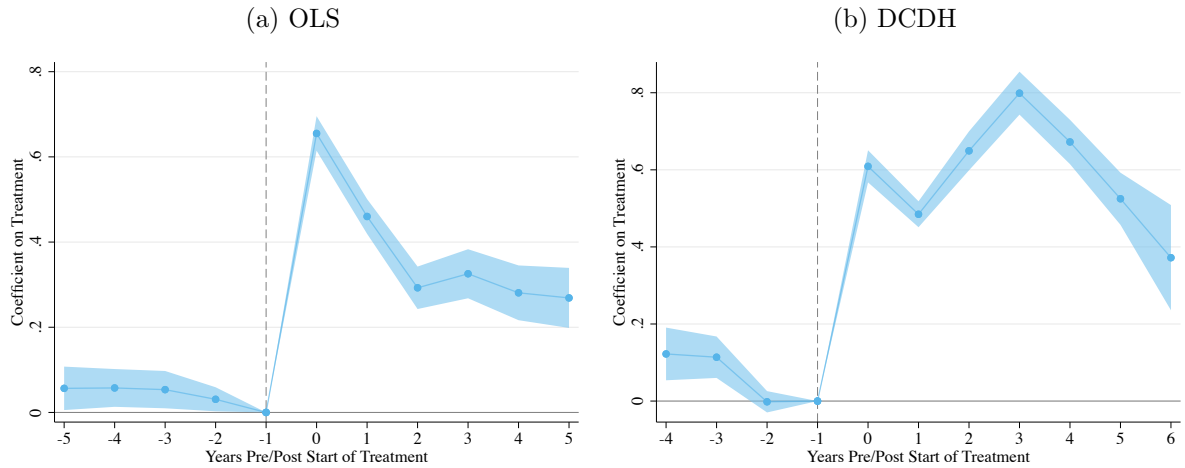
5 Results

5.1 Estimates of Fiber on Download Speeds

To begin I first estimate the effect of fiber on the maximum download speed in levels and on the inverse hyperbolic sine transformation using a panel of census block groups corresponding to the addresses of the students in my main sample. Figure 4 shows the first-stage effect of fiber availability on the inverse sine transformation of maximum download speeds using Equation 1 and the DCDH estimator in Panels (a) and (b) respectively.[28] From the figure it is clear that the arrival of fiber led to an economically and statistically meaningful increase in the maximum download speeds reported in treated census block groups. As expected the introduction of fiber sharply increases the advertised speeds in treated areas. Note that while the coefficients prior to treatment are sometimes significant, the pre-treatment effects hover near zero which I treat as evidence in support of the parallel trends assumption. Furthermore, the post-treatment interactions suggest that the introduction of fiber broadband increases maximum advertised download speeds by a little more than 60 percent on average. Depending on the model the observed effect declines in the subsequent years, yet treated students see persistent differences in maximum speeds even 6 years after fiber's arrival. This suggests a significant and economically meaningful improvement in the available technology in treated areas.

[28] I present the results in levels in Table 2.

Figure 4: First-Stage Effect of Fiber on Maximum Download Speeds



Notes: The figure plots the estimates of the effect of fiber on maximum download speeds in the event years before and after the arrival of fiber. Panel (a) plots the estimates of the β_τ coefficients from estimating Equation 1 on the inverse sine transformation of maximum download speeds. Similarly, Panel (b) plots the coefficients from the DCDH estimator. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level.

Table 2 reports the first-stage OLS and DCDH estimates where I vary the fixed effects. In addition, I report the coefficient on *Fiber* for the same models where the outcome is in levels (Mbps). The point estimates across each specification vary somewhat but suggest a large change in the maximum available download speed. Subsequently, my preferred specification, Column (3), indicates that the arrival of fiber increases the maximum download speed by 132 percent, or roughly 313 Mbps on average.[29].

[29]I approximate the semi-elasticity from Table 2 column (3), row (1) as $exp(\hat{\beta} - 0.5 * Var(\hat{\beta})) - 1$ as described by Bellemare and Wichman (2020).

Table 2: First-Stage Estimates of the Effect of Fiber on Maximum Download Speeds

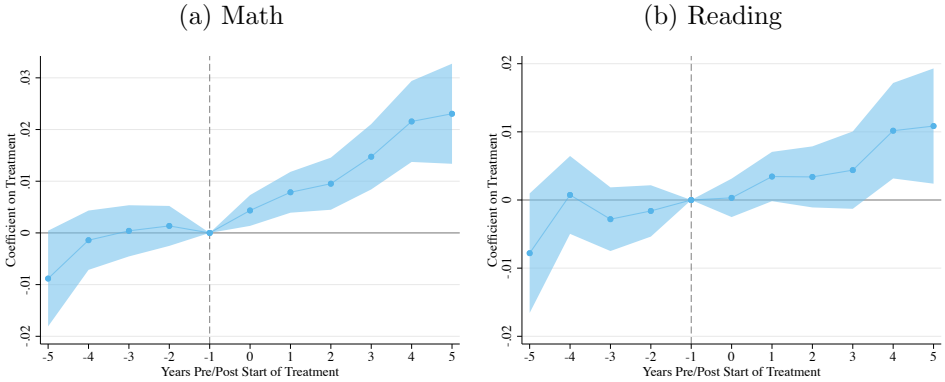
	(1) OLS	(2) OLS	(3) DCDH	(4) DCDH
			ASinh	
Fiber	0.74	1.01	0.843	0.929
	(0.00)	(0.00)	(0.0336)	(0.0366)
			Levels	
Fiber	285.93	366.38	312.747	323.335
	(0.35)	(0.48)	(4.0999)	(10.7062)
Student FE	X		X	
Year FE		X		X
Block FE		X		X
Tract-Year FE	X		X	
N			5,158,485	

Notes: DCDH are regressions estimated using the de Chaisemartin and D'Haultfoeuille (2022) estimator. Block FE refers to census block group fixed effects. Standard errors in parenthesis are clustered at the census block group level.

5.2 Estimates of Fiber on Standardized Test Scores

How do shocks to broadband speed affect standardized test scores? Figure 5, Panels (a) and (b) show the effect of fiber availability on math and reading standardized test scores respectively, based on estimating Equation 1 using OLS. Notice that none of the treatment leads are significant which provides support for the parallel trends assumption. The effects on math and reading standardized test scores monotonically increase after fiber becomes available, where six years of exposure increases math test scores by roughly 2.3 percent of standard deviation and by 1 percent of standard deviation for reading. Notably, this monotonic increase in test scores suggests that negative weighting is likely to bias my estimates of Equation 2 away from the true sign, motivating the use of DCDH's estimator which is robust to these dynamic effects.

Figure 5: OLS Estimates of the Effect of Fiber on Standardized Test Scores



Notes: The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level.

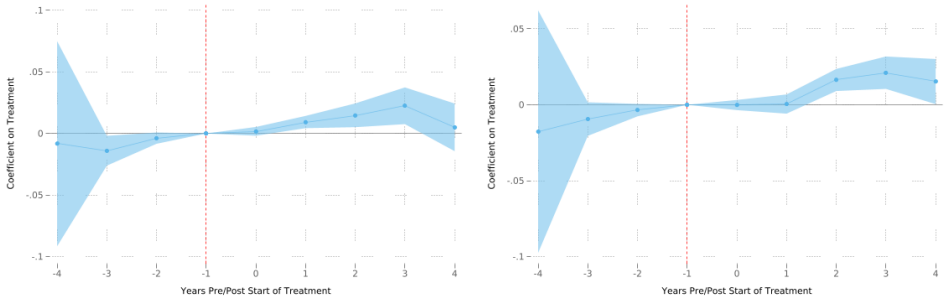
To show these event-study estimates are not being driven by treatment effect heterogeneity that could contaminate the leads and lags in the OLS model, I present the results from estimating DCDH in Figure 6, Panels (a) and (b). The results from this exercise suggest similar effects, for both math and reading, though we do not observe the same monotonic effect. The difference between the event-studies could be due to control group differences between OLS and DCDH, or due to bias arising from known issues with OLS. [30] Despite these concerns, the results provide further evidence that the parallel trends assumption is unlikely to be violated.[31]

[30] Sun and Abraham (2021) show that bias in OLS event-studies arises due to contamination from the effects of other periods and that the weights associated are known and can be computed. They show that (1) the own period weights sum to 1, (2) the weights for all other relative periods sum to zero, and (3) the weights for excluded relative periods sum to negative 1. I calculate these weights using eventstudyweights Sun (2021) in Stata. Figure A.4 plots the weights for each lead and lag estimated in Equation 1. From the figure, we can see how the weights vary by treatment by each group by relative-time pair. In general, the weights for the relative-time indicators estimated in Equation 1 are approximately zero for relative-time, treatment group pairs, with the exception of each indicator's own period. This is reassuring as bias from heterogeneous treatment effects should arise out of non-negative weighting on the treatment effects for relative-time-treatment-group pairs. I compare cohort-specific estimates (the convex hull of treatment effects) to those obtained from OLS in Figure A.5.

[31] I verify the robustness of these event-study results using the interaction weighted estimator proposed by Sun and Abraham (2021) in Figure A.3.

