THE UNIVERSITY OF CHICAGO

COMPLEMENTARITY OF BROADBAND INTERNET AND COLLEGE MAJORS: LESSONS FROM NORWEGIAN VACANCY DATA

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ABSTRACT

Broadband internet increases the hourly wages of college-educated workers. However, little is known about how broadband internet affects the wages of workers with different college majors. I combine several Norwegian data sets to answer this question. A public program with limited funding rolled out broadband infrastructure and provided plausibly exogenous variation in broadband internet coverage. I show substantial heterogeneity in the effect of broadband coverage on hourly wages across college majors. Law and Business graduates have the highest increase in hourly wages, while the effect for STEM graduates is similar to the average among all college-educated workers, and workers with Teaching major experience a decrease in their hourly wage. I explore possible explanations for this heterogeneity using information about Internet and Communication Technologies (ICT) skills from the near-population of vacancies and about ICT applications adopted in firms from a representative annual survey. I find evidence that broadband internet availability increases demand for General ICT skills and Basic ICT applications complementary to managerial skills. In contrast, I find substantially smaller or no effect for Advanced ICT skills and applications requiring technical expertise.

CHAPTER 1

COMPLEMENTARITY OF BROADBAND INTERNET AND COLLEGE MAJORS: LESSONS FROM NORWEGIAN VACANCY DATA

1.1 Introduction

The literature establishes that Internet and Communication Technologies (ICTs) adoption increases the hourly wages of high-skill (college-educated) workers (Kruger (1993), Autor and Dorn (2003), Forman, Goldfarb and Greenstein (2012), Atasoy (2013), Akerman, Gaarder and Mogstad (2015)). One argument points to the complementarity of ICTs and abstract job tasks abundant in high-skill occupations raising workers' productivity and hourly wages (Acemoglu and Autor (2011)). Another argument emphasizes the role of high-skill workers with technical education in producing new and advanced ICTs as the main channel of the hourly wage increase (Humlum and Bjørnsson (2020)). The latter argument points to potential heterogeneity in the effect of ICTs on high-skill workers by their educational specialization. However, there is a lack of empirical evidence to substantiate these differences for most ICTs.

In this paper, I study the heterogeneity of the effect of broadband internet coverage expansion on hourly wages across college majors. I use the empirical setting of Norway's publicly subsidized broadband infrastructure rollout from 2001 to 2007. My data comes from several Norwegian administrative and public sources linked through the unique firm, individual, and vacancy identifiers that provide information on workers' hourly wages and college majors, firms' ICT usage and vacancy postings, and broadband coverage over time and across Norwegian municipalities.

The coverage expansion reform aimed at providing broadband internet access at a reasonable price throughout Norway creates a source of exogenous variation in broadband coverage. Limited public funding ensures the progressive rollout of broadband internet access points in Norwegian municipalities from 2001 to 2007. Conditional on municipality and year fixed effects, temporal variation in broadband coverage is plausibly exogenous to the hourly wage outcomes. My identification strategy could be captured as the parallel trends assumption that municipalities with early and late broadband coverage expansion would, on average, have had the same time trends in workers' hourly wage outcomes.[1]

In the first part of my analysis, I estimate the heterogeneity of the effect of broadband coverage expansion on the hourly wages of college-educated workers by their major. I find that workers who major in Law and Business have the highest increase in the hourly wage of 0.115 percent per a percentage point increase in coverage while the average increase across all college-educated workers is 0.035 percent. Medicine graduates experience the second largest increase of 0.093 percent. In contrast, workers with Teaching major experience a decline in their hourly wage of 0.042 percent per a percentage point increase in coverage, which is larger than the decline for workers without a college degree. Furthermore, the estimate for workers with STEM major is a 0.031 percent increase and is statistically indistinguishable from the average across all college-educated workers on conventional confidence levels. These estimates should be interpreted as the intention-to-treat effect estimates for the population of workers affected by the access expansion from the publicly provided infrastructure (in contrast to workers in firms that adopted broadband internet before the reform).

I show that major-specific estimates are precise enough to construct informative confidence sets for their ranks using the methodology developed in Mogstad, Romano, Shaikh and Wilhelm (2021) and Bazylik, Mogstad, Romano, Shaikh and Wilhelm (2021). With 90% confidence the effect for Law and Business major could not be rejected from being among the best three, and the effect for Teaching could not be rejected from being among the worst two. This finding is particularly relevant in the context of the Norwegian college admission system, where prospective students submit rank preferences of majors. To improve the informativeness of the confidence sets for the ranks, I focus on choice-relevant margin and consider only four college majors among the next-best ranked alternatives for each other in

[1] My paper follows existing work that exploits Norwegian broadband coverage expansion reform including Bhuller, Havnes, Leuven and Mogstad (2013), Akerman et al. (2015), Bhuller, Kostøl and Vigtel (2020), Hvide, Meling, Mogstad and Vestad (2022), and Akerman, Leuven and Mogstad (2022)

Kirkeboen, Leuven and Mogstad (2016): Law and Business, Social Sciences, Humanities, and Teaching. In this subset with 90% confidence Law and Business could not be rejected from being the best and Teaching - the worst. Informative confidence sets for the ranks of college majors are crucial to policymakers interested in the best and the worst performing subpopulations in the broadband expansion reform.

