Cable and the Gender Gap in College Majors *

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Abstract

We examine the impact of gendered media representations on educational choices. We focus on computer science, which is highly paid, dominated by men, and yet had a higher female representation thirty years ago than today. We explore portrayals of computer science as an explanation, the exposure to which varied with the rollout of cable television in the United States. Creating a new dataset, we document variation in cable exposure by geography and birth cohort. We find that increased access to cable television is associated with a decline in women choosing computer science as a college major relative to comparable men. Thus, media likely plays a role in explaining gender differences in occupational sorting.

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1 Introduction

The gender wage gap, in which women earn less than men, continues to be a feature of the U.S labor market. Although the persistence of this gap is due to many factors, it is clear that an important one is occupation (Blau and Kahn, 2017; Goldin, 2014). Women are less likely to sort into higher-paid fields than men. One field where this is most evident is computer science, which is highly paid and yet dominated by men. However, the dominance of men in computer science was lower in the past than today. As shown in Figure 1, in 1983 the percentage of computer science majors who were women was almost twice that of 2010 (37% in 1983 versus approximately 17.6% in 2010). In part this is due to a reversal that is unique to computer science. Before the mid-1980s the percentage of female majors in computer science rose consistently, tracking trends in other Science Technology Engineering and Mathematics (STEM) fields. After the mid-1980s, however, the trend reversed and the number of female majors declined. Today the percentage of women majors in that field is less than half that of physical and biological sciences, mathematics and statistics (National Center for Education Statistics).[1]

What happened in the mid 1980s to lower the percentage of women going into computer science? This paper tests one theory for the change, which is that a rise in media portrayals of computer science as a profession for men discouraged women from entering the field (Cheryan et al., 2013).[2] In the early to mid-1980s, as computers became more widely available, television shows, commercials and, particularly, movies increasingly showed people using computers, but they were mostly boys and men. Meanwhile, the intensity of exposure to these media images was dependent upon access to cable television, whose expansion accelerated around the time that women's participation in computer science began to fall (see Figure 1 and Figure 2). The reasons for the timing of cable expansion are a relaxation in the late 1970s of federal regulation meant to protect local broadcasters combined with the advent of satellite broadcasting. Together these regulatory changes and technological advances improved cable operator's ability to

[1] For reference, see nced.ed.gov.

[2] We are grateful to Planet Money Episode 576: "When Women Stopped Coding" for introducing us to this argument.

provide content, spurring the subscriber growth necessary to justify large infrastructure investments.

To identify the impact of media exposure on the relative likelihood that women major in computer science, we construct a new dataset recording the expansion of cable television infrastructure through time. We compiled this dataset from industry publications from the 1960s through the 1980s that contain information on the providers, coverage, and date of initial service for all towns and cities in the United States. These data show a pattern of cable expansion that is difficult to explain in the absence of regulatory limits. For example, 56% of the largest 30 cities had no cable operator prior to 1979 and several had no operator until the mid 1980s (see Appendix Table A1). Given that large cities were the most attractive markets for cable operators, in the absence of regulatory limitations, they would have received cable access earlier (Parsons, 2008).

The subsequent rollout is unlikely to be driven by the computer science industry itself. During this time period cable had little industrial use, and we show that the timing of cable arrival is not correlated with the location of computer science jobs in the 1980s or 1990s. It also is not highly correlated with other factors that may be of concern, including the number or size of universities in an area, levels or changes in median household income, the total population, the college educated population, total employment and rates of home computer ownership. Instead the timing depended on the specific negotiations between cable operators, who were keen to expand into new markets, and local governments, who wanted to extract concessions in exchange for long term, and in many cases, monopoly franchise rights (Parsons, 2008). There is no clear factor that determined the success of these negotiations, or the speed at which cable operators built out their system after obtaining a license.

For many college educated individuals occupational choice begins with the selection of college major, and thus we combine our dataset on cable expansion with information on college major from the American Community Survey (ACS). We use geographic and birth year cohort variation to measure exposure to cable, based on the timing of the first entry of a cable operator. We define exposure as whether or not the area in which a person lives had a least one cable operator during their childhood or adoles-

cence (age 0 to 18). We then use a difference-in-differences model to estimate if exposure to cable affects the propensity of female college graduates to have a computer science major relative to men in the same geographic area and birth cohort.

We estimate the coefficients in our model using the imputation estimator of Borusyak et al. (2024) (BJS), given that there likely are heterogeneous, dynamic treatment effects. This is due to the fact that cable providers did not instantaneously build their systems after entering an area, leading potential exposure to cable to grow in years since entry. Meanwhile, the specific year treatment effects likely depend on when an operator began providing cable. Technological improvements in the 1980s and the associated growth in national cable channels (like HBO, CNN and MTV) allowed providers entering markets in later years to experience greater subscriber growth than those entering in earlier years. Recent literature has shown that in the presence of such effects, two way fixed effects models produce biased estimates of the average treatment effects, both in static and event studies (Roth et al., 2023).

Overall, we find that any exposure to cable television is associated with a decline in the probability that women have a computer science college major relative to comparable men. In our preferred specification, the gender gap increases by 77%. Women go from being 1.3 percentage points less likely to major in computer science than comparable men to 2.3 percentage points less likely. This is explained by a decline in the percentage of women studying computer science, but also an increase in the percentage of male college graduates who do. Thus, cable exposure had an opposite effect on each gender.

Our identification assumption is that any changes in the relative propensity of women versus men to sort into computer science (CS) are a function of exposure to cable television and not due to other time varying factors in a specific area that coincide with the rollout of cable. We provide evidence in favor of this assumption by showing that results are robust to the inclusion of state-birth year fixed effects, the inclusion of region-by-gender time trends, and excluding individuals born in a state different from their current residence. We also find that the results do not hold for foreign born individuals who arrived after age 18, which helps rule out differential selection as an explanation.

Furthermore, event studies provide little evidence that pre-existing trends explain our results. Relative differences in CS majors by gender did not exist prior to the arrival of cable television. The gaps begin after cable onset and grow with exposure. For example, the estimated impact of 11 years of cable access is almost twice as large as that of only 1 year.[3] For average years of exposure, which is six, the relative propensity declines by 67%. The event study also suggests the effects of years of exposure are nonlinear, as the size of the coefficients rises at seven years and stays roughly constant after that point. This coincides with individuals who were eleven years old when cable arrived, and suggests that exposure during the formative years of adolescence might be particularly relevant in influencing college major choice. This aligns with research that documents the importance of other pre-college factors on major choice (Anelli and Peri, 2015; Oguzoglu and Ozbeklik, 2016; Fischer, 2017; Anelli and Peri, 2019). It also is congruent with the fact that much of cable content during the time period we examine was not designed for children.

Meanwhile, event studies for other fields in STEM show that the negative effect of cable on women's propensity to major is unique to computer science. The same declining pattern of differences across gender do not hold for Biology, Chemistry, Physics and Mathematics. This partially alleviates concerns that cable arrival affects major choice through alternative channels, such as a change in high school science instruction or local demand for workers with STEM degrees. Overall, cable exposure *increased* women's relative propensity to major in any STEM field. This suggests that cable did not lead women to exit STEM altogether, but rather to shift out of CS and into other science related fields.

To better understand the particular relationship for Computer Science we investigate the specific channel of the content of cable programming and the extent to which this provided more images of boys and men using computers than girls and women. We do this by coding television guides for Home Box Office (HBO), the first national cable channel and the main one to show recent movies over the air

[3]The decline in the relative propensity of women to go into CS is 0.82 percentage points for one year, but 1.57 percentage points for 11 years.

(Mair, 1988). It was the primary way in which children and adolescents would have been able to see popular movies repeatedly. We catalog which movies portraying computers were shown most frequently to determine those that would have been available to cable subscribers. We then code the content of these popular movies using textual analysis of the scripts. We find that among the popular movies of the late 1970s and 1980s in which computers appear, 81% of the actions are done by men, while only 17% are done by women (the remaining percent are non-human entities, like robots). This indicates that some of the content shown over cable television during our period of interest did contain gendered representations of computer use. According to the HBO guides these movies were shown numerous times over many weeks and months, providing regular exposure to images of male dominated computer use. In our database on average, the movies were shown around 17 times, with an average showing of 1.55 times per day.

This project follows two strands of literature in economics. The first documents the patterns for low rates of representation of women in various STEM fields and offers several explanations (see Kahn and Ginther (2017) for a review). These include pre-college factors, such as preparation for STEM courses (Speer, 2017, 2023; Jiang, 2021), familial pressures (Anelli and Peri, 2015; Oguzoglu and Ozbeklik, 2016), peer effects at the pre-college level (Anelli and Peri, 2019; Fischer, 2017) and exposure to science programs or video games (De Philippis, 2023; Meza-Cuadra, 2023). They also include college level factors, such as sensitivity to lower grades (Rask and Tiefenthaler, 2008; Rask, 2008; Ahn et al., 2024), and differential sorting into majors based on the qualities and expectations about the economic and personal returns of related jobs (Aridiacono, 2004; Freeman and Hirsh, 2008; Zafar, 2013; Speer, 2020; Wiswall and Zafar, 2022). Finally, they include the impact of role models such as instructors or professors (Bettinger and Long, 2005; Carrell et al., 2010; Hoffmann and Oreopoulos, 2009; Rask and Bailey, 2002), alumni of programs (Porter and Serra, 2020) or female scientists (Breda et al., 2023).

The second strand of economics literature documents the influence that television more broadly and certain content specifically has on individual level outcomes. On the first point, the expansion of televi-

sion in the U.S has been found to lower labor force participation among retirement age adults (Fenton and Koenig, 2025), reduce voter turnout (Gentzkow, 2006), increase retail sales (Kim, 2022), and widen the wage disparity of entertainers (Koenig, 2023). On the second point, papers have documented the impact of a partisan cable news channel– Fox News– on voting behavior (DellaVigna and Kaplan, 2007; Martin and Yurukoglu, 2017), the preferences of voters and the policy decisions of local politicians (Ash and Galletta, 2023). With regard to gender, Jensen and Oster (2009); Chong and La Ferrara (2009); La Ferrara et al. (2012) find that exposure to shows with strong female protagonists impacts marriage, divorce, childbearing and household bargaining. Our paper contributes to this literature by examining the effect of cable television on the educational choices of women for a highly paid field.

The rest of the paper is structured as follows: in section 2 we provide information on cable regulation and expansion over time. In section 3 we provide detail on the mechanism of the content being shown over cable channels. Section 4 details the datasets constructed and used while section 5 explains our empirical strategy. Section 6 presents results of our static and dynamic (event study) models, as well as results for other STEM fields. Section 7 includes alternative specifications and robustness checks, and Section 8 concludes.

2 Background on Cable Expansion

Cable television started in the United States in the mid 1940s as a way to provide over the air broadcast signals to households in mountainous areas with poor signal reception. Cable continued to grow over the next decade, but primarily as a tool for rebroadcasting existing local channels. Cable operators provided little to no unique programming and technology limited their ability to provide programming from more popular local channels in other markets (for example, providing subscribers in New Jersey with New York City channels).[4] This meant cable television presented little competition to local television stations,

[4]Most local channels were affiliated with big broadcasting networks (NBC, CBS and ABC) and received the bulk of their programming from them. This was partially due to the fact that local channels lacked the scale to justify producing their own shows. However, local networks did produce some of their own programming. According to Mullen (2003) the bulk of local

and thus the Federal Communications Commission (FCC) exerted limited regulatory authority on it. Instead, most rules and regulations governing cable were set by local governments, who uniquely granted operators rights to place cable wires either under ground or over telephone lines (Stern, 1981; Crandall and Furchtgott-Roch, 1996).