Figure 6: DCDH Estimates of the Effect of Fiber on Standardized Test Scores

(a) Math (b) Reading



Notes: The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber. Panels (a) and (b) plot the coefficients from estimating DCDH. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level.

In Table 3, I present the ITT estimates of the effect of fiber broadband on student math and reading test scores. Columns (1)-(3) report the coefficient on treatment from estimating Equation 2. Column (2) includes school fixed effects to account for time-invariant differences across schools, while column (3) adds school-by-year fixed effects to account for school-year-specific shocks. The inclusion of these fixed effects has no meaningful impact on the coefficient on fiber. Columns (4) and (5) report the coefficients from estimating DCDH. Column (4) reports a specification analogous to column (1), while column (5) includes school fixed effects analogous to column (2). Depending on the estimator and specification used, the effect of fiber on math ranges from 0.4 to 1 percent of standard deviation. The estimated effects on reading range from 0.1 to 1.1 percent of a standard deviation, and are insignificant across OLS specifications but are significant using the DCDH estimator. My preferred specification in column (4) indicates that fiber increases math and reading test scores by 1 and 1.1 percentage points respectively. The OLS estimates reported in columns (1)-(3) are considerably smaller than those in column (4), consistent with negative weighting biasing the effect of fiber away from its true sign.

Table 3: Estimates of the Effect of Fiber on Test Scores

	(1) OLS	(2) OLS	(3) OLS	(4) DCDH	(5) DCDH
			Math		
Fiber	0.004	0.004	0.004	0.010	0.009
	(0.0015)	(0.0015)	(0.0014)	(0.0035)	(0.0063)
			Reading		
Fiber	0.001	0.001	0.002	0.011	0.010
	(0.0014)	(0.0014)	(0.0014)	(0.0034)	(0.0045)
Student FE	X	X	X	X	X
Year FE					
Block FE					
Tract-Year FE	X	X	X	X	X
School FE		X			X
School-Year FE			X		
N			5,158,485		

Notes: DCDH are regressions estimated using the de Chaisemartin and D'Haultfœuille (2020) estimator. Standard errors in parenthesis are clustered at the census block group level.

Relative to prior work on broadband and student test scores these reduced form estimates are in contrast to Vigdor et al. (2014) but consistent with Sanchis-Guarner et al. (2022). With regards to Vigdor et al. (2014), given the recent developments in the DiD literature, we might expect that they are likely biased away from the true sign due to negative weighting. Alternatively, given that they study access to cable or DSL we might not necessarily expect similar results. Sanchis-Guarner et al. (2022) find that changes in the intensive margin for DSL generate medium-sized positive changes in test scores. Nevertheless, my results suggest that large changes in the intensive margin and available technology generate meaningful positive changes in student outcomes. These estimates are modest relative to other interventions but are equivalent to increasing per-pupil spending by roughly \$422, or 4% on average.[32]

[32]This estimate comes from calculating the cost to increase test scores by one percent by reducing class sizes. The cost of reducing class size by seven students amounts to roughly a 47 percent increase in spending per pupil per year (Schanzenbach, 2006). The returns amount to an increase of 0.152 standard deviations per year. Spending for pupil in North Carolina for 2019-2020 was \$10,632, such that the marginal cost of reducing class sizes is \$4,997.04.Source. Assuming that both costs and returns are linear in the number of students a dollar towards reducing class sizes increases test scores by $\frac{0.152}{4{,}997.04}$. The cost of increasing test scores by 1% of a standard deviation such that the final cost of reducing class size that increases test scores by 1% is roughly \$422 per pupil when adjusted from 2005 dollars to 2018 dollars.

5.3 Heterogeneity

I explore heterogeneity in two ways. First, I leverage the rich set of demographic characteristics available in the North Carolina administrative data. Second, I classify areas based on the baseline available technology and assess the effect of fiber along this margin. Diminishing returns on the intensive margin of broadband access have not yet been studied, but potentially could drive differences in the effects on achievement.

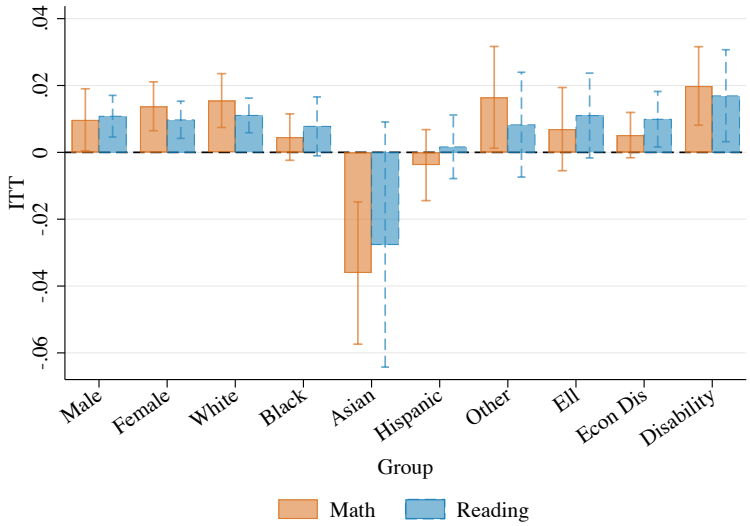
Vigdor et al. (2014) frame their heterogeneity analysis around how productively different groups use the internet. In particular, parental constraints and use may affect the magnitude of the effect. Furthermore, they point to survey results suggesting that girls are more likely to use the internet for homework, whereas boys we more likely to use the internet for non-productive uses. They find evidence consistent with these hypotheses, which suggest that internet access widens the gap between low- and high-income students. Other studies (Dettling, 2017; Sanchis-Guarner et al., 2022) similarly find that the benefits of broadband access accrue to students with more resources. A model of productivity is compelling but does not account for how many households actually take up a fiber subscription. Disadvantaged individuals may be less likely to be able to afford an internet subscription anyway so we might expect a smaller effect for these students.

To explore heterogeneous responses to fiber by demographic groups, I implement the DCDH estimator on each group of interest. Figure 7 presents these estimates, as well as, the associated 95% confidence interval for each group.[33] I find that male and female students benefit similarly from fiber, somewhat counter to Vigdor et al. (2014). When breaking down the results by race, White students experience positive effects for both math and reading, while students of other races only see significant effects on math. The effects on Black, Asian, and Hispanic students are each insignificant, or even negative, consistent with prior work. The effects for ELL students are both insignificant, while the effect on reading for economically disadvantaged students is positive. Lastly, students with disabilities benefit for both math and reading.

Table 7 presents the results from estimating DCDH on both math and reading, as well as the maximum download speed first-stage for each group. While the first-stage estimates for broadband speeds are largely consistent, the underlying subscription rates for these groups could differ substantially. Nevertheless, these results broadly suggest that fiber could exacerbate existing gaps, but leaves some room for optimism where economically disadvantaged students and students with disabilities both benefit.

[33]The OLS event-study for each demographic group is presented in Appendix A.7-A.16.

Figure 7: Effect of Fiber on Test Scores by Group



Notes: The figure plots estimates of the effect of fiber on standardized math and reading test scores by each demographic group. Sex and race/ethnicity categories are mutually exclusive. Whiskers on the boxes plot the 95 percent confidence interval where standard errors are clustered at the census block group level.