I explore two potential mechanisms for this heterogeneity. First, I examine the effect of coverage expansion on firms' demand for ICT skills in Norwegian vacancy postings. I find an increase of 0.034 standard deviations in the number of vacancies mentioning General ICT skills that include basic office software applications, use of PC and internet, automated paperwork turnover, and information search. In contrast, there is a substantially lower effect on the total number of posted vacancies and vacancies mentioning advanced and new ICT skills that require specific technical knowledge. General ICT skills are complementary to managerial skills, thus disproportionally benefiting the workers with managerial education.

Second, I show that broadband coverage expansion leads to higher usage of basic ICT applications in firms, including information search, filing taxes and governmental forms, and using the internet for personnel recruitment. In contrast, I find no statistically or economically significant effect on the usage of advanced ICT applications such as establishing an online store or conducting marketing research on the internet. Basic ICT applications do not require specific human capital to use. In contrast, advanced ICT applications require workers with technical knowledge for a streamlined running of online stores or conducting marketing research. Thus, firms increase usage of management-enhancing and readily available ICT applications while there are no such effects on applications requiring technical expertise.

My results directly contribute to the research on the positive effect of ICT adoption on high-skill workers' wages. The complementarity framework of abstract tasks and ICTs argues that college graduates are employed in occupations abundant in abstract tasks and, thus, receive the primary benefits from ICT adoption (Acemoglu and Autor (2011); Adão, Beraja and Pandalai-Nayar (2020); Akerman et al. (2015); Autor, Chin, Salomons and Seegmiller (2022);

Autor and Dorn (2003); Autor, Levy and Murnane (2013); Goos, Manning and Salomons (2014)). Specifically for managerial employees, the adoption of PCs and the internet in firms' daily operations decreases communication and organizational costs improving their managerial productivity (Bartel, Ichniowski and Shaw (2007); Bresnahan, Brynjolfsson and Hitt (2002); Caroli and van Reenen (2001); Deming (2017,2); Kruger (1993)). Kruger (1993) finds that as early as 1984-1989, electronic communication was one of the most rewarded activities where managerial employees used personal computers. Similarly, Caroli and van Reenen (2001) show that computerization and ICT adoption in British and French firms in the late 1980s positively affected managers' wages. I take one step back and show that managerial education already defines the group that benefits the most from broadband internet expansion among college-educated workers. My evidence point to particular complementarity between managerial human capital and ICT skills and applications adopted during broadband coverage expansion. My results are more specific to managerial human capital rather than abstract tasks abundance. In my sample, Law and Business major has a substantially lower share of graduates in abstract occupations than STEM and Medicine. Furthermore, estimates from the coverage expansion reform emphasize the effect on the policy-relevant population of workers affected by the new technology with public assistance.

The more recent literature states that only workers with STEM and related technical degrees experience an increase in hourly wages from the introduction of advanced ICTs as these employees are likely to be directly involved in the development of new software and hardware (Agrawal, Gans and Goldfarb (2018,1,2); Autor, Mindell and Reynolds (2021); Humlum and Bjørnsson (2020); Li, Linde and Shimao (2021); Webb (2020); Zhang, Maslej, Brynjolfsson, Etchemendy, Lyons, Manyika, Ngo, Niebles, Sellitto, Sakhaee, Shoham, Clark and Perrault (2022)). The argument emphasizes cutting-edge technologies such as Artificial Intelligence (AI) and its applications, where research and development are paramount. Humlum and Bjørnsson (2020) show a wage increase for computer science and mathematics majors specializing in AI research and no effect for majors specializing in using AI applications for production (including other STEM majors). My paper shows the contrasting case of broadband internet expansion, where half of the private firms had access to broadband before the reform and where technology users ended up benefiting the most. I show that the effect on demand for advanced and novel ICT skills and applications requiring technical expertise is substantially lower than for management augmenting General ICT skills and Basic ICT applications. The combined pattern of new technologies' initial adoption benefiting technical specialists and the expansion of access to established technologies benefiting a wider class of non-technical users aligns with the evidence on the diffusion of new technologies in the US vacancy data from geographically narrow technical hubs to a broader population of users (Bloom, Hassan, Kalyani, Lerner and Tahoun (2021)).