The regulatory environment changed in the mid-1960s, as cable's increasing ability to provide content led it to be viewed as a threat by local television providers. In 1966 the FCC placed several limits on the industry, including: requiring cable operators to carry all local stations; prohibiting cable operators from carrying programs that duplicated those provided by local stations, even in hours when the local stations were off the air; and prohibiting the importation of distant signals by cable operators in the top 100 markets.[5] There were also limits on the amount and quality of unique programming cable operators could provide.[6] These rules reduced the ability of cable to offer more than existing broadcast television stations, lowering demand from consumers. Meanwhile, cable operators needed subscriber growth to justify the intensive capital investments involved with running cable lines across a city or town and into domiciles, and expansion fell.[7] These restrictions, particularly the ban on imported signals, had the largest effect on the top 100 markets, where an estimated two thirds of potential cable subscribers lived (Parsons, 2008). These markets were well served by existing local stations, which meant that cable operators had to offer unique programming to appeal to consumers (Stern, 1981). The ban on imported signals frequently is presented as a freeze on cable development in the top 100 markets (Straubhaar et

programming consisted of local news, coverage of local sports teams and old movies made available by Hollywood studios at a low cost.

[5]The importation of distant signal means importing stations from other cities or towns. The rule was designed to meet concerns among local channel operators about competition from larger markets. According to Mullen (2003) this fear is succinctly captured by one station owner in Montana, who stated in 1958 that "all tv can be obliterated except for two stations– one in New York and the other in Hollywood– brought to the populace of the United States via catv (cable tv) systems, boosters, translators and satellites" (page 38). It is worth noting that such technology did not exist until the mid 1970s.

[6]For example,.the FCC required cable broadcasters to make channels available for local public access and, in some cases, to provide the facilities for the production of local programming (a studio, for example) (Mullen, 2003). This was in line with the FCC's desire to maintain local programming and raised the costs for cable operators. It is important to note, however, that this did not lead to the development of high quality programming, as for most cable operators the subscriber base was too small to justify the costs of producing something on par with that of the main broadcast networks or studio movies.

[7]The construction costs of cable were significantly higher in large cities, as many required the lines to go underground. Parsons (2008) documents that the costs to lay a mile of cable were five to eight times higher in large markets than in smaller ones.

al., 2009; Mullen, 2003).[8]

Starting in 1972, court cases, growing political clout of the cable industry, and personnel changes at the FCC led to a gradual erosion of the earlier rules put in place, and by 1979 almost all federal restrictions on the amount and type of content cable operators could carry were removed. In addition, advances in satellite technology made it feasible to have national cable networks, as cable operators around the country could receive the same signal via satellite.[9] Satellite broadcasts and smaller, less expensive receivers lowered the cost to cable providers of providing additional programming, allowing them to expand. Thus by 1979 cable was poised to take off, particularly in large markets, as the FCC allowed operators to import distant signals and technological advances made it financially feasible to do so (Crandall and Furchtgott-Roch, 1996). The 1980s subsequently was marked by cable operators aggressively bidding for local franchises, most of which were long term and exclusive (Parsons, 2008). By the end of the decade, cable had reached most of the country.

3 Content of Cable Programming

The main channel through which people would have seen recent movies repeatedly in their homes was HBO. HBO began in 1972 with the aim of offering movies and live sports without advertising to paid subscribers. It directly negotiated with film studios to gain exclusive rights to movies after they left the theatre, allowing HBO to become the first cable channel to offer more than access to existing or imported local stations. It also was the first cable channel to broadcast its signal exclusively via satellite, amplifying its reach beyond a local area. The combination of exclusive content plus expanded range made HBO the first national cable channel (Mair, 1988). HBO's main competitor in terms of home access to recent movies was rented or purchased videos for use with a Videocassette Recorder (VCR)

[8] According to Parsons (2008), by 1979 in the top 25 markets, only 8 percent of households subscribed to cable.

[9] HBO broadcast the first cable satellite signal in 1975 (it was a Mohammed Ali boxing fight). This broadcast represented a major advance as it meant that the complex system of receivers along the route to enhance microwave signals was no longer necessary. Following HBO's launch, several other networks followed. For example, Ted Turner's TBS Superstation launched in 1976, Pat Robertson's Christian Broadcast Network in 1977, ESPN in 1979, and BET in 1980 (Mullen, 2003).

(Parsons, 2008). However, VCRs did not offer the same intensity of exposure to media images, as repeated viewing necessitated purchasing copies of videos. Several of these movies were rated PG-13 or R, and while we do not have data on videocassette purchases, it is unlikely many parents purchased these movies for their children to watch at will. Meanwhile, television parental controls did not begin until 1997, which means that during the time period we study it was difficult for parents to limit the television content their children viewed. As we document below, movies were shown repeatedly on HBO over several weeks and months, providing subscribers with the ability to watch the same movie numerous times.

We quantify the relevant content provided by HBO by creating a list of the frequently shown movies on the channel and by linking these movies to specific images surrounding computers. To do this we digitize monthly guides from HBO and its sister station, Cinemax, from the years 1979 to 1988. An example of a page in a guide is provided in Appendix Figure A2.[10] Each guide presents days and times for everything shown on a channel in a given month. Our database contains 30,752 showings, of which over 63% were movies that together accounted for over 77% of the screen time. From the list of frequently shown movies we select those listed on the IMDB website under the keywords "computer", "technology", and "science fiction". To verify the IMDb-filtered results, we used Wikipedia's list of "movies about computers", "movies about computing", "list of science fiction films of the 1970s", and "list of science fiction films of the 1980s".

We then obtain 51 of these movie scripts to analyze how characters interact with computers (listed on Appendix Table A2). We start by composing a list of keywords related to computer science (available in Appendix Table A3), and then create a text search algorithm program to identify film shots where these keywords appeared.[11] Our goals were to identify instances where a character needs to work with computers or exhibits strong understanding of them. For example, reading and understanding technical

[10] We gathered cable guides from the Barco library at the Cable Center and from purchases online.

[11] This program searched the script for these keywords and returned an interactive output with the script for scene direction that hints at a character working with technology.

output on screen; talking, presenting or explaining technical details; or discussing computer output with other characters. We did not include scenes where computers were simply in the background. For instance, scene direction may say "[character] works on computer." In this example, the program would ask the user whether we should count this case as an instance in which computer use is relevant. After confirmation, the program using a list of characters would then determine the character's identifying sex and calculate the proportion of time in the film in which each sex displayed computer skills or knowledge. Across the 51 movie scripts we analyzed, we coded 910 meaningful actions with computers. We found that 81% were by male characters, 17% by female characters and 2% by others (e.g. robots or machines). This confirms that the vast majority of meaningful actions with computers shown in movies during the time period we consider were done by male characters. Since our results could be sensitive to changes in key words and in approval criteria, we hired a different researcher who had not worked with the algorithm nor had access to the output of it, to watch five randomly selected movies from the list and manually code when they saw a character have a meaningful computer action.[12] We only had minimal differences between the script analysis results from the algorithm and those achieved by the researcher watching the movies. For example for the movie, "The Terminator" our algorithm recorded 93% male and 7% female actions; while our researcher recorded 89% male and 11% female actions. Importantly, both concluded that in these movies, male characters are much more likely to interact meaningfully with computers.

As to the timing of exposure to movies with dominant male use of computers, we graph the year of release for movies with any computer usage and the percentage of meaningful actions with computers done by men. As shown in Appendix Figure A1, there is a consistent stream of movies through the mid 1970s and 1980s where 80% or more of all computer actions are done by men. Thus, the incidence of such movies is not concentrated in any year, but instead stable across years. In terms of potential exposure via cable, all of these movies were shown on HBO or Cinemax, and usually were shown multiple times in

[12]The researcher had to record the characters' sex, and length of the action with a computer.

any given week or month. For example, in one month alone (February 1985), the movie War Games was shown 12 times. As a result, an individual growing up in a household with HBO could have experienced repeated exposure to images of male dominated computer use.

4 Data

4.1 Cable Data

The data on cable come from the Television and Cable Factbooks (hereby referred to as the Factbooks).[13] The Factbooks are cable industry publications that contain information for all cable networks in the U.S, including the date when these providers began service and total subscribers. We digitized five years of Cable Factbooks: 1968, 1973, 1978, 1983 and 1988.[14] The timing of cable expansion can be seen in Figure 2, which graphs the distribution of cable operators in the 1988 Factbook based on year of entry, from 1947 (the first year listed) to 1987 (the year before the publication). Vertical lines are placed in 1966, the date when the FCC implemented restrictive regulations; 1979, the date by which these regulations had been removed; and 1984, the date of the Cable Act, which fully deregulated the cable industry. The graph shows a clear slow-down in cable expansion following the 1966 regulations and a large increase following their relaxation in 1979. Indeed, entry is the highest during the 1980 to 1984 period in our data. As of the 1988 Factbook, 45% of registered operators began in 1980 onward.

Major cities also provide clear examples of the slowdown in cable expansion in large markets after 1966. Appendix Table A1 shows arrival dates for all operators in the largest 30 cities in the U.S.[15] More than half of the cities (17 out of 30) have no cable operator prior to 1979 and some cities, like Detroit, Baltimore and Washington D.C., did not get a cable operator until 1986. Furthermore, among the cities

[13]These data were used by Waldman et al. (2012) on autism and by DellaVigna and Kaplan (2007) on the effects of Fox news on voting.

[14]We also use a secondary source of information for places that appear in the 1988 Factbook but have a missing start date. This is the Broadcasting Cablecasting Yearbook (hereby referred to as the Yearbook) from 1988, another cable industry publication which we digitized.

[15]We took these rankings as of the 1990 U.S Census: www2.census.gov/library/working-papers/1998/demographics/pop-twps0027/tab22.txt

that did have an operator prior to 1979, almost all have additional operators entering from 1980 onward. This suggests that the existing operators did not cover the whole city and that additional operators helped meet subscriber demand. Given that these large cities are the most attractive markets for cable operators, in the absence of regulatory limitations, they likely would have received cable access earlier.

Although entry into larger cities after 1979 was driven by federal regulatory changes, local factors play a larger role in the timing of entry into markets after that point. The concern is that places that got cable sooner exhibited other trends, such as a greater demand for male computer scientists than female ones, that led to more sorting of men into CS in these areas. Although we cannot entirely rule out this story, several things make it unlikely that it drives our results. First, as documented in (Parsons, 2008), the "franchise wars" that took place after 1979 contain no clear story of which areas received cable earlier or later. Cable operators were eager to enter lucrative, big city markets, but the timing of entry to a specific market depended on negotiations with local authorities, who were keen to extract concessions (such as revenue sharing, the provision of studio facilities, or agreement to connect less affluent parts of a city) in exchange for long term, and in many cases, monopoly franchise rights. It also depended on the structure of the city and on a cable operator's ability to obtain financing to build the network.[16] All of these factors varied case to case, with the result that the same cable operator entered multiple cities at different times.[17]

Second, our time frame predates the use of cable lines for internet service and thus covers a period when cable television was almost entirely a consumer good. Given limited industrial use, from a firm perspective, cable availability would have been appealing only as an area amenity available to workers. Third, as shown in the Appendix, there is an economically insignificant correlation between the arrival of cable operators and multiple factors that might be predictive of differential demand for CS majors. This

[16] L.A. for example, is made up of numerous localities, each of which had its own process for granting cable licenses. Meanwhile, some cities required operators to run cable lines underground, which was more expensive.

[17] For example, (Parsons, 2008) notes that one factor that improved a cable operator's chance of obtaining a license was local support, ideally in the form of a community member with influence on the city council. In a scheme called "rent-a-citizen" cable operators would offer equity stakes to these individuals, sometimes even lending them the funds to purchase the shares.

includes the log of median household income and population in 1980 and their growth between 1980 and 1990, the size or change in the college educated population for these same years, and the number or size of colleges and universities in a county (see Appendix Table A4). It also includes total employment as of 1980 and employment growth between 1980 and 1990, and total computer science jobs, either as a percentage of the total nationwide or as a percentage of county level employment (Appendix Table A5).[18]

Finally, the timing of cable rollout is not significantly correlated with rates of household computer ownership at the state level (Appendix Table A6). These data come from the Computer and Internet Use supplement of the October 1984 and 1989 Current Population Surveys (as accessed through IPUMS, Flood et al. (2024)), and are the only data we are aware of with information on computer use during this time period.[19]

4.2 Outcome Data

For outcomes we focus on college major. This is a decision most people make between the ages of 18 and 22 and therefore is more closely linked to experiences in childhood and adolescence than choices made later in life, such as occupation. For information on college major we use the American Community Survey (ACS), as accessed through IPUMS (Ruggles et al., 2023). We use all ACS samples from the year 2009, when the survey began collecting data on college major, to the year 2022. The main advantage of the ACS is that it contains information on college major and is a large sample, representative of the entire U.S population. As a result the ACS provides high levels of geographic and birth year cohort variation, allowing us to model cable exposure based on when cable arrived in different locations and how many

[18]For this we examined the correlation between years of cable in a county and the number of colleges and universities and total enrollment from the 1988 IPEDS data. For computer science jobs, we use the 1980 and 1990 U.S Census, as accessed through IPUMS. For each census year, we calculate the percentage of all computer science jobs in the country located in a county and the percentage of all jobs in a county that are in computer science. We also calculated the change in the log of these values over the two census years. There is no significant correlation between any of these variables and the number of months cable had been in operation as of 1988.