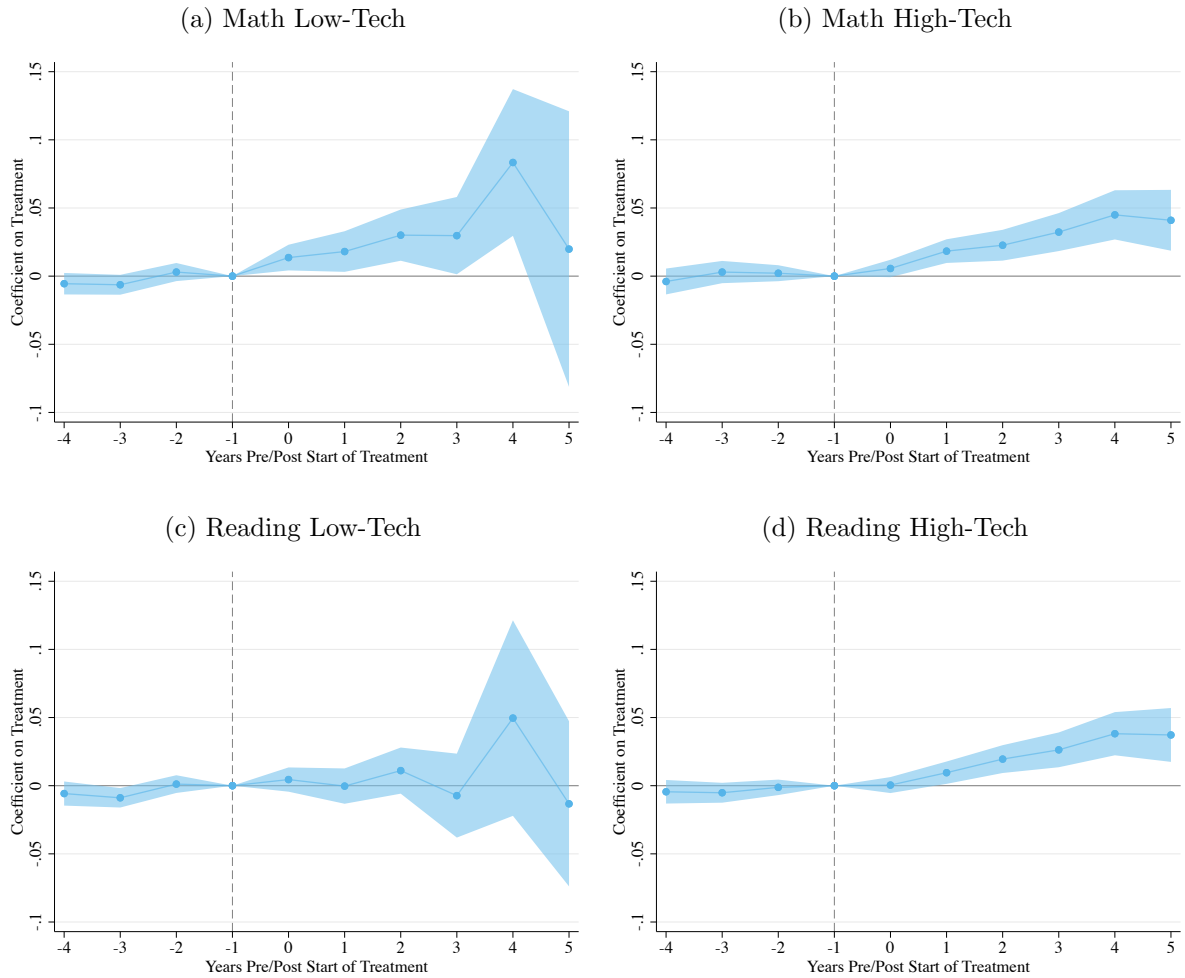
Next, to explore how the effect might vary based on the available technology in the area at baseline, I split students for whom fiber becomes available into two groups based on the maximum available download speed at baseline. I first define a low-tech group which consists of students whose baseline speed fell below the median of download speeds in the year before fiber become available. The second, high-tech group, consists of students whose baseline speed was greater than or equal to the median of download speeds.[34] The intuition behind this classification is that areas defined as low-tech experienced larger changes in speed relative to high-tech areas, which could generate differences in the response to fiber. If the relative difference in speed matters we might expect larger effects for low-tech students versus high-tech students.

To test this hypothesis I separately estimate Equation 1 on the sample of low-tech students and students that never gained access to fiber, then do the same for high-tech students. Figure 8, Panels (a) and (b) report the effect of fiber on math test scores for low- and high-tech groups respectively.[35] These results suggest there is little difference between low- and high-tech groups. Alternatively, Panels (c) and (d) show the same estimates but for reading. Here, I find that low-tech areas are unaffected by the arrival of fiber, while high-tech areas see gains similar to math. This is potentially concerning as low-tech areas are more likely to be rural, and therefore fiber could widen the digital divide along this margin.

[34]In practice this threshold is 100 Mbps.

[35]Figure A.6 plots the effect of fiber on maximum download speeds by low- and high-tech groups.

Figure 8: Effect of Fiber by Baseline Technology



Notes: The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber separately by baseline technology. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math by low-tech and high-tech areas respectively. Similarly, Panels (c) and (d) plot the estimates of the β_τ coefficients from estimating Equation 1 for reading by low-tech and high-tech areas respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level.

5.4 Robustness

The identifying assumption of my research design is that students that gained access to fiber and students that did not would have had parallel trends in outcomes in absence of the arrival of fiber. While Figure 5 provides evidence in favor of this assumption, one concern is that peer effects from compositional changes are driving the effects on test scores. To test this I calculate what share of the students in each block group are Black, Hispanic, economically disadvantaged, etc. I then estimate the effect of fiber on the share of each demographic group using the DCDH estimator. The first row of Table 4 presents the results from this exercise. Across each of these specifications, the effect of fiber access on the share of each demographic group is small and tightly estimated. Only

the estimate on the fraction of Asian students is significant at the 5% level and suggests that the arrival of fiber increases the fraction of Asian students by 0.1 percentage points.

A related concern is that students sort to schools that get access to fiber. To address this I redefine treatment as when the block a school is located in gets access to fiber. I estimate the effect of fiber access in the school's block group on the fraction of each demographic group, just as in the previous exercise. The second row of Table 4 presents the results from this exercise. Only the effect on Hispanic students is significant and implies that fiber increases the share of Hispanic students by 0.4 percentage points. The results do not appear to be economically meaningful and suggest that sorting is unlikely to drive the results.

Table 4: Effect of Fiber on Block and School Composition

	(1) Male	(2) Female	(3) White	(4) Black	(5) Asian	(6) Hispanic	(7) Other	(8) ELL	(9) Econ. Dis.	(10) Disability
					Block Group Composition					
Fiber	-0.002	0.002	-0.000	0.001	0.001	-0.000	-0.001	0.000	-0.002	-0.000
	(0.0015)	(0.0015)	(0.0016)	(0.0011)	(0.0005)	(0.0011)	(0.0006)	(0.0007)	(0.0023)	(0.0012)
N					58,101					
					School Composition					
Fiber	0.001	-0.001	-0.000	-0.001	0.001	0.004	-0.003	0.000	-0.006	0.001
	(0.0014)	(0.0023)	(0.0022)	(0.0019)	(0.0009)	(0.0010)	(0.0009)	(0.0011)	(0.0036)	(0.0017)
Block FE	X	X	X	X	X	X	X	X	X	X
Tract-Year FE	X	X	X	X	X	X	X	X	X	X
N					14,066					

Notes: Each estimate is estimated using the DCDH estimator for the relevant demographic group. Block FE refers to census block group fixed effects. Standard errors in parenthesis are clustered at the census block group level.

6 Evidence on Mechanisms for Broadband Effects

6.1 Income Effects

While the main results point to modest effects of fiber on student outcomes, the path through which fiber affects students is not clear. Previous literature has shown that broadband broadly increases employment and earnings, but has not identified the effect of changes on the intensive margin (Zuo, 2021; Hjort and Poulsen, 2019; Beem, 2022; Atasoy, 2013). It is unclear if improvements in the intensive margin or technology could drive changes in outcomes. Fiber could affect student achievement through changes in household income, whereby households may allocate more resources to students, in turn improving test scores. To test this I use data from LODES, which contains data on aggregate employment at the census block level but does not have information on earnings from 2010 through 2018.

To estimate the effect of fiber on employment I estimate Equation 1, as well as the DCDH estimator. Table 5, columns (1) and (3) report the estimated effect of fiber

on log employment and in levels from Equation 2 using OLS and DCDH respectively, while columns (2) and (4) report the effect from estimating Equation 2 and DCDH with tract-by-year fixed effects. Similar to the estimates for test scores, the OLS regressions in columns (1) and (2) are likely biased away from the true sign, such that I rely on the DCDH estimator for table estimates. My preferred specification in column (4) indicates that employment increased by 2.4 percent or 36 new individuals found jobs. The coefficients between columns (3) and (4) are roughly equivalent in magnitude and are significant.[36]

Table 5: Effect of Fiber on Labor Market Outcomes

	(1)	(2)	(3)	(4)
	OLS		DCDH	
	log(*Employment*)			
Fiber	0.021	-0.008	0.030	0.024
	(0.005)	(0.008)	(0.0058)	(0.0069)
	Employment (Levels)			
Fiber	24.405	-1.068	38.993	35.721
	(3.715)	(5.299)	(4.4641)	(4.3842)
Year FE	X		X	
Block Group FE	X	X	X	X
Tract-Year FE		X		X
N	51,864			

Notes: DCDH are regressions estimated using the de Chaisemartin and D'Haultfoeuille (2022) estimator. Standard errors are clustered at the block group level.

Provided that these estimates on employment suggest that fiber meaningfully improves local labor market conditions one might suspect that improvements to test scores may be fully explained by income effects. Ananat et al. (2011b) find that a one percent loss in employment decreases test scores by 0.076 standard deviations. Similarly, Ananat et al. (2011a) estimate the effect of parental job losses in North Carolina on children's test scores. They find a 1% increase in layoffs decreases 8th grade math test scores by 0.024 standard deviations. Comparing these estimates to estimates of the ITT suggests that income effects could fully explain the effect on test scores.

[36]Figure A.17 present the event-studies for employment using OLS and DCDH estimators. The OLS event-studies indicate a negative effect of fiber access on employment; these results could be biased by treatment effect heterogeneity which is accounted for in the DCDH event-studies.

6.2 Competition

While students are likely to benefit from direct access to fiber where families take up fiber as it becomes available, it's also possible that students indirectly benefit if internet service providers compete. For families on the margin of taking up broadband, if the arrival of fiber drives down prices across all technologies, this could induce take-up and increase student test scores as a result. Alternatively, if firms do not compete on prices they may compete on speed or quality. Recent structural industrial organization work suggests that rather than improving on the existing speeds, firms that enter tend to match on quality (Kearns, 2022). Yet, researchers that estimate the reduced-form relationship between competition and quality find that quality rises with firm entry (Fister, 2019; Molnar and Savage, 2017). It follows that if firms improve the speeds of the existing technologies in response to the arrival of fiber, individuals that already have a broadband subscription may also benefit.