My results show the effect of publicly subsidized broadband coverage expansion on the evolution of returns to college majors. Literature on returns to college majors finds substantial differences in returns between majors that rival college premia in size (Altonji, Arcidiacono and Maurel (2016a); Altonji, Blom and Meghir (2012); Altonji, Kahn and Speer (2016b); Andrews, Imberman, Lovenheim and Stange (2022); Arcidiacono (2004); Lovenheim and Smith (2022)). Causal evidence from discontinuities produced by admissions cutoffs in Chile (Hastings, Neilson and Zimmerman (2013)) and Norway (Kirkeboen et al. (2016)) confirms the heterogeneity in returns and highlights the largest premia for Law, Business, Medicine, and STEM degrees. However, much less is known about the evolution of this heterogeneity over time. Broadband internet is one of the main recent technological changes in the labor market that contribute to the change in skill premia. I show sizable and statistically significant differences in the effect of broadband coverage expansion on returns to college majors. Some majors with high wage premia, Law and Business and Medicine, experienced a large increase in hourly wage, while the effect for another high wage premia major, STEM, is similar to the effect for Social Sciences that have low wage premia.

The rest of the paper proceeds as follows. The next two sections describe the data and the broadband infrastructure installation program. In Sections 4 and 5, I estimate the heterogeneity in the effect of broadband coverage expansion on hourly wages over college majors and construct confidence sets for the ranks of majors by this effect. In Section 6, I explore a near-universe of Norwegian vacancies to find the effect of broadband coverage expansion on ICT skills demand. Section 7 shows the effect of coverage expansion on ICT applications usage in Norwegian firms. The final section concludes the paper.

1.2 Data and Summary Statistics

In this paper, I use Norwegian administrative data sets on workers and firms, a representative survey of IT usage in firms, and a near-universe of posted vacancies. I link workers to firms and vacancies to firms using unique worker, firm, and vacancy identifiers.[2]

1.2.1 Workers Data

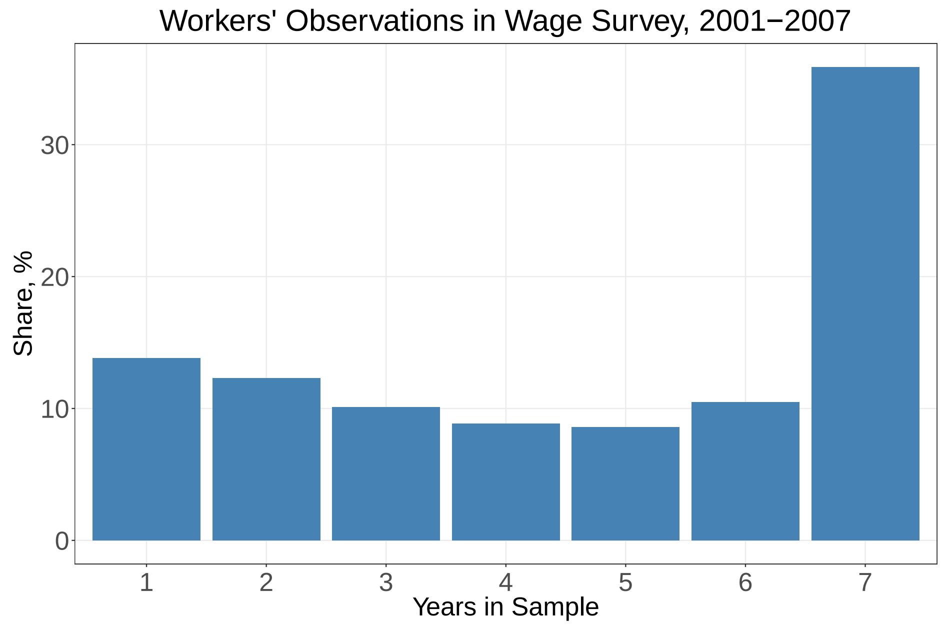
Most workers' socio-economic data come from administrative registers provided by Statistics Norway. This longitudinal data set covers every resident and provides demographic data on workers' age, sex, and municipality of residence. Educational attainment data, including information on college majors, comes from the annual reports of Norwegian educational establishments.

The hourly wage data comes from Statistics Norway's Wage Statistics Survey. The annual wage survey covers all public sector and about 70 percent of private sector employees from a stratified random sample of private firms. I study the effect of broadband coverage expansion on workers' hourly wages in private non-financial joint-stock firms.