[19]The CPS data are only available at the state level. We therefore calculate various statistics of years of cable at the state level, including the mean, median and maximum number of years for all counties in the state.

years of childhood were covered by any operator. The main disadvantage, however, is that the ACS is a cross-section and contains little information on people's residential history. Specifically, the ACS tells us where people currently live, but not much on where they grew up. This is sub-optimal, but we are unaware of any dataset that has wide geographic and birth cohort coverage and detailed information on where individuals grew up.[20] Therefore, our results are best interpreted as estimates of the intent to treat, as opposed to treatment on the treated. In section 7.1 we show our results are robust to various controls for selection bias due to migration, including removing those born outside their state of residence and only including foreign born individuals who arrived after age 18.

To map individuals to cable operators we use the current county of residence.[21] In the cases where places listed in the Factbook span more than one county, we select the most populous one to match to the ACS.[22] At the individual level, we limit the sample to people with a bachelor degree or higher. Since our interest is in variation in exposure to cable television during childhood, we also restrict the sample to people born in the U.S between 1950 and 1970. The first computer science undergraduate degree programs in the U.S began around 1968, and thus the 1950 birth cohort would be among the first cohorts to be able to choose computer science as an undergraduate major.[23] Meanwhile, the 1970 birth cohort turned 18 in 1988, at which point all counties in our data had a least on cable operator. Thus years after this point provide no untreated group for comparison.

[20]To the best of our knowledge, the private version of the PSID is the only dataset that has this information, which would allow us to see the trajectory of individuals from childhood to adulthood and link them to cable operators across time. The sample size and geographical coverage however is much more limited in comparison to the ACS.

[21]While the cable data are at the level of place (for example Poughkeepsie, NY or Denver, CO) the ACS does not include this level of detail. The closest possible match would be Core Based Statistical Areas (CBSA), but these definitions of metropolitan areas span state lines and thus include multiple local governments that granted cable licenses. Since local governments had exclusive discretion over granting cable licenses, adjacent areas could face different timing and numbers of cable operators. For example, exposure to cable television likely looked different in Manhattan than in Jersey City, New Jersey– two areas that are included in the New York City CBSA but are in different states.

[22]The ACS has missing county data for approximately 40% of our sample. In the case where an individual lives in an MSA and has missing county data, we impute the county based on the largest one within the MSA and state. For example, for observations in Albuquerque, New Mexico, we assign Bernalillo County. Observations with imputed counties account for approximately 10% of our final sample. In Appendix Table A7 we estimate our main results excluding these imputed observations. The sign and size of the coefficients are almost equivalent to those of our main sample, showing that our conclusions are not driven by imputed counties.

[23]Purdue is credited with being the first U.S university to launch computer science department in 1962. However, a computer science undergraduate degree was not approved until 1967 (History of the Purdue Computer Science Department).

Summary statistics from our ACS sample are provided in Table 1. They clearly show gender gaps in sorting into STEM fields, as women are less likely than men to have majored in any of subjects in the table. For computer science, as shown in the first row of Panel A, 1.6% of female college graduates in our sample had a computer science major, compared with 3.6% of male college graduates. Thus on a relative basis men are 125% more likely to have a computer science degree than women. The gender gaps are less extreme for some of the other STEM fields like Biology and Mathematics. Here men are 42% and 38% more likely than women to major in these subjects, respectively. On the other hand, the gender gaps are more extreme for Engineering and Physics, where men are 757% and 700% more likely than women to major in these subjects.

We graph changes in sorting into computer science over time in Figure 3. This shows the percentage of all male college graduates or female college graduates who turn 18 in a given year who eventually have a computer science degree. The graph shows a clear widening of this gap for cohorts who turn 18 after the early 1980s. For example, in the cohort that turned 18 in 1971, the year before HBO launched, 1.89% of male college graduates have a computer science degree compared to only 0.74% of female college graduates. In other words, in 1971 women are 1.17 percentage points less likely than men to have a computer science degree. By 1983 this gap grows to 2.9 percentage points and by 1988 it grows to 3.3 percentage points. Thus, over a period of approximately twenty years, the gap in sorting into computer science close to doubles.

The widening gender gap in sorting into computer science degrees is the result of two phenomena. First, the rates at which male college graduates enter computer science increase faster before 1981 and decline less after that point. Second, the rates at which female college graduates enter computer science rises less quickly and declines by more. For example, from 1968, when the first computer science programs began, to 1988, the end of our sample, the percentage of male college graduates who get a computer science degree increases by 3.5 percentage points. For female graduates, the increase is only 1 percentage point– approximately three times smaller. It is this change in trends we aim to explain.

5 Empirical Strategy

We model cable treatment at the county level based on the maximum of either the first arrival date of any cable operator or the beginning of HBO in 1972. For example, if the first cable operator arrived in a county in 1980, then the county is considered as "treated" starting in that year. Meanwhile, if the first cable operator arrived in 1968 we consider the county as "treated" in 1972. We use the HBO start date as the minimum because this marks the beginning of national cable channels and the provision of content, such as recent movies, that went beyond local, over the air stations. Prior to this, cable operators provided the same content as local television. Thus their presence did not provide the intensity of content exposure that HBO (and later cable channels) brought. For comparison, however, we also consider a measure of exposure using the original first arrival date.

We then construct a variable $CableAvailable_{lt}$ which equals 1 if cable arrived in county (l) before a birth year cohort (t) turned 18 and 0 otherwise. Treatment therefore is defined as a birth cohort having more than zero years of childhood and adolescence with the potential presence of at least one cable operator. Consider the example of Oklahoma City, where cable entered in 1980. Individuals born before 1962 turned 18 in or before 1980, which means that none of their childhood or adolescence was covered by cable. This puts them in the control group. Meanwhile, individuals born in or after 1962 would have some part of their childhood covered by cable, placing them in the treatment group.

We estimate college major choice as a linear function of cable exposure as follows:

$$\begin{aligned} CSM_{glt} &= \beta_0 + \beta_1 Female_g * CableAvailable_{lt} + \beta_2 Female_g \\ &+ \beta_3 CableAvailable_{lt} + \psi_l + \delta_t + \epsilon_{glt} \end{aligned} \tag{1}$$

Where CSM_{glt} is the average percent of college graduates of gender g, in county l and birth cohort t, who have an undergraduate major in computer science. Thus our outcome variable is the proportion of male and female college graduates, respectively, who major in computer science. For example, one cell

would be women born in 1971 who live in Harris County, Texas. $Female$ takes a value of 1 for female averages and 0 for male ones. We include county fixed effects (ψ_l) to control for time invariant county characteristics, such as industrial composition. We include birth year fixed effects (δ_t) to control for common shocks across individuals within a year, such as changing interest in computer science relative to other majors. In some of the estimations we also control for within state time trends by birth year by including year of birth interacted with state fixed effects. This would control for things like changing exposure to computer science through school curricula or employers that are general to all counties in a state. Standard errors are clustered at the county level.

Our coefficient of interest is β_1, which represents the differential effect of any exposure to cable television in childhood and adolescence on the probability that women choose a computer science major relative to comparable men. The key source of variation to identify this impact comes from the birth year and county variables. For example, consider two pairs of men and women born in 1968. One pair was born in Chicago, where cable started in 1980. The other pair was born in Detroit, where cable started in 1986. The Chicago pair had six years of potential cable exposure by age 18, while the Detroit pair had zero. We compare the probability that the Chicago woman has a computer science degree relative to the Chicago man, considering this same relative difference for the Detroit woman and man. Our strategy therefore compares women and men within the same birth cohort and county, which allows us to account for the fact that, say, the 1968 and/or Chicago cohort exhibited different propensities to major in CSM.

The identification assumption underlying our approach is that changes in the relative propensity of women and men to major in computer science across locations in the specific years we examine are due to cable television. Alternative stories would have to explain why changes in gender sorting into computer science across locations coincide with the timing of the first operator entering an area. Continuing with our example above, another factor would have to explain why a separation in relative propensities to major in computer science between Chicago and Detroit began in 1980. In essence, the concern is that the timing of cable entry is linked to alternative factors that also may explain a deviation in trends. While

we cannot completely rule this out, in section 4.1, we argue the timing is fairly random to negotiations between local governments and cable operators. We also show the timing is not highly correlated with local level factors that might capture alternative mechanisms, such as the location of computer science jobs, college education rates, or home computer ownership. Nevertheless, in later sections we examine this possibility in more detail.

We estimate the coefficients of the model using the imputation estimator of Borusyak et al. (2024). This estimator is preferable to an OLS one (also referred to as two way fixed effects (TWFE)), because we have staggered timing of cable entry and the possibility that the treatment effects are heterogeneous and dynamic (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). Heterogeneity arises from the fact that cable operators do not instantaneously build out their systems once they enter a market. Instead operators grow their subscriber base over time, leading possible exposure to cable to be higher the longer cable operators have been in an area. This problem is compounded by the likelihood that treatment effects also are dynamic, as they depend on treatment onset. In other words, not only do cable treatment effects increase over time, they also likely increase in calendar years. For example, treatment one year after cable arrival probably is not the same in areas that received cable in 1980 as those that received cable in, say, 1984. This is due to technological advances in satellites and receivers, which lowered costs for cable operators, and increased the number of national cable channels. Cable operators entering markets later in the 1980s could offer more channels and add subscribers more rapidly than those that entered earlier. As indicated by Sun and Abraham (2021), in the face of such effects TWFE results are difficult to interpret due to the possibility of negative weights that arise when using an already treated group as a comparison group. This likely will lead TWFE estimators to underestimate the negative impact of cable (Roth et al., 2023).

To address these possible issues we implement the robust and efficient estimator in the presence of heterogeneous and dynamic treatment effects proposed by Borusyak et al. (2024) (BJS). We choose the

BJS estimator over other ones because it uses both never treated and not yet treated groups as controls. This is preferable to estimators that only use never treated units as the comparison, as we have few untreated counties (cable eventually reaches all areas) and many fully treated birth cohorts. For comparison, we also present TWFE results for the sample that is used in the BJS estimation.

6 Results

6.1 Static Model: Main Specification

The results in Table 2 indicate that any cable exposure negatively impacted the relative probability that women majored in computer science. Panel A presents results using 1972 as the minimum start date for cable while Panel B presents results using the actual start date, not adjusted for the entry of HBO in 1972. We begin with the coefficient on cable availability, which speaks to the impact of exposure on men. This coefficient is positive and, in three out of four estimations, significant. This shows that exposure to cable increased the likelihood that men majored in computer science. This is in line with Figure 3, in which men became increasingly likely to sort into computer science while women did not.

Meanwhile, the coefficient on the interaction term of female and any exposure to cable television is negative and significant in all of the estimations. The coefficient from our preferred model, in column (3), is -0.0101. This means that for men and women in the same birth cohort and county, any exposure to cable caused the gender gap in having a computer science degree to increase by 1.01 percentage points (pp). This effect is large and constitutes a 77 percent increase over the gap prior to the arrival of cable. In other words, women in birth cohorts with any childhood or adolescence exposure to cable television are 2.3 percentage points less likely to major in computer science relative to comparable men, while women with no potential exposure are only 1.3 percentage points less likely to do so.