I do not observe prices nor take-up so I cannot directly test whether price competition increases take-up for households on the margin. To attempt to answer this question I first estimate the effect of fiber on the maximum download speed of all other available technologies. Rows (1) and (2) from Table 6 present the OLS and DCDH results in both levels and the inverse sine transformation respectively. Columns (1), (3), and (4) suggest that fiber increases the maximum download speed of other technologies by 15.7 to 22 percent (67 to 89 Mbps), while column (2) suggests that other speeds only increase by 5.5 percentage points. Columns (2) and (4) are analogous to my preferred specifications for my main results with tract-by-year fixed effects. Just as in my main results, OLS is likely biased due to negative weighting, subsequently my preferred specification in column (4) uses the DCDH estimator with tract-by-year fixed effects.[37] Similarly, I estimate how fiber affects the number of providers which is presented in row (3) of Table 6. The results suggest that fiber increased the number of providers by between 0.09 and 0.39 providers. The coefficients in columns (2) and (4) are similar and suggest that the arrival of fiber led to a meaningful increase in the number of providers.[38] These results indicate that fiber has clear competitive effects on both the maximum download speeds of other technologies and the number of providers.[39]

[37]Figure A.18 shows a clear pre-trend which suggests that the speed of other available technologies would have increased even in absence of the arrival of fiber. However, this is not present in the DCDH event-study.

[38]Figure A.18 shows a flat pre-trend, providing evidence in favor of parallel trends.

[39]Figure A.18 presents the event-studies for both the number of providers and the maximum speed of other technologies.

Table 6: Effect of Fiber on Competition

	(1)	(2)	(3)	(4)
	OLS		DCDH	
	Other Speed (Levels)			
Fiber	67.433	6.453	88.855	79.472
	(5.837)	(3.330)	(6.4117)	(6.3649)
	Other Speed (Asinh)			
Fiber	0.146	0.054	0.201	0.199
	(0.017)	(0.012)	(0.0180)	(0.0204)
	Number of Providers			
Fiber	0.092	0.392	0.233	0.304
	(0.028)	(0.029)	(0.0492)	(0.0401)
Block Group FE	X	X	X	X
Year FE	X		X	
Tract-Year FE		X		X
N	51,864			

Notes: DCDH are regressions estimated using the de Chaisemartin and D'Haultfoeuille (2022) estimator. Standard errors in parenthesis are clustered at the census block group level.

6.3 Supplementary Educational Materials

Lastly, I turn to how fiber might affect the consumption of supplementary educational materials. As fiber becomes available, increased reliable and fast internet may make it easier for students, parents, and teachers to supplement students learning with other materials that could positively affect test scores. Platforms like Khan Academy regularly provide lessons, exercises, and personalized curricula for math, science, computing, history, art history, economics, and more for students, free of cost. Khan Academy routinely cites that students that use their platform meet performance and growth targets (Phillips and Cohen, 2015) at higher rates than students that do not. To test whether areas, where fiber became available experienced subsequent change in Khan Academy usage I gather data on searches for Khan Academy from Google Trends.

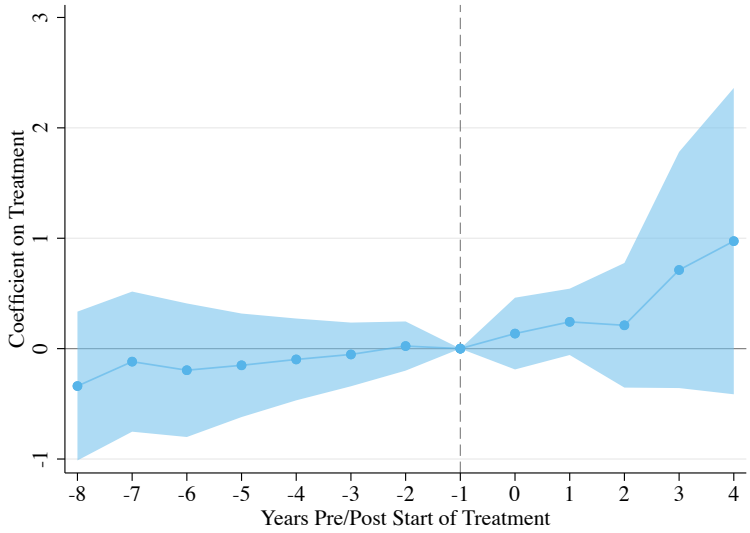
The primary challenge with using Google Trends data is that the total number of searches for Khan Academy for a given area or year may not pass some threshold, and therefore go unreported. To overcome this obstacle I employ a method proposed by Stephens-Davidowitz (2013) for analyzing the data, which relies on comparing potentially low-volume searches to high-volume searches, such as "weather".[40] I then standardize

[40]To get around the search intensity threshold I download samples for the following searches: "Khan

search intensity to be mean zero, standard deviation one.

Since the Google Trends data is at the media market year level I define treatment as equal to one if 25% of the housing units in a media market have access to fiber.[41] Figure 9 plots the event-study estimates from estimating a variation of Equation 1 on search intensity, which includes year and media market fixed effects. I find that 5 years of exposure to fiber increases the search intensity of Khan Academy searches by roughly one standard deviation.

Figure 9: Effect of Fiber on Khan Academy Search Intensity



Notes: The figure plots the estimates of the effect of fiber on Khan Academy search intensity in the event years before and after the arrival of fiber. Specifically, I regress Google Trends search intensity for Khan Academy on media market and year fixed effects and leads and lags of availability of fiber. I define the year of availability as when 25 percent of the housing units in a media market had access to fiber. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the media market level.

These are sizable estimates that suggest that fiber could affect Khan Academy usage. While the point estimates are insignificant the effect is growing over time following a flat pre-period. [42] Furthermore, it is not clear if the effect is driven by students in my sample or older students. Khan Academy resources are likely also useful for college students

Academy", "weather", and "Khan Academy+weather". I then calculate a media market's average score for "weather," "Khan Academy," and "Khan Academy+weather." I regress "Khan Academy" average score on "weather" average score and "Khan Academy+weather" average score for the markets that never score a 0 or 100 on "Khan Academy," Use coefficients from this regression to back out "Khan Academy," for remaining markets, using their average search volume for "weather" and "Khan Academy+weather".

[41]To test the robustness of the treatment definition I vary the percentage of housing units that must be covered for a unit to be treated from 20% to 40%. Appendix A.19 plots each of these definitions on the same figure. For lower levels of coverage, the estimates are similar, but the effect disappears as I require more and more of the media market to be covered. Furthermore, I show that these estimates are robust to which estimator I choose.

[42]I cannot see either take-up or Khan Academy usage statistics that would more clearly inform my results.

which could drive changes in searches as these students likely also benefit from fiber becoming available.

7 Conclusion

While broadband has been around for a long time we are still uncovering and quantifying much of the associated benefits. Public policy decisions that expand broadband access generally rest on the assumption that broadband has far-reaching benefits and is often a silver bullet for economic development. So much so, the recent Infrastructure Investment and Jobs Act has allocated $65 billion for broadband, $42.5 billion of which funnels money to states to deploy broadband to un- and underserved areas. The efficacy of this expansion is likely to depend on not only the speed and cost of the forthcoming broadband connections but crucially on the technology.

This paper informs this policy discussion by assessing the broad impacts of fiber broadband while zeroing in on education as a salient avenue. The results indicate that 6 years of exposure to fiber increases student test scores by 0.023 and 0.011 standard deviations for math and reading respectively. I conduct heterogeneity analyses that suggest that some traditionally marginalized students benefit from availability but broadly confirm past work that finds that gains were concentrated among higher-SES students.

I present evidence that the results are driven by changes in the consumption of supplementary educational materials, as well as, through spillovers that arise from firm competition. In addition, I provide evidence that fiber increases local employment, and given the magnitude suggests that income effects could drive the observed effect on test scores. Despite these results, further work should be done disentangling the contributions of each of these mechanisms.

The findings of this paper open exciting avenues of interest for researchers and policymakers seeking to close the achievement gap between students with different backgrounds and anchor our understanding of the benefits of fiber broadband. While policymakers should strive to equalize both availability and take-up of broadband, particular attention should be paid to the quality of these connections. Failure to do so would unduly restrict the educational outcomes for those that live too remote to permit access to high-quality broadband or those too poor to afford a subscription.