The estimates presented above capture the impact of *any* potential exposure to cable television in childhood and adolescence. However, it is reasonable to think the impact might vary depending on the total number of years of exposure. In particular, exposure in adolescence may be important, given that

much of the programming on cable television at the time was not destined for children. For example, many of the movies whose content we code in Section 3 are rated PG-13. We therefore turn to event studies to estimate the impacts for distinct years of potential exposure.

6.2 Dynamic Specification: Event Study

In this section we use event studies to estimate the impact of different years of potential exposure to cable television. These also provide support to our identification assumption. Specifically, our difference-in-differences estimators produce unbiased estimates of the Intent to Treat Effect (ITT) under the assumption that the propensity to major in computer science would have trended similarly for women and men growing up in the same areas in the absence of cable television. To give credence to this assumption, we estimate the following equation:

$$\begin{aligned} CSM_{glt} &= \beta_0 + \sum_{h=-16, h\neq 0}^{14} \gamma_h \mathbf{1}(t=h) * \mathbf{1}(CableExposure_l = h) \\ &+ \sum_{h=-16, h\neq 0}^{14} \lambda_h \mathbf{1}(t=h) * \mathbf{1}(CableExposure_l = h) * Female_g \\ &+ \beta_1 Female_g + \gamma_l + \delta_t + \epsilon_{glt} \end{aligned} \tag{2}$$

Where (g) denotes aggregates at the gender level since we collapse the individual data for males and females at the county (l), birth year (t) level. Our coefficients of interest are the λ_h, which estimate the difference of CSM propensity of women relative to men as a consequence of cable exposure for each year. The indicator of the year before cable arrived in a location is omitted, which normalizes estimates of λ_h to zero in the year before the event. If the introduction of cable adversely affected the probability women chose a computer science major relative to men, the coefficients on λ_h after cable entered will be negative. If the exact timing of cable entry and thus increasing exposure matters, these negative coefficients should grow as the number of years increases. Meanwhile, the λ_h coefficients in the pre-period checks for the existence of a pre-trend in the relative probability that women major in computer science. If there was no difference in these probabilities prior to the arrival of cable television, these

coefficients will be zero in this specification.

We again estimate the coefficients using the imputation estimator of Borusyak et al. (2024), given that the presence of dynamic effects could lead OLS estimates to vary from the average treatment effects (Sun and Abraham, 2021). The results in Figure 4 indicate a negative relationship between exposure to cable television and the probability that women major in computer science relative to comparable men. All of the λ_h coefficients in the post period are negative and significant at the 95% level. Their size also increases in years. For example, the estimated coefficient on one year of cable exposure is -0.0082, while the coefficient on 11 years is -0.0157. The first group would have been 17 when cable first arrived (1 year of exposure), while the second group would have been 7 (11 years of exposure). The coefficients suggest that the negative gender sorting effect of cable is twice as large for the second group than the first one.

The event study also suggests that the effects of years of potential cable exposure are not linear, as the size of the coefficients rises at seven years and stays roughly constant after that point. This coincides with individuals who were age 11 when cable arrived, and confirms that adolescent exposure is more important than early childhood exposure. We further explore this possibility by considering alternative measures of potential cable exposure in Section 7.

In terms of reconciling our results with the static model, the average years of exposure for those with non-zero values is approximately six (see Table 1). This coincides with individuals who were 12 when cable arrived. The estimated coefficient for this group is -0.0087, which is slightly smaller, but within a similar range as the estimate from the static model (-0.0101 from our preferred specification). The estimated effect remains economically significant, constituting a 67% increase in the gender gap in sorting into CS.

Regarding the pre-trends, the λ_h coefficients in the pre-period are close to zero and statistically insignificant. Therefore there is no evidence of relative differences between men and women in majoring in computer science prior to the arrival of cable. The absence of evidence of a pre-trend combined with

evidence that the negative effects of exposure grow over time alleviate some concerns that our results are spurious, simply capturing a deviation in sorting that would have happened anyway. In section 7 we provide further checks for spurious time trends.

6.3 Other STEM Fields

Before considering alternative specifications, we estimate event studies for other STEM majors. We do this to address the concern that cable exposure negatively affected the probability that women majored in any STEM field, not just computer science. If this is the case, the channel through which cable arrival operates might be something else that occurred around the same time, like a change in high school science instruction or local demand for workers with STEM degrees. We therefore consider other STEM majors, including Mathematics, Biology, Chemistry, Physics and Engineering.[24][25]

The results, in Figure 5, show that none of the other fields follow the trend exhibited by Computer Science. Years of cable exposure are associated with no change in the relative probability that women major in Physics or Mathematics, and are associated with an *increase* in the relative probability that women major in Biology and Chemistry. In other words, exposure to cable increased rather than decreased the relative propensity of women to choose the last two majors.

The one field that shows any significant decline is Engineering. Here the relative probability that women major declines significantly in some years of exposure. One explanation is that that during our period of study various types of engineering were perceived as more computer intensive than the lab intensive fields. For example, many Computer Science departments grew out of, and remain housed in engineering schools. This has been put forth as a possible explanation for fewer female CS and engineering majors (Camp, 1998). We cannot test if individuals saw engineering as a complement to or a substitute for CS, but we conclude that something unique indeed occurs between cable exposure and the

[24] We code STEM field using 2 digit degree field codes in the ACS. We include Engineering, Biological and Life Sciences, Mathematics and Statistics and Physical Sciences.

[25] In our original estimations we include Computer Engineering in Engineering rather than Computer Science. As shown in Section 7.1 our results are robust to including it in computer science.

propensity of women to go into that field for two reasons. First, for Engineering the negative coefficients are insignificant in many years and do not increase in years of exposure, as they do for CS. Second, the relative change in sorting is much lower than for CS, given the dramatically higher pre-period sorting gap (women were 9.9 percentage points less likely to have an Engineering degree than men). Thus any change in the relative sorting gap is smaller for engineering than CS.

In total, these results confirm a unique relationship between cable exposure and the relative propensity of women to go into Computer Science. Was this decline enough to shift women out of STEM fields entirely? The results in the last panel of Figure 5 show it was not, as years of potential exposure to cable do not lead to declines in the relative propensity that women major in any STEM discipline. This suggests that women shifted into other STEM fields, in particular Biology and Chemistry, as they shifted out of CS.[26] The extent to which cable programming is responsible for this, by showing positive images of women in these lab related science fields, is beyond the scope of our paper. However, it is an interesting area for future research.

7 Alternative Specifications

In this section we consider alternative specifications of our model. Despite the fact that the event studies do not show a differential pre-trend between men and women's propensity to major in CS, to further explore the effects of cable from a trend, we estimate two additional versions of our model. By doing so, given the inclusion of birth-year fixed effects, we run the risk of overfitting the model and having the trend absorb part of the treatment effect. However, acknowledging that we are demanding much of the data, in the first version, we include Census Region time trends separately by gender.[27] The results are shown in columns (1) and (2) of Table 3. Second, we instead use decade of birth fixed effects interacted with a female dummy variable. These results are shown in columns (3) and (4) of Table 3. All coefficients

[26] We find similar results when we estimate a static model using other fields, as shown in Appendix Table A8.

[27] We use four Census Regions, where the West is our left our region. We then construct a linear time trend and interact this with the remaining regions for men and women.

on the female cable exposure interaction terms remain negative, confirming the negative relationship between cable exposure and the propensity that women choose a CS major relative to comparable men. As expected, however, we lose precision and only the TWFE are statistically significant. The size of the coefficients is also smaller; in column one (-0.0022) it is approximately 20% of the size as our main one. These results are informative in providing a potential lower bound on our estimates.

Next, we explore continuous measures of potential exposure to cable television. This complements the event study results, but considers a model in which exposure has a linear, rather than a non-linear, effect. We consider two such measures. First, we use a variable that measures years of cable exposure (0-18) rather than an indicator for any exposure to cable. Second, we use subscriber accounts per capita as of the year when an individual turns 18 (and accounts per capita weighted by the percentage of years from 0 to 18 which were covered by any cable operator).[28] Subscribers per capita exhibit greater variation across areas than years of cable exposure, but it also is more likely to be correlated with local area changes that may explain differential sorting into CS (for example, increases in income). For this reason, this is not our preferred measure of exposure, and we view these results as secondary to our main ones.

The results are reported in Table 4 and also show a decrease in the relative propensity of women to major in CS when exposed to cable. The magnitude of the effect shows that a decline in women sorting into CS majors of around 0.14 percentage points (columns 1-4). This constitutes an 11 percent increase in the sorting gap. If multiplied by the average potential exposure of 6 years (from age 12 to age 18), we arrive at estimates very similar to those reported in Table 2.

7.1 Robustness

In this section, we conduct robustness checks using alternative samples, the definition of computer science, and the timing of cable rollout. We begin with movers, since we are only able to link people to

[28] We construct annual, country subscriber account numbers by using the five Cable Factbooks (1968, 1973, 1978, 1983 and 1988) and calculate five year growth rates to interpolate the missing years. To convert these into per capita values, we use county population data from the National Cancer Institute Surveillance, Epidemiology, and End Results Program (SEER) and the 1960 Census (1968 must be interpolated).

cable expansion using their current place of residence as opposed to where they grew up. The concern is that the timing of cable rollout is correlated with the evolution of jobs in computer science, and that our results capture differential selection into areas in the United States. While we find no evidence of this when looking at County Business Pattern data (see Appendix Table A5), we assess this possibility in two ways. First, we estimate the robustness of our results to the exclusion of movers, defined as individuals who do not reside in their state of birth.[29] This removes 52% of the sample, and yet the results for CSM, that appear in the first panel of Figure A3, show coefficients that are very similar to our main ones. The same is true for other college majors (see Appendix Figure A4), suggesting any bias from movers might be small.

Second, we limit the sample to foreign born men and women who arrived in the U.S after the age of 18. These individuals likely had no childhood exposure to local cable providers in their current place of residence. Thus, any relationship between their propensity to major in CS and cable could be indicative of selective sorting into locations. However, as shown in the second panel of Figure A3 we find no relationship between cable rollout and the relative propensity that foreign-born women have a computer science degree. This reduces the concerns that selection drives our results.

We also estimate the model by limiting the sample to individuals in top 100 markets, which were the areas that experienced the greatest increase in cable access after regulatory changes in the late 1970s. Despite the fact that we might expect the effects to be larger in these places, we again find coefficients that are very similar as our main ones (panel 3 of Figure A3). Following this we consider a more expansive definition of Computer Science major, which includes "Mathematics and Computer Science" and "Computer Engineering" (panel 4) and an alternative start year for HBO of 1975 (panel 5), which is the date of its first broadcast. In all cases we see no major changes in our results, indicating that our findings are not sensitive to the particular definition of a computer science major nor the start year for

[29]IPEDS Data from Fall 1992 indicate that 80 percent of all college freshman that graduated from high school in the past 12 months attended college in their home state. This number may have been even higher in earlier years due to transportation and communication costs acting as barriers to moving (Hoxby, 2009).

HBO.[30]

8 Conclusion

We examine if differential exposure to cable television affected the propensity of women to go into computer science, a field that is highly paid and where male dominance has increased over time. The theory is that as computer science grew as a field, movies and television increasingly showed computer use, but mostly by boys and men. Meanwhile, exposure to these images likely varied geographically in the U.S as regulatory changes and technological advancement dramatically increased cable expansion in the late 1970s and 1980s. We document this expansion by constructing a new dataset on cable expansion from industry publications, and estimate if years of potential exposure to cable television affected the probability that female college graduates have computer science degrees relative to comparable men. We find that cable did have a negative impact, decreasing the probability that female college graduates went into computer science while increasing the probability that male college graduates did. Our evidence does suggest that cable exposure can explain a portion of the rising gap in sorting into computer science.

Results from our project contribute to research that explores drivers of occupational sorting by gender and the role this plays in explaining wage differentials between men and women. Media portrayals are just one part of this story, and may not even be a dominant factor in explaining these gaps. However, from a policy perspective media representations may be less costly to change and potentially may reach more people. This is evidenced by recent efforts like the Google Computer Science in Media intervention (Smith et al., 2017), which worked directly with Hollywood studios to increase portrayals of women in computer science. As such, it is important to better understand the role media might play. Along these lines our paper contributes to new data collection efforts to document the effect of media on various individual level outcomes.

[30] In results available upon request, we estimate the model at the individual level (as opposed to the birth-year cohort county level), as this allows us to include individual control variables, such as whether individuals have a bachelor or graduate degree, their race, and an indicator for Hispanic origin. The results are consistent with our original ones.

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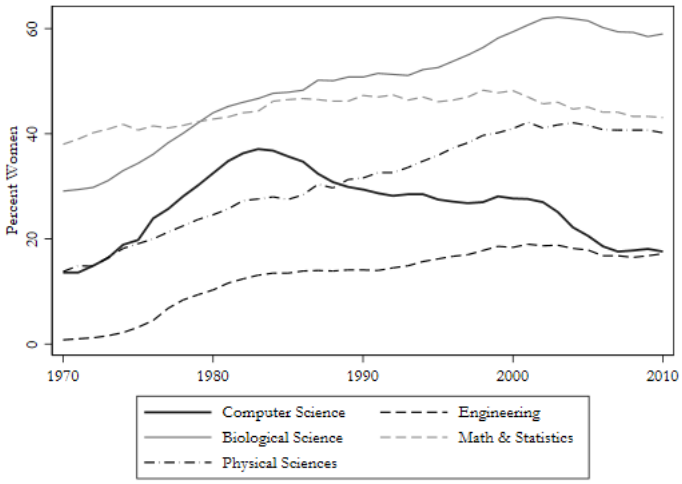
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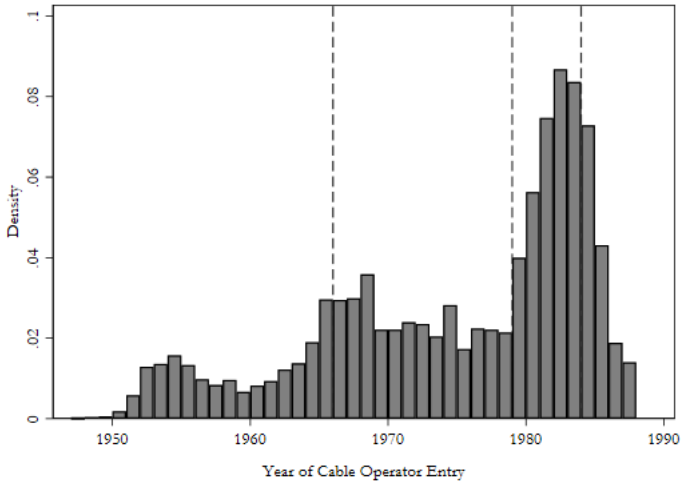
9 Figures and Tables

Figure 1: Proportion of graduates in each field who are women



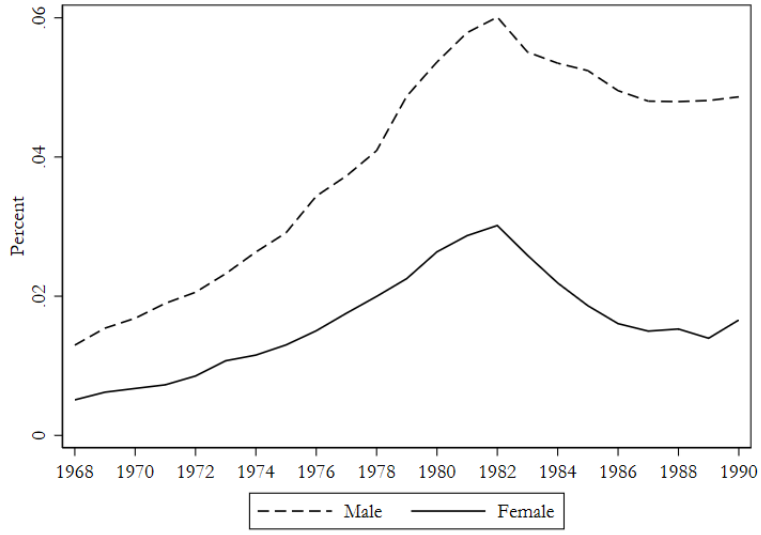
Note: Percent is calculated as the number of female degree recipients in a given field over the total degree recipients in that field. Unlike the other STEM fields, the proportion of female graduates in Computer Science exhibits a strong decline starting in the early 1980s.
Source: National Center for Education Statistics.

Figure 2: Evolution of Cable Operator Entry 1940-1988



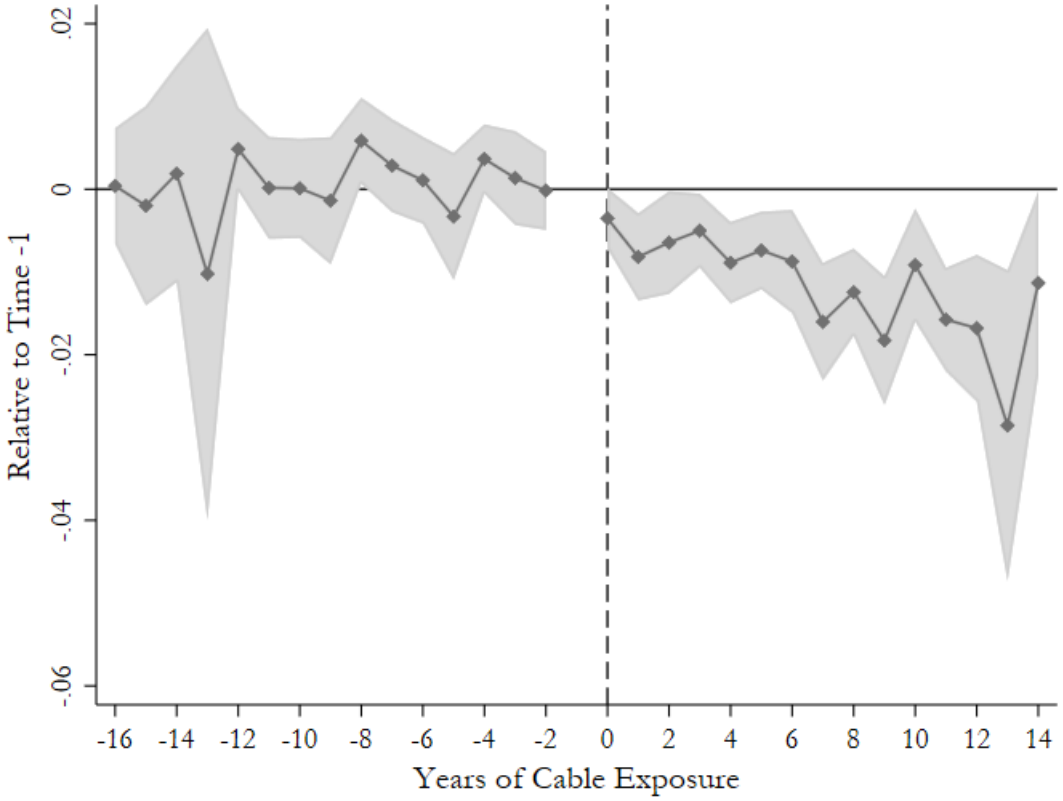
Note: Vertical lines placed in 1966 (the FCC placed limits on the cable industry), 1979 (FCC allowed cable operators to import distant signals) and 1984 (*The Cable Communications Policy Act* eliminated local and federal restrictions). See section 2 for more information.
Source: Cable Factbook 1988.

Figure 3: Proportion of college graduates with a computer science degree



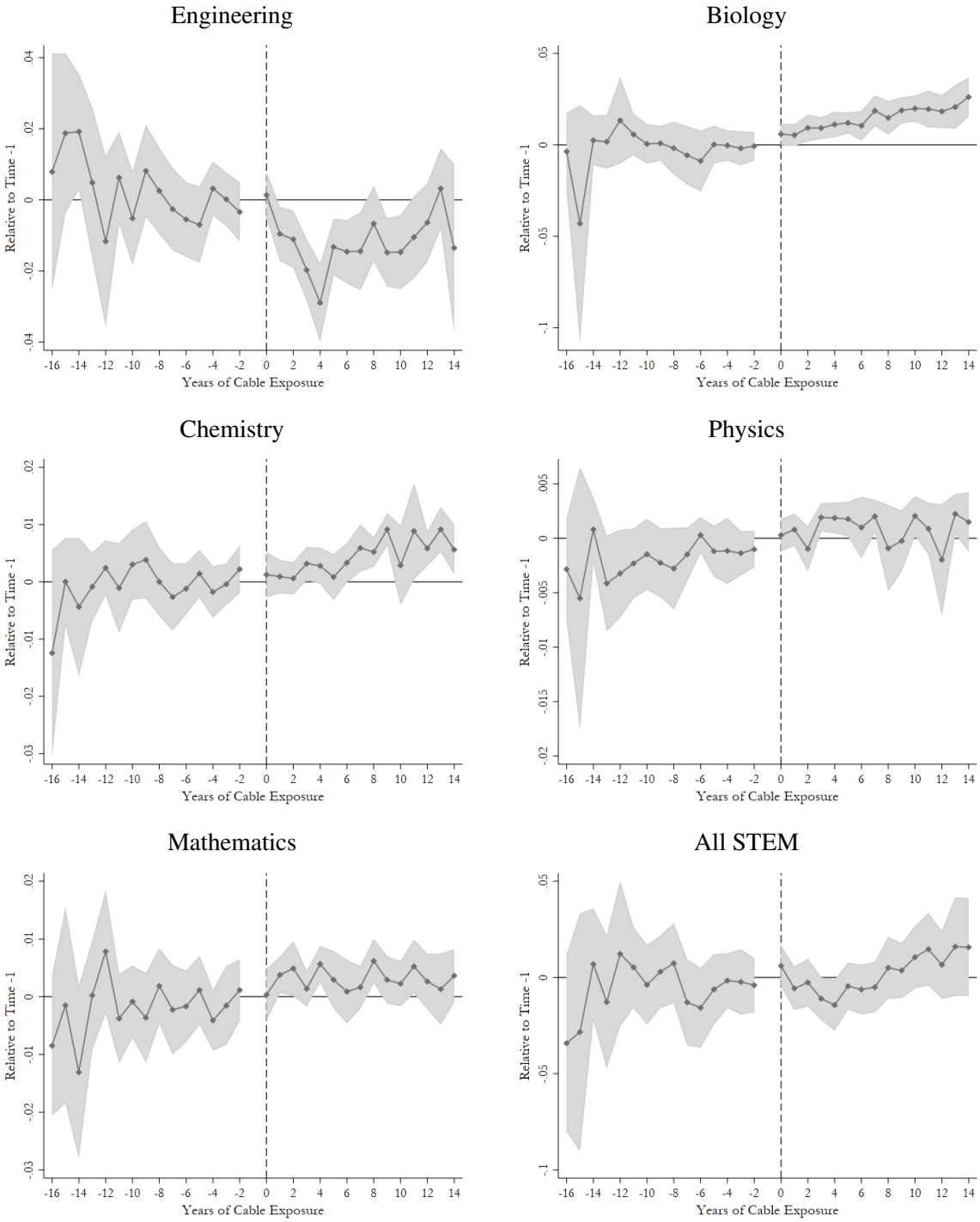
Note: Each line is the percentage of female and male college graduates, respectively, with a computer science degree. Starting in the late 1970s the gap between the two lines widens. The x-axis is the year in which each cohort turned 18.
Source: American Community Survey 2009-2022.

Figure 4: Event Study, Computer Science Major



Note: Regression adjusted estimates with 95% CI for the female interaction term of CS for birth cohorts from 1950 to 1970. See section 6.2 for equation and further information.
Source: ACS for 2009-2022 and 1988 Cable Factbook.

Figure 5: Event Study: Other STEM Fields



Note: The figure shows regression adjusted estimates with 95% CI for birth cohorts 1950-1970. See section 6.2 for equation and further information.
Source: ACS for 2009-2022 and 1988 Cable Factbook.

Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) Mean	(4) SD
	Female		Male	
Panel A: College Major				
Computer Science	0.016	0.127	0.036	0.187
Mathematics	0.013	0.113	0.018	0.132
Economics	0.011	0.104	0.029	0.168
Chemistry	0.006	0.080	0.016	0.125
Physics	0.001	0.033	0.008	0.086
Biology	0.033	0.178	0.047	0.211
Engineering	0.014	0.118	0.120	0.325
Panel B: Cable				
Yrs Cable Exposure	6.119	3.667	6.071	3.659
Accounts per cap.	0.062	0.069	0.061	0.068

Note: Individual level data summary statistics reported for ease of exposition. Sample restricted to people born in the U.S between 1950 and 1970 with a bachelor degree or higher. $N_{female} = 1,074,542$, $N_{male} = 993,544$. Weighted values reported. Panel A reports among male and female college graduates what proportion in each group has a degree in each discipline. Panel B reports statistics for measures of cable exposure using HBO start date, conditional on years being greater than zero. Henceforth we will use data collapsed at the county birth-year level.
Source: Cable Factbook for 1988. ACS data for 2009-2022 accessed through IPUMS.

Table 2: County-Birth Year Level Regressions for Cable Available

	Outcome: Computer Science Major			
	(1)	(2)	(3)	(4)
	TWFE		BJS	
Panel A: HBO start date				
Female*Cable Available in County	-0.0101***	-0.0077***	-0.0101***	-0.0078***
	(0.0011)	(0.0014)	(0.0011)	(0.0014)
Cable Available in County	0.0058***	0.0053***	0.0041	0.0035**
	(0.0014)	(0.0016)	(0.0026)	(0.0016)
Female	-0.0126***	-0.0126***	-0.0126***	-0.0126***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Observations	18,388	14,504	18,388	14,505
Pre-treatment Mean Female	0.0097	0.0096	0.0097	0.0096
Pre-treatment Mean Male	0.0227	0.0223	0.0227	0.0223
Pre-treatment Difference	-0.0130	-0.0127	-0.0130	-0.0127
Panel B: Cable start date				
Female*Cable Available in County	-0.0107***	-0.0077***	-0.0106***	-0.0078***
	(0.0014)	(0.0019)	(0.0014)	(0.0019)
Cable Available in County	0.0046***	0.0045**	0.0040	0.0028
	(0.0017)	(0.0021)	(0.0033)	(0.0031)
Female	-0.0144***	-0.0144***	-0.0144***	-0.0144***
	(0.0011)	(0.0011)	(0.0010)	(0.0011)
Observations	11,902	9,081	11,902	9,081
Pre-treatment Mean Female	0.0114	0.0113	0.0114	0.0113
Pre-treatment Mean Male	0.0264	0.0259	0.0264	0.0259
Pre-treatment Difference	-0.0150	-0.0147	-0.0150	-0.0147
Birthyear FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Birthyear-State FE	No	Yes	No	Yes

Note: The outcome is the average incidence of a computer science major for a given birth-year, county and gender cohort. All regressions are population weighted and include county fixed effects. Panel A present results using 1972 as the minimum start date for cable while Panel B presents results using the actual start date, not adjusted for the entry of HBO in 1972. Treatment is coded as having at least one year of childhood exposure to cable. Standard errors are reported in parentheses and clustered by county. We restrict the TWFE models to the observations used by the Borusyak et al. (2024) (BJS) estimator.
Source: Cable Yearbook 1988. ACS data for 2009-2022.

Table 3: Alternative Specifications Allowing for Different Trends by Gender

	Outcome: Computer Science Major			
	(1)	(2)	(3)	(4)
Female*Cable Available in County	-0.0022	-0.0048***	-0.0017	-0.0036**
	(0.0023)	(0.0015)	(0.0022)	(0.0014)
Cable Available in County	0.0000	0.0031**	-0.0001	0.0025
	(0.0032)	(0.0016)	(0.0032)	(0.0016)
Female	-0.0069***	-0.0088***	0.0046	0.0008
	(0.0012)	(0.0009)	(0.0033)	(0.0018)
Observations	18,388	18,388	18,388	18,388
Pre-treatment Difference	-0.0130	-0.0130	-0.0130	-0.0130
*Female*Cohort Trend*	Yes	Yes	No	No
*Female*Region*Trend*	No	No	Yes	Yes
Estimator	BJS	OLS	BJS	OLS

Note: All regressions include birthyear and county fixed effects. The outcome is the average incidence of a computer science major for a given birth-year, county and gender cohort. Columns (1) and (2) include female age cohort, defined by decade, trends. Columns (3) and (4) include Census region time trends, separately by gender. Standard errors are reported in parentheses and clustered by county.

Source: Cable Yearbook 1988. ACS data for 2009-2022.

Table 4: County-Birth Year Level Regressions for Alternative Measures of Cable Exposure

	Outcome: Computer Science Major					
	(1)	(2)	(3)	(4)	(5)	(6)
	Years, HBO start date		Years, Cable start date		Accounts per cap.	
Female*Yrs Exposure	-0.0014***	-0.0015***	-0.0014***	-0.0014***		
	(0.0002)	(0.0003)	(0.0002)	(0.0004)		
Yrs Cable Exposure	0.0005**	0.0003	0.0007**	0.0005		
	(0.0003)	(0.0004)	(0.0003)	(0.0005)		
Female* Accounts					-0.0196**	-0.0115
					(0.0077)	(0.0071)
Accts. per pop					0.0164	-0.0006
					(0.0120)	(0.0075)
Observations	18,388	14,504	11,902	9,081	17,924	14,152
Pre-treatment Difference	-0.0130	-0.0128	-0.0150	-0.0147	-0.0128	-0.0126
Birthyear FE	Yes	No	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Birthyear-State FE	No	Yes	No	Yes	No	Yes

Note: The outcome is the average incidence of a computer science major for a given birth-year, county and gender cohort. All regressions are population weighted and include county fixed effects. Columns (1)-(4) measures years of cable exposure (0-18). Columns (1) and (2) present results using 1972 as the minimum start date for cable. Columns (3) and (4) presents results using the actual start date, not adjusted for the entry of HBO in 1972. Columns (5) and (6) use cable subscribers accounts per capita as of age 18. Standard errors are reported in parentheses and clustered by county.

Source: Cable Yearbook 1988. ACS data for 2009-2022.

Appendix

Table A1: Year of Cable Arrival for Top 30 Cities

City	Years of Arrival
1. New York, NY	1967
2. Los Angeles, CA	1957, 1961, 1967, 1980, 1981, 1986, 1987
3. Chicago, IL	1980, 1984, 1985, 1986
4. Houston, TX	1979, 1980
5. Philadelphia, PA	1972, 1986, 1987
6. San Diego, CA	1962, 1963
7. Detroit, MI	1986
8. Dallas, TX	1982
9. Phoenix, AZ	1960, 1981
10. San Antonio, TX	1979
11. San Jose, CA	1968
12. Baltimore, MD	1986
13. Indianapolis, IN	1979, 1981
14. San Francisco, CA	1953
15. Jacksonville, FL	1979
16. Columbus, OH	1971, 1973, 1978
17. Milwaukee, WI	1984
18. Memphis, TN	1976
19. Washington, D.C.	1986
20. Boston, MA	1982
21. Seattle, WA	1962, 1983
22. El Paso, TX	1972
23. Cleveland, OH	1966, 1987
24. New Orleans, LA	1982
25. Nashville, TN	1979
26. Denver, CO	1979, 1983
27. Austin, TX	1963
28. Fort Worth, TX	1982
29. Oklahoma City, OK	1980
30. Portland, OR	1952, 1982

Note: City designations from the 1990 Census.

Source: 1988 Cable Factbook.

Table A2: List of Movies Used in Script Analysis

1	”2010”	18	Highlander	35	Steel Dawn
2	2001: A Space Odyssey	19	Killer Klowns from Outer Space	36	Strange Brew
3	A Nightmare on Elm Street 3: Dream Warriors	20	License to Drive	37	Superman III
4	Above the Law	21	Looker	38	Telefon
5	Airplane!	22	Megaforce	39	The Final Countdown
6	Airplane II	23	Metalstorm	40	The Fly
7	Alien	24	Outland	41	The Philadelphia Experiment
8	Back to the Future	25	Performance	42	The Stuff
9	Blade Runner	26	Running on Empty	43	The Terminal Man
10	Brainstorm	27	Scanners	44	The Terminator
11	Brazil	28	Serpent and the Rainbow	45	The Thing
12	Cloak and Dagger	29	Short Circuit	46	Three Days of the Condor
13	Damnation Alley	30	Somewhere in Time	47	Wall Street
14	Die Hard	31	Soylent Green	48	Wargames
15	Dreamscape	32	Star Trek: The Motion Picture	49	Watchers
16	F/X	33	Star Wars: Episode V - The Empire Strikes Back	50	Wolfen
17	Heartbeeps	34	Star Wars: Episode VI - Return of the Jedi	51	World Gone Wild

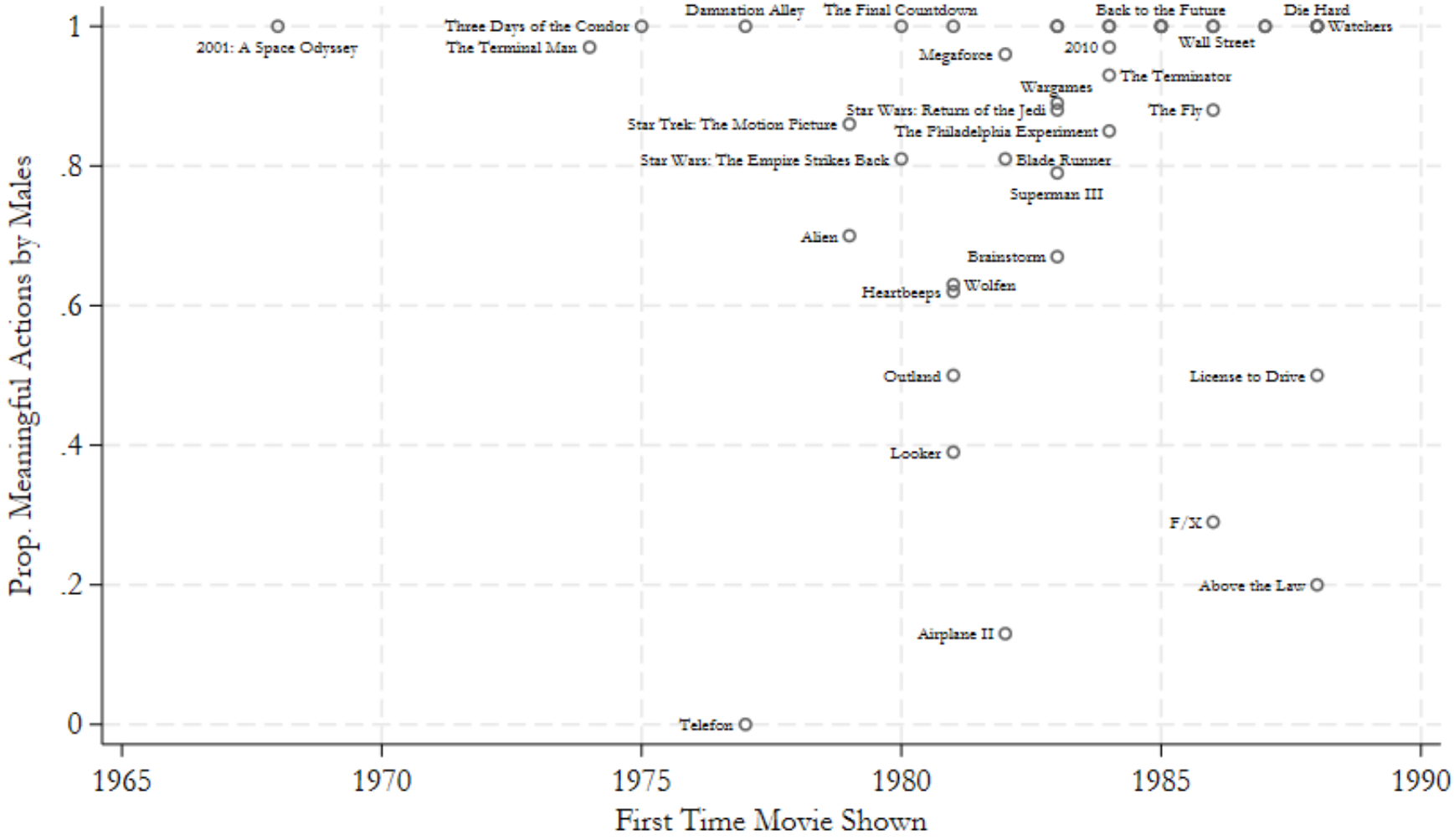
Note: Movies about computers, science fiction or technology. See Section 3 for more information.