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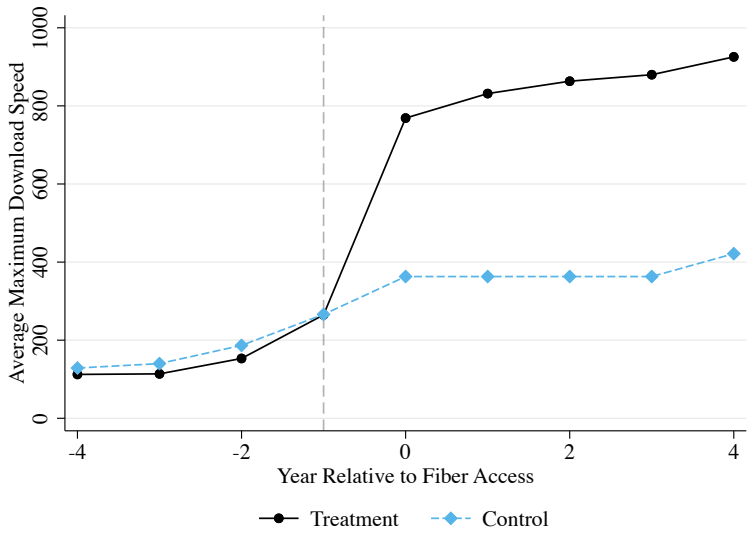
Appendices

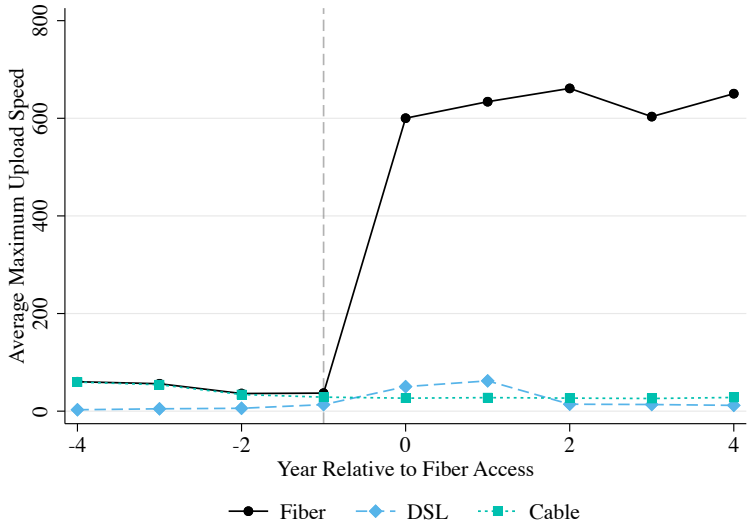
A Graphs

Figure A.1: Maximum Download Speeds Relative to When Fiber was Available, Post-2014



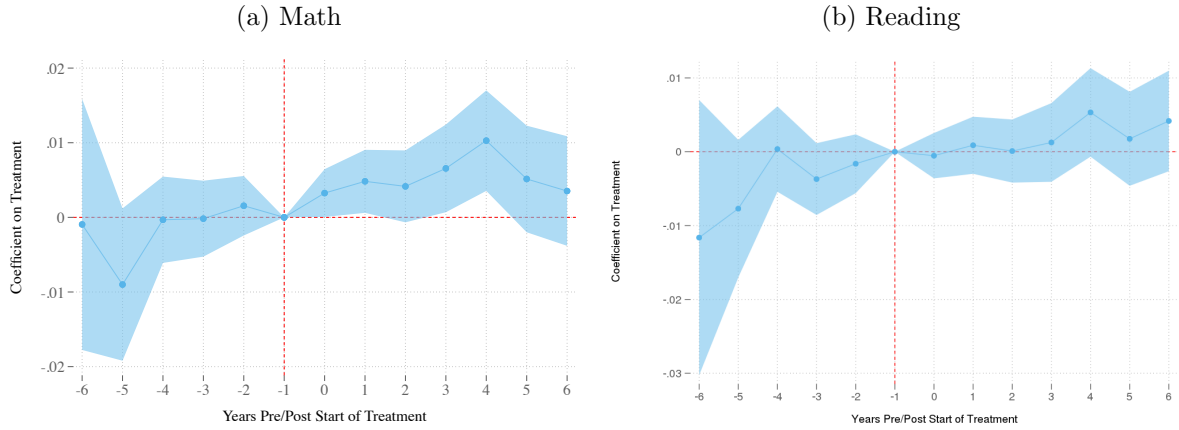
Notes: The figure plots the average maximum download speeds by future fiber access, in the event years before and after the arrival of fiber. To avoid measurement error in download speeds from the NBM data I restrict to the years after 2013 and keep only the untreated blocks and those whose treatment occurs in 2014 or later. Go back to page 12.

Figure A.2: Maximum Upload Speeds Relative to When Fiber was Available, Post-2014



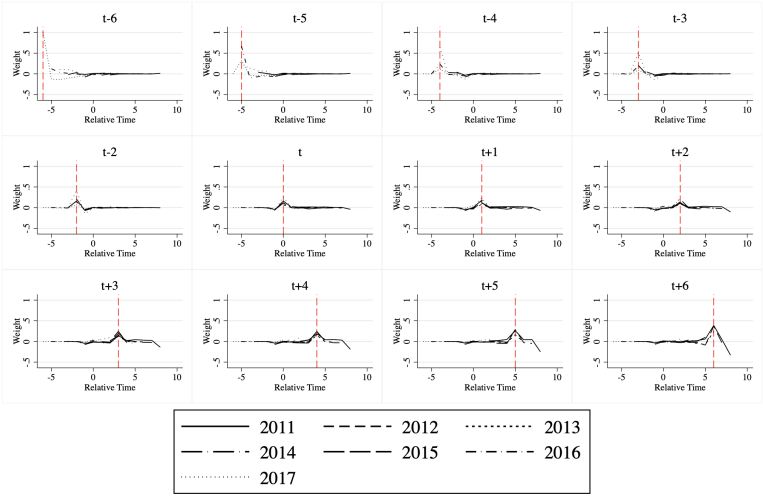
Notes: The figure plots the average maximum upload speeds by fiber, DSL, and cable respectively, in the event years before and after the arrival of fiber. To avoid measurement error in upload speeds from the NBM data I restrict to the years after 2013 and keep only the untreated blocks and those whose treatment occurs in 2014 or later. Go back to page 12.

Figure A.3: Effect of Fiber on Test Scores Using Interaction Weighted Estimator



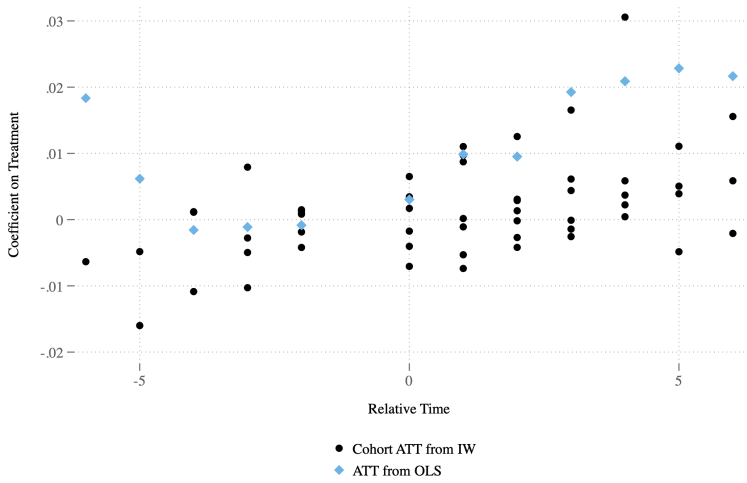
Notes: The figure plots the estimates of the effect of fiber on math and reading scores in the event years before and after the arrival of fiber. Panels (a) and (b) plots the coefficients from estimating the interaction weighted estimator proposed by Sun and Abraham (2021), where the control group is never treated students. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 20.

Figure A.4: Decomposition of Event-Study Weights



Notes: The figure plots the weights associated from estimating Equation 1 using eventstudyinteract (Sun and Abraham, 2021) for each treatment lead and lag. Each line plots the weights for each lead and lag in Equation 1 from the effect of being event years away from the arrival of fiber for a group treated at time t. Red dashed lines mark each own period. Go back to page 20.

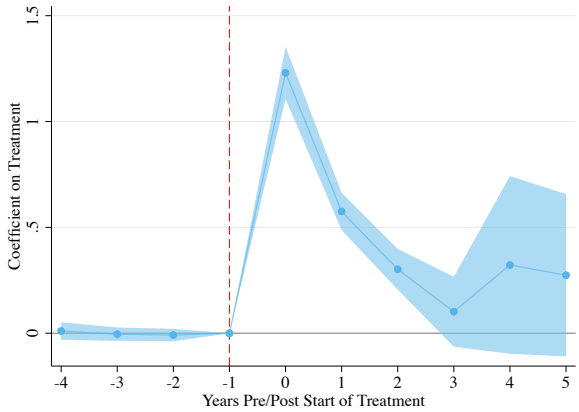
Figure A.5: DCDH and OLS Event-Study Estimates



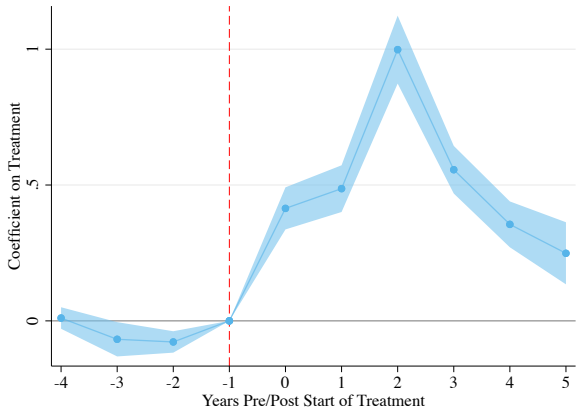
Notes: The figure plots the cohort-specific estimates from the interaction weighted estimator, as well as, the OLS estimates. Go back to page 20.