Table A3: Keywords Used by Text Recognition Software

Browser	Panels	Encrypted	Mouse	Spam
Browsing	Cyber	Floppy Disc	Network	Terminal
Code	Data	Hack	Online	Technology
Coding	Desktop	Hacker	Password	Technological
Coded	Download	Hacking	Printer	Type
Compute	Downloading	Hacked	Program	Typing
Computed	Downloaded	Hardware	Programming	Typed
Computer	Email	Hard Drive	Programmed	Username
Computing	Emailing	Internet	Router	Web
Controller	Emailed	IP Address	Screen	Website
Control	Encryption	Keyboard	Server	
Panel	Encrypting	Macintosh	Software	

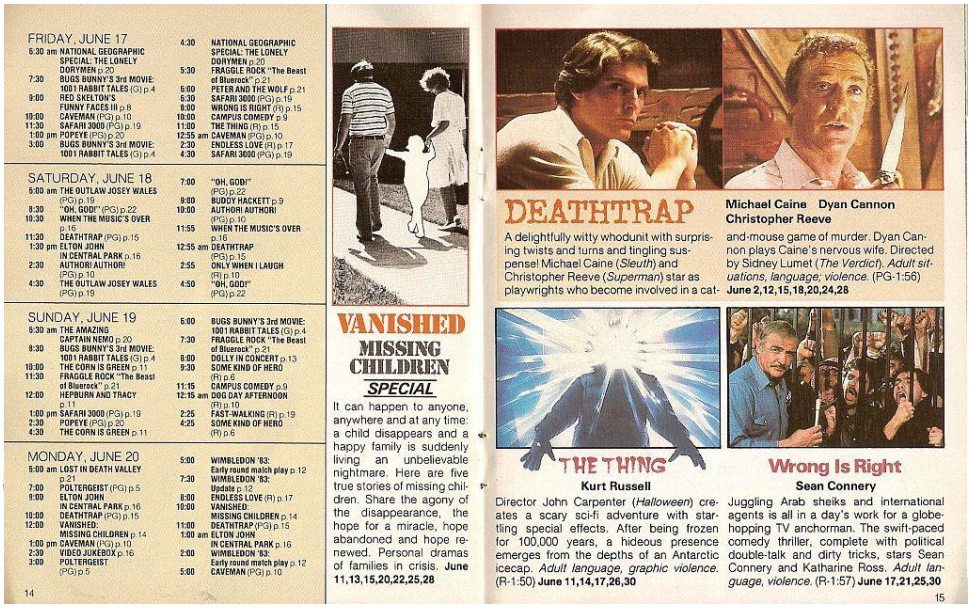
Note: Words used to identify computer related content in movies. See Section 3 for more information.

Figure A1: Script Analysis Results of Proportion of Meaningful Actions with Computers by Males



Note: First time shown corresponds to movie release dates. For ease of exposition, not all the movies analyzed are listed, but their markers are shown. Movies analyzed where there were no meanigful actions with computers by any character are omitted.
Source: Authors' calculations.

Figure A2: Example of Page from HBO Guide



FRIDAY, JUNE 17

6:30 am NATIONAL GEOGRAPHIC SPECIAL: THE LONELY DORYMEN p.20
7:30 BUGS BUNNY'S 3rd MOVIE: 1001 RABBIT TALES (G) p.4
9:00 RED SKELTON'S FUNNY FACES III p.8
10:00 CAVEMAN (PG) p.10
11:30 SAFARI 3000 (PG) p.19
1:00 pm POPEYE (PG) p.20
3:00 BUGS BUNNY'S 3rd MOVIE: 1001 RABBIT TALES (G) p.4
4:30 NATIONAL GEOGRAPHIC SPECIAL: THE LONELY DORYMEN p.20
5:30 FRAGGLE ROCK "The Beast of Bluerock" p.21
6:00 PETER AND THE WOLF p.21
6:30 SAFARI 3000 (PG) p.19
8:00 WRONG IS RIGHT (R) p.15
10:00 CAMPUS COMEDY p.9
11:00 THE THING (R) p.15
12:55 am CAVEMAN (PG) p.10
2:30 ENDLESS LOVE (R) p.17
4:30 SAFARI 3000 (PG) p.19

SATURDAY, JUNE 18

6:00 am THE OUTLAW JOSEY WALES (PG) p.19
8:30 "OH, GOD!" (PG) p.22
10:30 WHEN THE MUSIC'S OVER p.16
11:30 DEATHTRAP (PG) p.15
1:30 pm ELTON JOHN IN CENTRAL PARK p.16
2:30 AUTHOR! AUTHOR! (PG) p.10
4:30 THE OUTLAW JOSEY WALES (PG) p.19
7:00 "OH, GOD!" (PG) p.22
9:00 BUDDY HACKETT p.9
10:00 AUTHOR! AUTHOR! (PG) p.10
11:55 WHEN THE MUSIC'S OVER p.16
12:55 am DEATHTRAP (PG) p.15
2:55 ONLY WHEN I LAUGH (R) p.10
4:50 "OH, GOD!" (PG) p.22

SUNDAY, JUNE 19

6:30 am THE AMAZING CAPTAIN NEMO p.20
8:30 BUGS BUNNY'S 3rd MOVIE: 1001 RABBIT TALES (G) p.4
10:00 THE CORN IS GREEN p.11
11:30 FRAGGLE ROCK "The Beast of Bluerock" p.21
12:00 HEPBURN AND TRACY p.11
1:00 pm SAFARI 3000 (PG) p.19
2:30 POPEYE (PG) p.20
4:30 THE CORN IS GREEN p.11
6:00 BUGS BUNNY'S 3rd MOVIE: 1001 RABBIT TALES (G) p.4
7:30 FRAGGLE ROCK "The Beast of Bluerock" p.21
8:00 DOLLY IN CONCERT p.13
9:30 SOME KIND OF HERO (R) p.6
11:15 CAMPUS COMEDY p.9
12:15 am DOG DAY AFTERNOON (R) p.10
2:25 FAST-WALKING (R) p.19
4:25 SOME KIND OF HERO (R) p.6

MONDAY, JUNE 20

6:00 am LOST IN DEATH VALLEY p.21
7:00 POLTERGEIST (PG) p.5
9:00 ELTON JOHN IN CENTRAL PARK p.16
10:00 DEATHTRAP (PG) p.15
12:00 VANISHED: MISSING CHILDREN p.14
1:00 pm CAVEMAN (PG) p.10
2:30 VIDEO JUKEBOX p.16
3:00 POLTERGEIST (PG) p.5
5:00 WIMBLEDON '83: Early round match play p.12
7:30 WIMBLEDON '83: Update p.12
8:00 ENDLESS LOVE (R) p.17
10:00 VANISHED: MISSING CHILDREN p.14
11:00 DEATHTRAP (PG) p.15
1:00 am ELTON JOHN IN CENTRAL PARK p.16
2:00 WIMBLEDON '83: Early round match play p.12
5:00 CAVEMAN (PG) p.10

14

VANISHED
MISSING CHILDREN
SPECIAL

It can happen to anyone, anywhere and at any time: a child disappears and a happy family is suddenly living an unbelievable nightmare. Here are five true stories of missing children. Share the agony of the disappearance, the hope for a miracle, hope abandoned and hope renewed. Personal dramas of families in crisis. **June 11,13,15,20,22,25,28**

DEATHTRAP

Michael Caine Dyan Cannon Christopher Reeve

A delightfully witty whodunit with surprising twists and turns and tingling suspense! Michael Caine (*Sleuth*) and Christopher Reeve (*Superman*) star as playwrights who become involved in a cat-and-mouse game of murder. Dyan Cannon plays Caine's nervous wife. Directed by Sidney Lumet (*The Verdict*). *Adult situations, language; violence.* (PG-1:56) **June 2,12,15,18,20,24,28**

THE THING

Kurt Russell

Director John Carpenter (*Halloween*) creates a scary sci-fi adventure with startling special effects. After being frozen for 100,000 years, a hideous presence emerges from the depths of an Antarctic icecap. *Adult language, graphic violence.* (R-1:50) **June 11,14,17,26,30**

Wrong Is Right

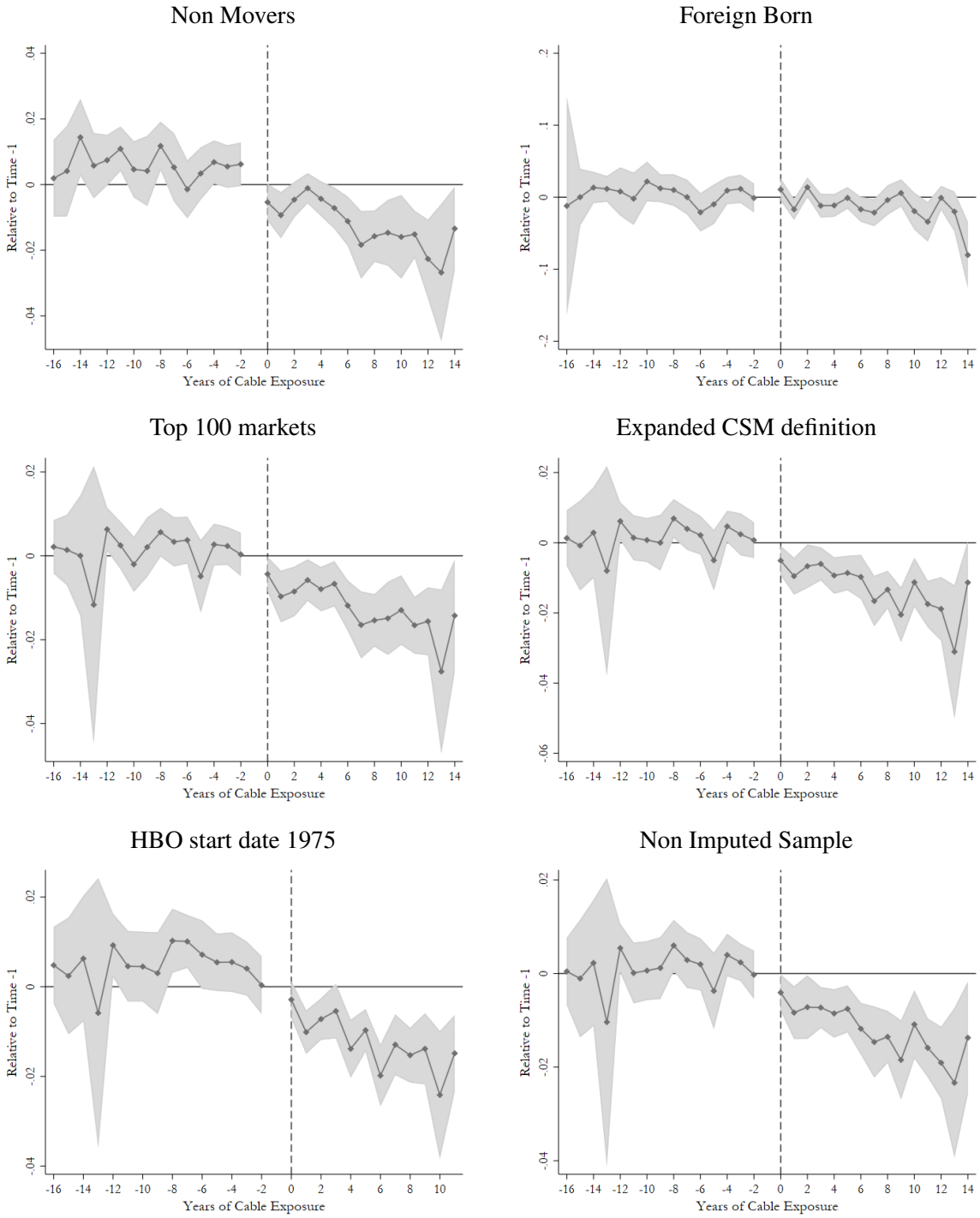
Sean Connery

Juggling Arab sheiks and international agents is all in a day's work for a globe-hopping TV anchorman. The swift-paced comedy thriller, complete with political double-talk and dirty tricks, stars Sean Connery and Katharine Ross. *Adult language, violence.* (R-1:57) **June 17,21,25,30**