Figure A.6: First-Stage Effect by Technology Group

(a) Low-Tech



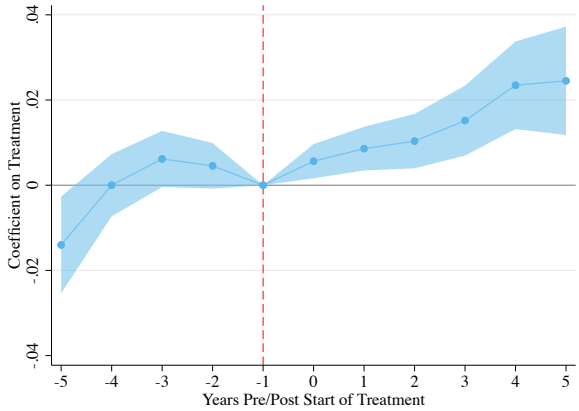
(b) High-Tech



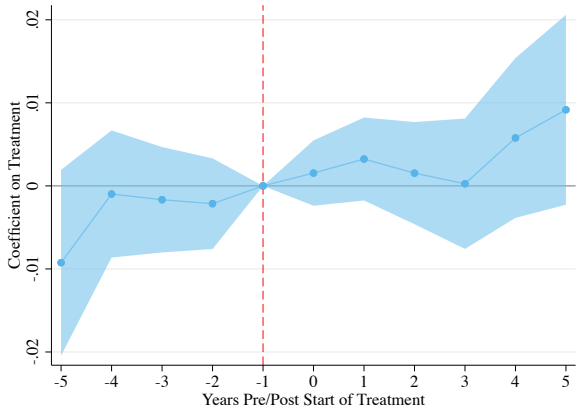
Notes: The figure plots the estimates of the effect of fiber on the inverse sine transformation of download speeds in the event years before and after the arrival of fiber separately by baseline technology. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for low-tech and high-tech areas respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 24.

Figure A.7: Effect of Fiber on Test Scores - Male

(a) Math



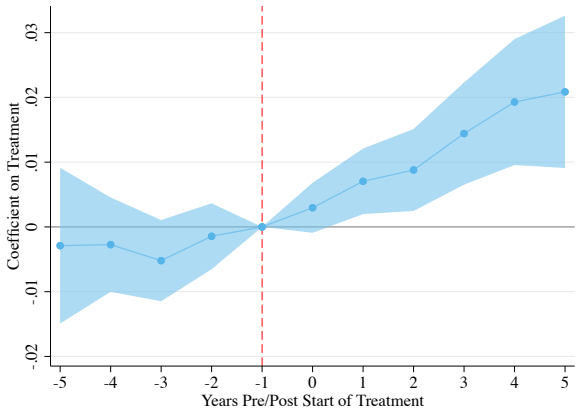
(b) Reading



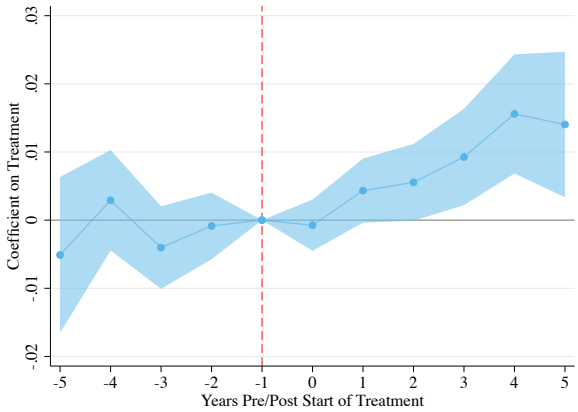
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for male students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.8: Effect of Fiber on Test Scores - Female

(a) Math



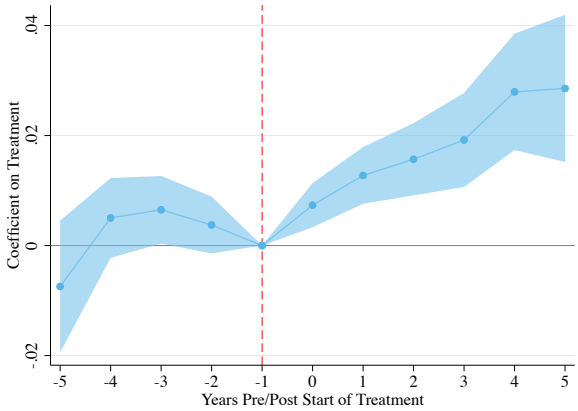
(b) Reading



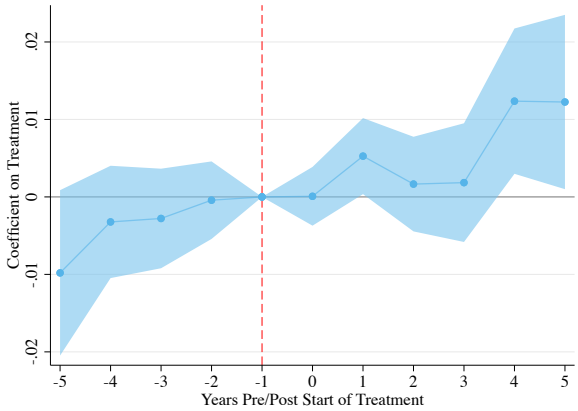
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for female students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.9: Effect of Fiber on Test Scores - White

(a) Math



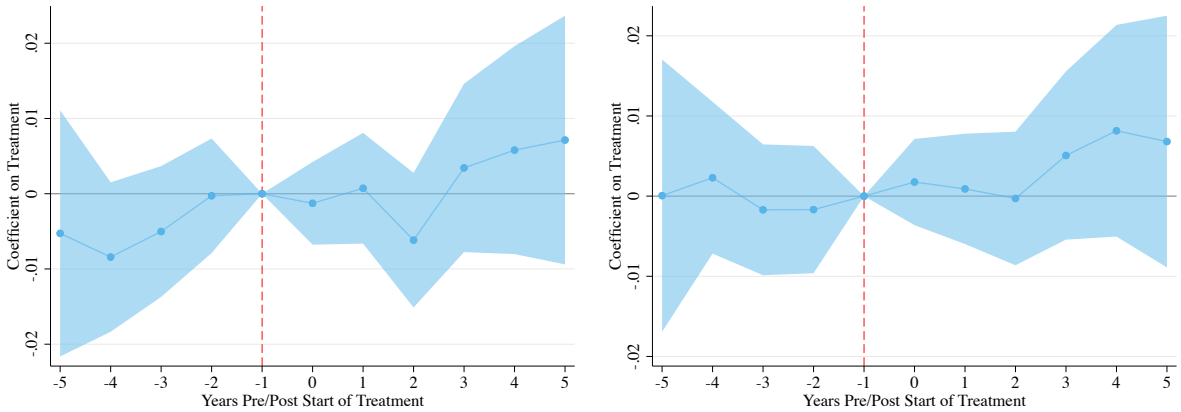
(b) Reading



The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for White students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.10: Effect of Fiber on Test Scores - Black

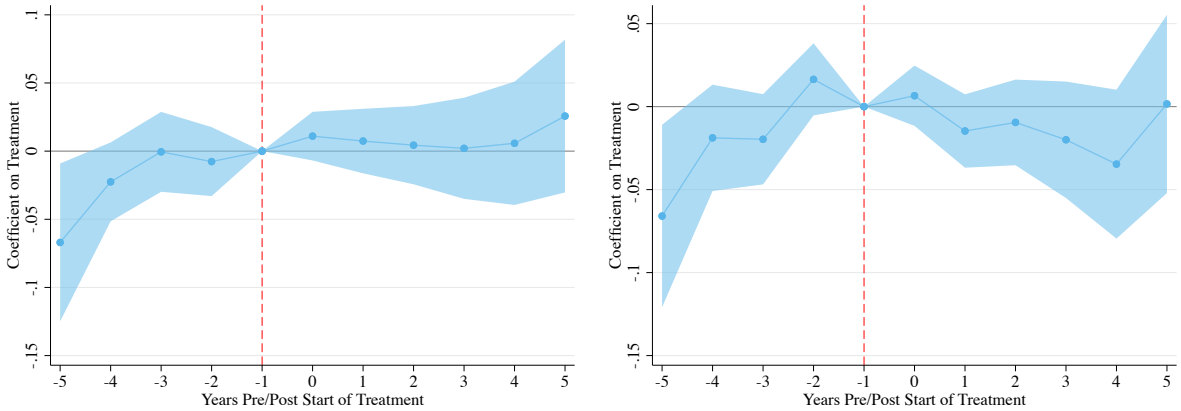
(a) Math (b) Reading



The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for Black students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.11: Effect of Fiber on Test Scores - Asian

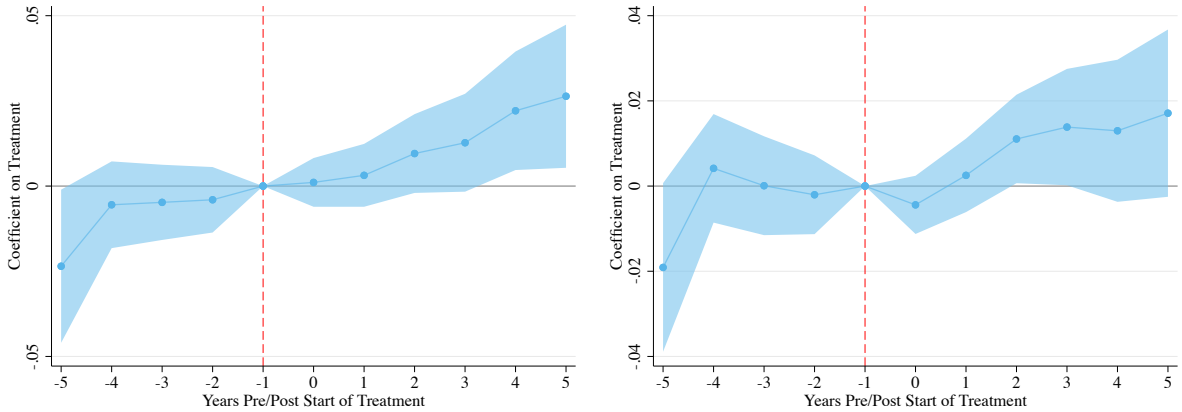
(a) Math (b) Reading



The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for Asian students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.12: Effect of Fiber on Test Scores - Hispanic

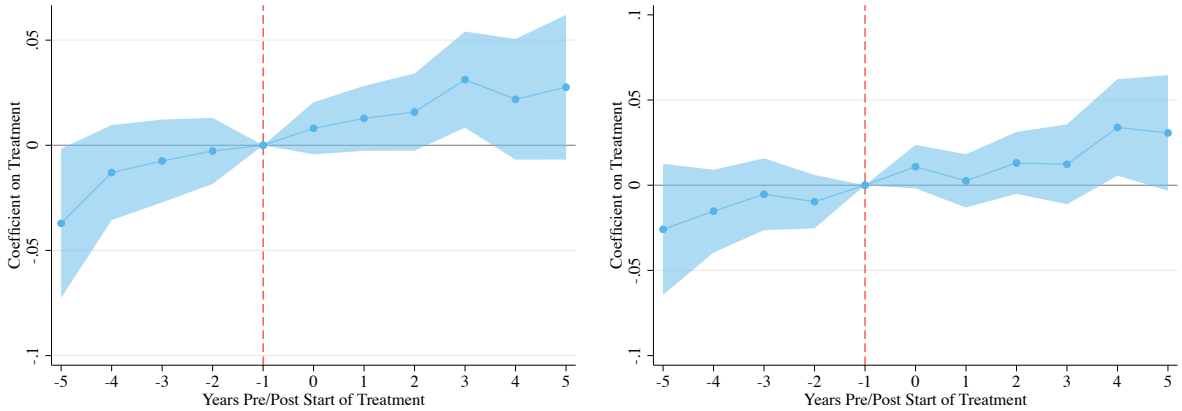
(a) Math (b) Reading



The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for Hispanic students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.13: Effect of Fiber on Test Scores - Other

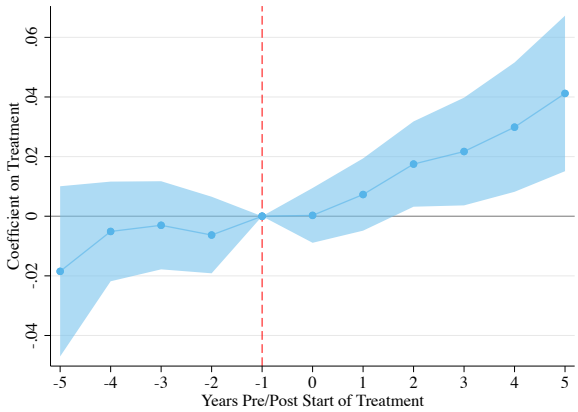
(a) Math (b) Reading



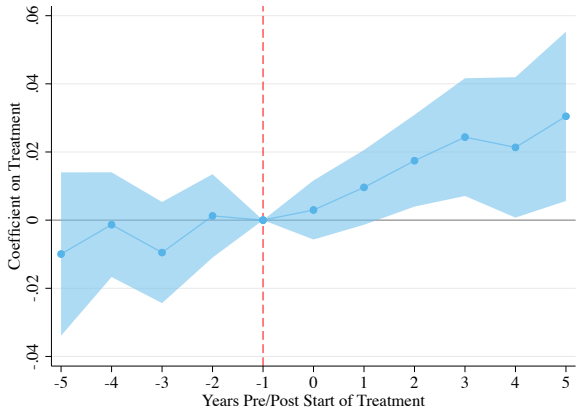
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for students of other races. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.14: Effect of Fiber on Test Scores - ELL

(a) Math



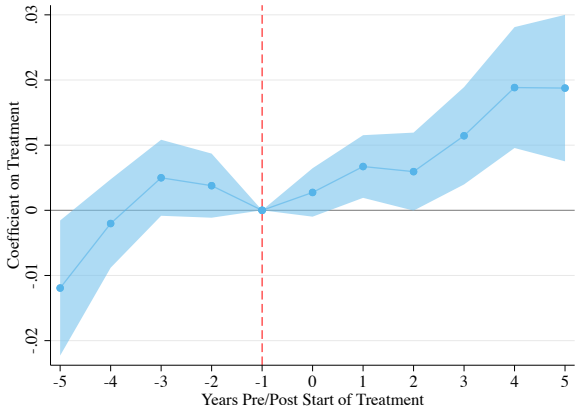
(b) Reading



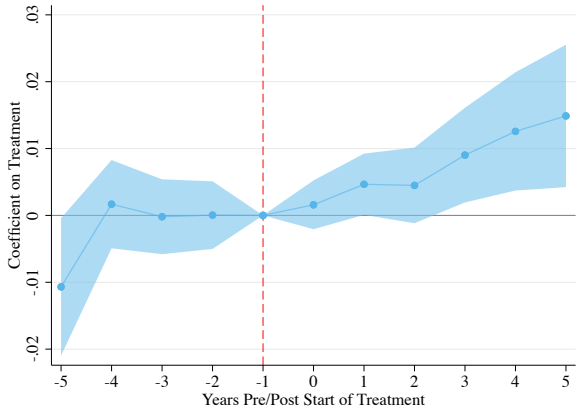
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for ELL students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.15: Effect of Fiber on Test Scores - Economically Disadvantaged

(a) Math



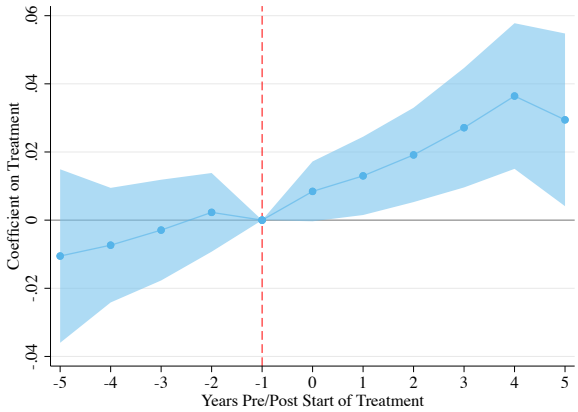
(b) Reading



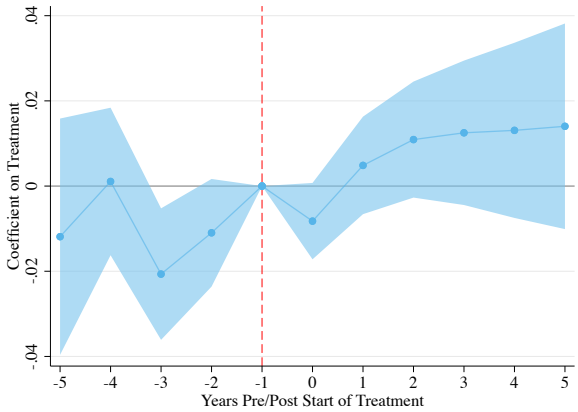
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for economically disadvantaged students. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.16: Effect of Fiber on Test Scores - Students with Disabilities

(a) Math



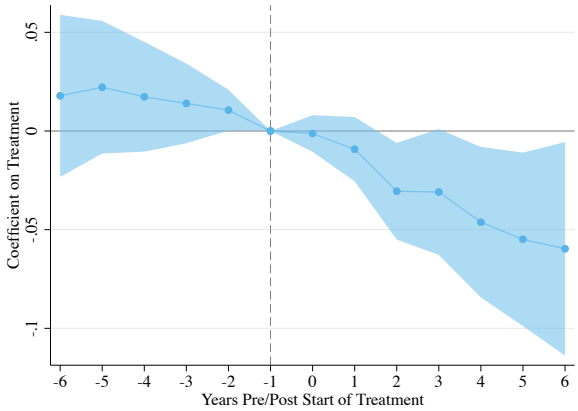
(b) Reading



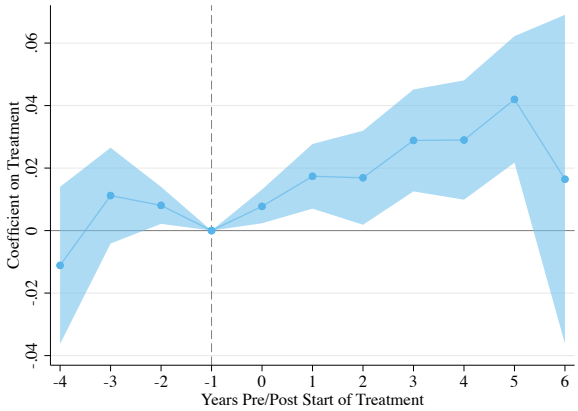
The figure plots the estimates of the effect of fiber on standardized math and reading scores in the event years before and after the arrival of fiber for students with disabilities. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 for math and reading respectively. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 22.