15

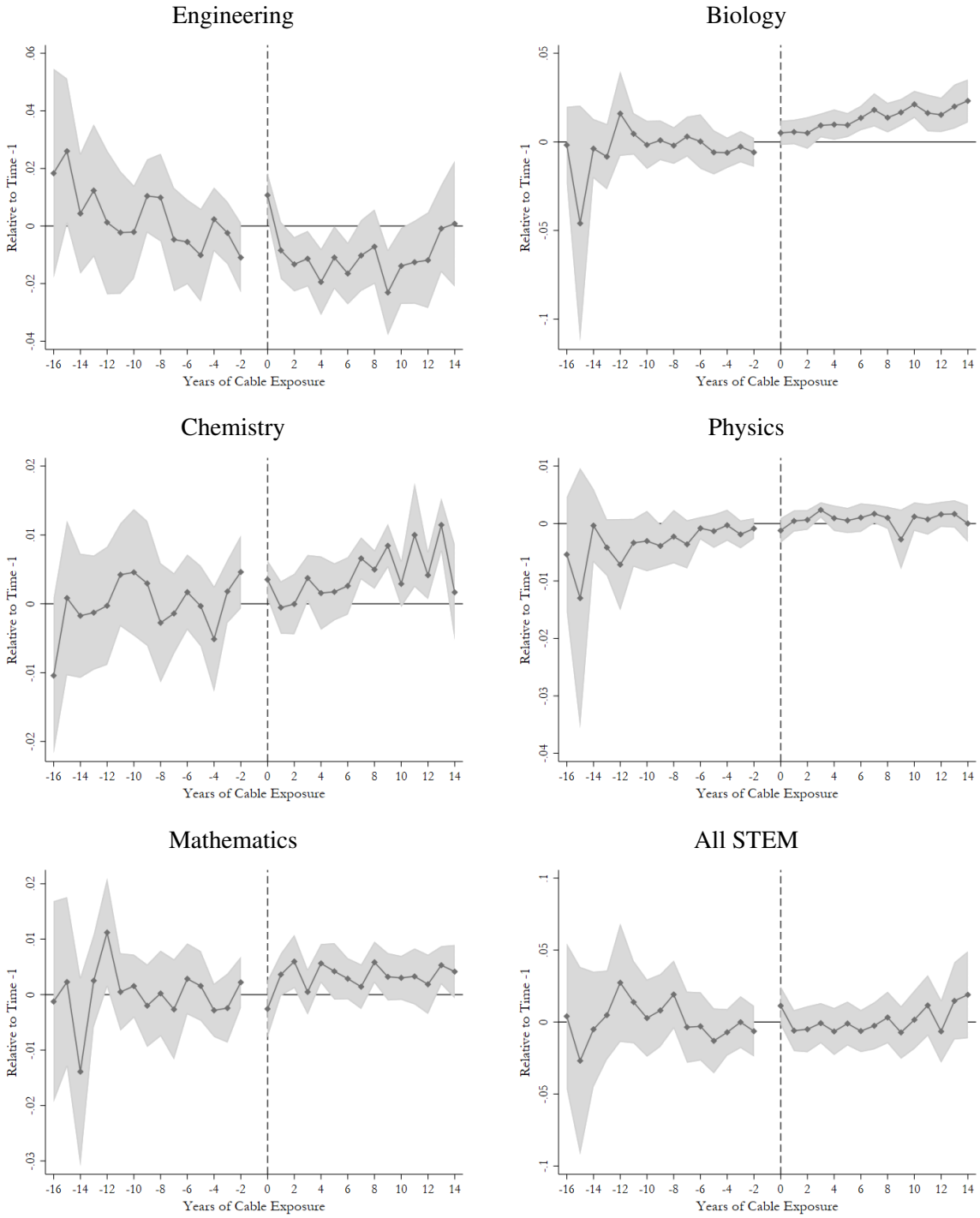
Source: HBO guide from June 1983.

Figure A3: Computer Science: Robustness Checks



Note: The figure shows regression adjusted estimates with 95% CI for birth cohorts 1950-1970. See section 6.2 for equation and section 7.1 further information.
Source: ACS for 2009-2022 and 1988 Cable Factbook.

Figure A4: Other Fields: Non Movers



Note: The figure shows regression adjusted estimates with 95% CI for birth cohorts 1950-1970. See section 6.2 for equation and section 7.1 further information.
Source: ACS for 2009-2022 and 1988 Cable Factbook.

Table A4: Years of Cable and Educational Outcomes

	Log Med. HH Income		Log Population		Per. Col. Educated		Change Per. College		1988 Higher Ed.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1980	1980 to 1990	1980	1980 to 1990	1980	1990	1970 to 1980	1980 to 1990	Total 4 Year Inst.	Total Undergrad. Students
Correlations										
Years Cable, as of 1988	-0.0007	-0.0019+	0.0212+	-0.0009+	0.0267**	0.0177	-0.0083*	-0.0090**	0.0074	0.0429+
	(0.000)	(0.000)	(0.002)	(0.000)	(0.011)	(0.013)	(0.005)	(0.004)	(0.006)	(0.014)
Mean Outcome	9.5419	0.5085	10.1088	0.0279	11.4789	13.5175	4.1410	2.0425	0.8715	2.3145
Observations	2,936	2,936	2,899	2,899	2,939	2,944	2,936	2,939	2,945	2,945
R^2	0.0009	0.0240	0.0245	0.0032	0.0021	0.0006	0.0011	0.0018	0.0005	0.0032

Source: 1980 and 1990 U.S Census (from IPUMS and USDA), 1988 IPEDS and 1988 Cable Yearbook

Note: Columns 1 and 2 contain the log of nominal, median household income in 1980 and the change from 1980 to 1990, from the U.S Census (NHGIS). Columns 3 and 4 contain the log of population in 1980 and the change in log population between 1980 and 1990, from the U.S Census (NHGIS). Columns 5 and 6 contain percent of adults age 15 and older with at least a college degree (USDA County Level Data). Columns 7 and 8 contain the change in these percents across census years. Columns 9 and 10 contain the total number of 4 year colleges and universities and the total number of undergraduate students in a county as of the 1988 IPEDS. All percentage values are multiple by 100.

Table A5: Years of Cable and Employment Outcomes

	Total Employment		1980 Industry		1990 Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
	Level 1980	Change 1980 to 1990	Per. All CSM Jobs	Per. County Jobs	Per. All CSM Jobs	Per. County Jobs
Correlations						
Years Cable, as of 1988	0.3091	-0.0033+	0.0000+	-0.0001	0.0000+	-0.0003+
	(0.203)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Outcome	23.4447	0.1568	0.0001	0.0332	0.0001	0.0374
Observations	2,930	2,928	2,930	2,930	2,937	2,936
R^2	0.0008	0.0116	0.0072	0.0004	0.0093	0.0025

Source: County Business Patterns, 1980 and 1990 U.S Census, and 1988 Cable Yearbook

Note: Columns 1 and 2 contain the total number of employed individuals, in thousands. Columns 3 and 5 contain the percentage of all Computer Science related jobs nationally that are located in a specific county, as of the 1980 and 1990 County Business Pattern data (Eckert et al. 2021). Columns 4 and 6 contain the percentage of all jobs in a county that are in Computer Science, also as of the 1980 and 1990 County Business Patterns. Computer Science jobs were defined using any 2 or 4 digit 2012 NAICS code that was related to computer hardware or software manufacturing, software publishing, data storage services, software publishing or development, and computer related research and development. The specific codes used are available upon request. Columns 7 through 10 have similar variables, but use 2010 occupation data from the 1980 and 1990 Census (as accessed via IPUMS). We code computer science occupations as computer scientists, computer programmers, software developers, and computer hardware engineers. All percentage values are multiplied by 100.

Table A6: Years of Cable and Computer Ownership

	Outcome= Per. HHs with a Computer					
	(1)	(2)	(3)	(4)	(5)	(6)
	1984	1989	1984	1989	1984	1989
Correlations						
Years Cable, as of 1988	0.0775	0.0313	0.0635	0.0411	0.0620	-0.1300
	(0.066)	(0.121)	(0.051)	(0.094)	(0.061)	(0.111)
State Level Statistic	Mean	Mean	Median	Median	Maximum	Maximum
Mean Outcome	9.3510	18.3895	9.3510	18.3895	9.3510	18.3895
Observations	51	51	51	51	51	51
R^2	0.0278	0.0014	0.0307	0.0039	0.0208	0.0273

Source: CPS March Supplement, 1984 and 1989, as access through IPUMS, and 1988 Cable Yearbook

Note: Columns 1 and 2 contain the mean years of cable as of 1988 for all counties in a state. Columns 3 and 4 contain the median value, while columns 5 and 6 contain the maximum value. The outcome variables are the percentage of households at the state level that own a computer. All percentage values are multiplied by 100.

Table A7: Robustness Checks: Non-Imputed Sample

	Outcome: Computer Science Major			
	(1)	(2)	(3)	(4)
	TWFE		BJS	
Panel A: HBO start date				
Female*Cable Available in County	-0.0108***	-0.0086***	-0.0107***	-0.0086***
	(0.0011)	(0.0014)	(0.0012)	(0.0014)
Observations	16,517	13,091	16,517	13,041
Panel B: Cable start date				
Female*Cable Available in County	-0.0112***	-0.0087***	-0.0112***	-0.0088***
	(0.0014)	(0.0016)	(0.0014)	(0.0016)
Observations	10,849	8,297	10,849	8,269
Birthyear FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Birthyear-State FE	No	Yes	No	Yes

Note: The outcome is the average incidence of a computer science major for a given birth-year, county and gender cohort. All regressions are population weighted and include county fixed effects. Panel A presents results using 1972 as the minimum start date for cable while Panel B presents results using the actual start date, not adjusted for the entry of HBO in 1972. Standard errors are reported in parentheses and clustered by county. We restrict the TWFE models to the observations used by the Borusyak et al. (2024) (BJS) estimator.

Source: Cable Yearbook 1988. ACS data for 2009-2022.

Table A8: Field Comparison: College Major for Any Cable

	(1) CSM	(2) Engineering	(3) Biology	(4) Chemistry	(5) Physics	(6) Math	(7) All Non CS STEM
Panel A: HBO start date							
Female*Cable Available in County	-0.010***	-0.012***	0.013***	0.004***	0.001*	0.003***	0.009***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.003)
Cable Available in County	0.004	0.011***	-0.007***	-0.002*	0.000	0.000	-0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)
Female	-0.013***	-0.095***	-0.025***	-0.012***	-0.006***	-0.006***	-0.156***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
Observations	18,388	18,388	18,388	18,388	18,388	18,388	18,388
Pre-treatment Difference	-0.013	-0.095	-0.024	-0.012	-0.006	-0.006	-0.154
Panel B: Cable start date							
Female*Cable Available in County	-0.011***	-0.010***	0.011***	0.003***	0.001*	0.003***	0.010***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.000)	(0.001)	(0.004)
Cable Available in County	0.004	0.011***	-0.005**	-0.001	-0.000	0.001	0.002
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.005)
Female	-0.014***	-0.099***	-0.021***	-0.012***	-0.006***	-0.005***	-0.153***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.003)
Observations	11,902	11,902	11,902	11,902	11,902	11,902	11,902
Pre-treatment Difference	-0.015	-0.099	-0.020	-0.011	-0.006	-0.005	-0.152

Note: Coefficients are estimated using the BJS imputation estimator. Outcome are the average incidence of a specific college major within a birth-year, county and gender cohort. The specific majors are listed on the column header. All regressions include birth-year and county fixed effects. Standard errors are reported in parentheses and clustered by county.
Source: Cable Yearbook 1988. ACS data for 2009-2022.