Figure A.17: Effect of Fiber on Aggregate Employment (LODES)

(a) OLS

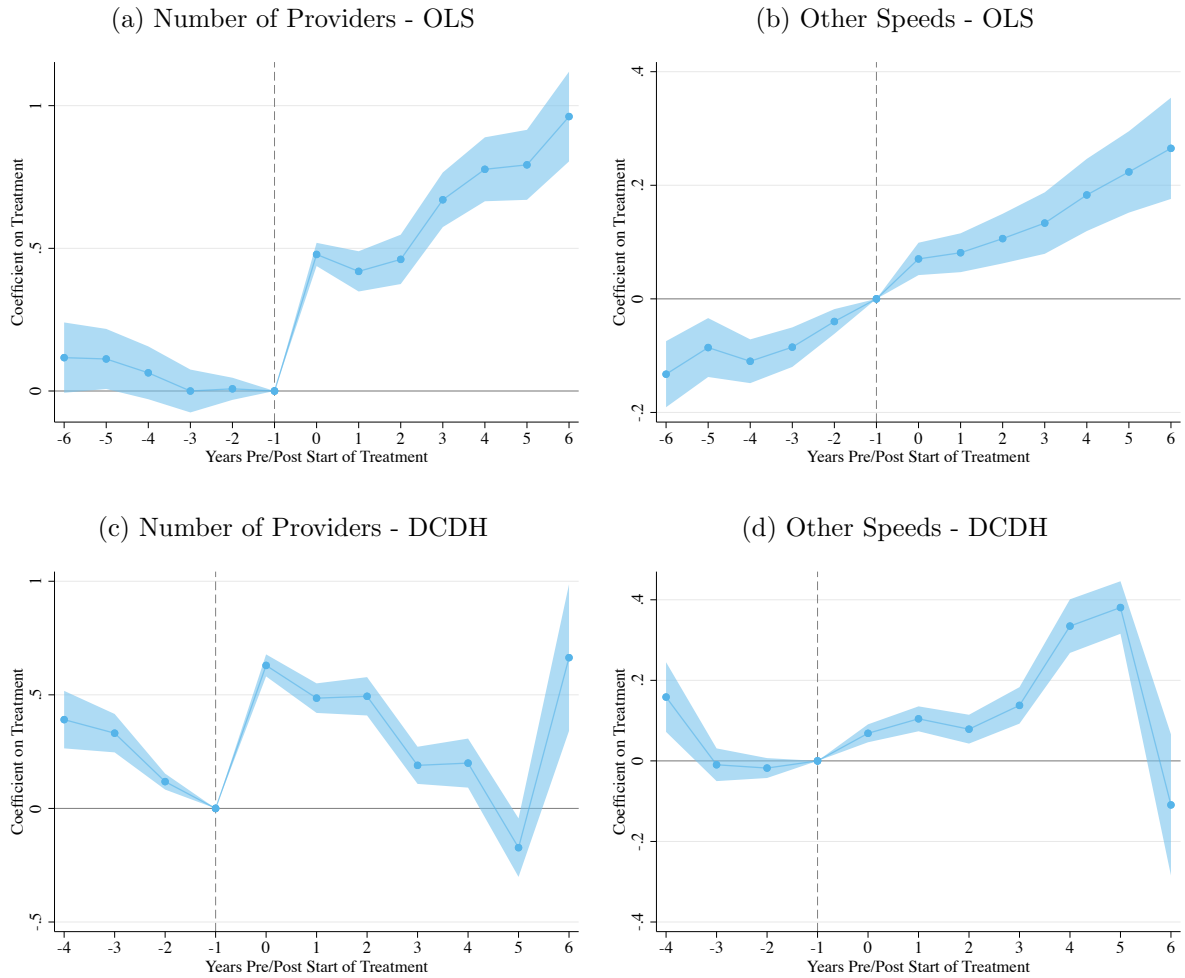


(b) DCDH



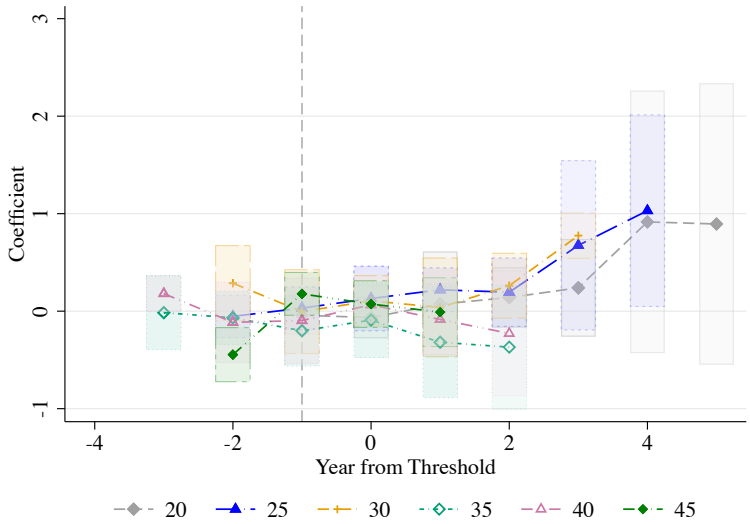
Notes: The figure plots the estimates of the effect of fiber on log employment in the event years before and after the arrival of fiber. Panels (a) and (b) plots the estimates of the β_τ coefficients from estimating Equation 1 and the DCDH estimator on log employment. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 24.

Figure A.18: Effect of Fiber on Number of Providers and Other Speeds



Notes: The figure plots the estimates of the effect of fiber on the number of providers and the download speed of other technologies in the event years before and after the arrival of fiber. Panels (a) and (b) plot the estimates of the β_τ coefficients from estimating Equation 1 for the number of providers in levels and the inverse sine transformation of the maximum download speed of all other available technologies. Panels (c) and (d) plot the analogous DCDH event-studies. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the census block group level. Go back to page 26.

Figure A.19: Effect of Fiber on Khan Academy Search Intensity Robustness



Notes: The figure plots the estimates of the effect of fiber on Khan Academy search intensity in the event years before and after the arrival of fiber for different thresholds of housing unit coverage. All estimates are using the DCDH estimator. The shaded regions give the 95 percent confidence interval where standard errors are clustered at the media market level. Go back to page 27.

B Tables

Table 7: Heterogeneous Effect of Fiber on Outcomes

	(1) Male	(2) Female	(3) White	(4) Black	(5) Asian	(6) Hispanic	(7) Other	(8) ELL	(9) Econ. Dis.	(10) Disability
					Math					
Fiber	0.010	0.014	0.015	0.005	-0.036	-0.004	0.016	0.006	0.005	0.020
	(0.0048)	(0.0036)	(0.0041)	(0.0035)	(0.0107)	(0.0054)	(0.0082)	(0.0063)	(0.0035)	(0.0062)
					Reading					
Fiber	0.011	0.010	0.011	0.008	-0.027	0.001	0.009	0.010	0.010	0.016
	(0.0032)	(0.0029)	(0.0025)	(0.0046)	(0.0188)	(0.0050)	(0.0071)	(0.0067)	(0.0043)	(0.0074)
					Maximum Download Speed					
Fiber	323.464	325.848	338.543	316.403	391.839	302.726	279.457	316.268	298.838	323.733
	(3.9249)	(5.3793)	(9.9012)	(7.9039)	(11.0379)	(10.4217)	(8.7577)	(10.8416)	(8.0051)	(7.3903)
Student FE	X	X	X	X	X	X	X	X	X	X
Tract-Year FE	X	X	X	X	X	X	X	X	X	X
N	2,584,185	2,588,966	2,596,140	1,325,743	147,593	859,051	302,051	553,131	3,218,194	522,299

Notes: Each estimate is a separate regression for the specific demographic group. Standard errors in parenthesis are clustered at the census block group level.
Go back to page 21.

Table 8: First-Stage Estimates by Baseline Technology

	(1)	(2)	(3)	(4)
	OLS		DCDH	
	Levels	Asinh	Levels	Asinh
		Low-Tech		
Fiber	173.42	1.15	377.75	1.85
	(20.31)	(0.07)	(41.81)	(0.19)
N				
		High-Tech		
Fiber	163.51	0.41	241.95	0.57
	(3.94)	(0.01)	(6.27)	(0.02)
Tract-Year FE	X	X	X	X
N				

Notes: DCDH are regressions estimated using the de Chaisemartin and D'Haultfoeuille (2022) estimator. Standard errors in parenthesis are clustered at the census block group level. Go back to page 23.