Figure 1.1 shows the histogram of private firms workers' duration of stay in the wage survey sample in 2001-2007. For every worker who appeared in the survey at least once in the 2001-2007 period, I count the years they are in the sample. Only a third of individuals are always present, while nearly 40 percent are present in less than four years of data. For this reason, my main analysis will not rely on the individual-level panel structure.

[2] My data does not allow linking vacancies to hired workers.

Figure 1.1: Workers' Duration of Stay in Survey Sample



Note: The histogram of private firms workers' duration of stay in the wage survey sample in 2001-2007.

The firm-level data comes from the annual administrative registers from Statistics Norway and the Norwegian Tax Authority. The data includes labor inputs and total paid wages, industry classification, and firms' geographical identifiers at the municipality level. I merge firm and employee data from registers and wage statistics survey using unique firm and worker identifiers.

Table 1.1 shows summary statistics for the workers' hourly wages and socio-economic characteristics. The sample consists of all private non-financial joint-stock firms workers aged 18 to 65 recorded in the wage statistics surveys. The top half of the table shows the means of the log hourly wages measured in 1998 USD, with standard deviations in parentheses. Hourly wages steadily increase in both education groups over the entire observation period. The bottom half of the table shows shares of college-educated workers, the share of male workers, the share of men among college-educated workers, and the average age with standard deviations in parentheses. Notably, the percentage of college-educated workers grew from 22 to 25 over the 2002 to 2007 period and the percentage of men among college-educated workers decreased from 61 to 58. In contrast, there is no change in the share of men in the total sample of workers.

Appendix Figure A.1 provides more details on the rapid increase in the percentage of college-educated workers and the decrease in the share of men among them. Figure A.1 shows that each consecutive cohort of Norwegian workers has a significantly higher share of college-educated men and women. As younger cohorts complete their higher education (blue and red line increase from 2002 to 2007 at the two bottom panels) and older cohort leaves the survey, the share of college-educated workers increases. However, the share of women with college degrees grows more substantially in the younger cohorts than the share of men, which leads to a change in the gender composition of the college-educated workforce. [3]

Table 1.2 shows the shares of college majors among college-educated workers in the wage survey and corresponding means of log hourly wages.[4] STEM and Law and Business majors are the two most numerous majors in the sample and are similar in size. These two majors combine for more than half of the college-educated workers. Shares of the majority of college majors are stable over the reform period. However, the share of STEM decreases by one percentage point and the share of Law and Business increases by two percentage points. Workers with Medicine major have the highest hourly wage, while those with STEM and Law and Business majors have the second and the third largest hourly wages, respectively. In contrast, workers with Social Sciences major have the lowest hourly wage. Hourly wages increased throughout the reform period for all college majors.

[3] Women compose $\approx 60\%$ of college graduates in the recent Norwegian cohorts.

[4] I use groups of college majors that include several closely related majors in my analysis. This choice is driven by data availability and the tradeoff between the granularity and precision of the estimates. With a slight abuse of notation, I refer to these college major groups as majors throughout the paper. I provide the list of majors in each group in Appendix A

Table 1.1: Hourly Wages and Demographic Characteristics of Workers

	2002	2004	2007
Log Hourly Wage, 1998 USD:			
All	2.99	3.03	3.12
	(0.39)	(0.38)	(0.39)
College	3.23	3.25	3.33
	(0.39)	(0.39)	(0.39)
No College	2.92	2.96	3.05
	(0.37)	(0.37)	(0.38)
Demographics:			
Share College	0.22	0.23	0.25
	(0.41)	(0.42)	(0.44)
Share Male	0.62	0.62	0.62
	(0.49)	(0.49)	(0.49)
Share Male|College	0.61	0.60	0.58
	(0.49)	(0.49)	(0.49)
Age	38.39	38.85	38.87
	(12.23)	(12.33)	(12.60)
N of workers in wage survey, aged 18-65	1,214,140	1,190,323	1,306,282

Note: Hourly wages come from Statistics Norway's Wage Statistics Survey. Demographic data comes from Statistics Norway's administrative registers. Information on educational attainment is from the annual reports of educational establishments. Standard deviations in parentheses.

Appendix Figure A.2 shows the shares of each college major among college-educated men and women by birth cohort in 2002 and 2007. Male college graduates are substantially more likely to have STEM degree, especially in older cohorts. In contrast, for all cohorts, female college graduates have a higher share of Humanities, Social Sciences, Health, and

Teaching majors. The percentages of Law and Business major are similar for male and female college graduates, and there is a pronounced growth of this major starting from the 1961-1970 cohort for both sexes. Similarly, there is a gradual increase in the share of graduates with Social Sciences degrees for both sexes and in the percentage of female graduates with STEM major. In contrast, the share of Health major is substantially lower for recent cohorts of college-educated women.

Table 1.2: College Majors Shares and Log Hourly Wages

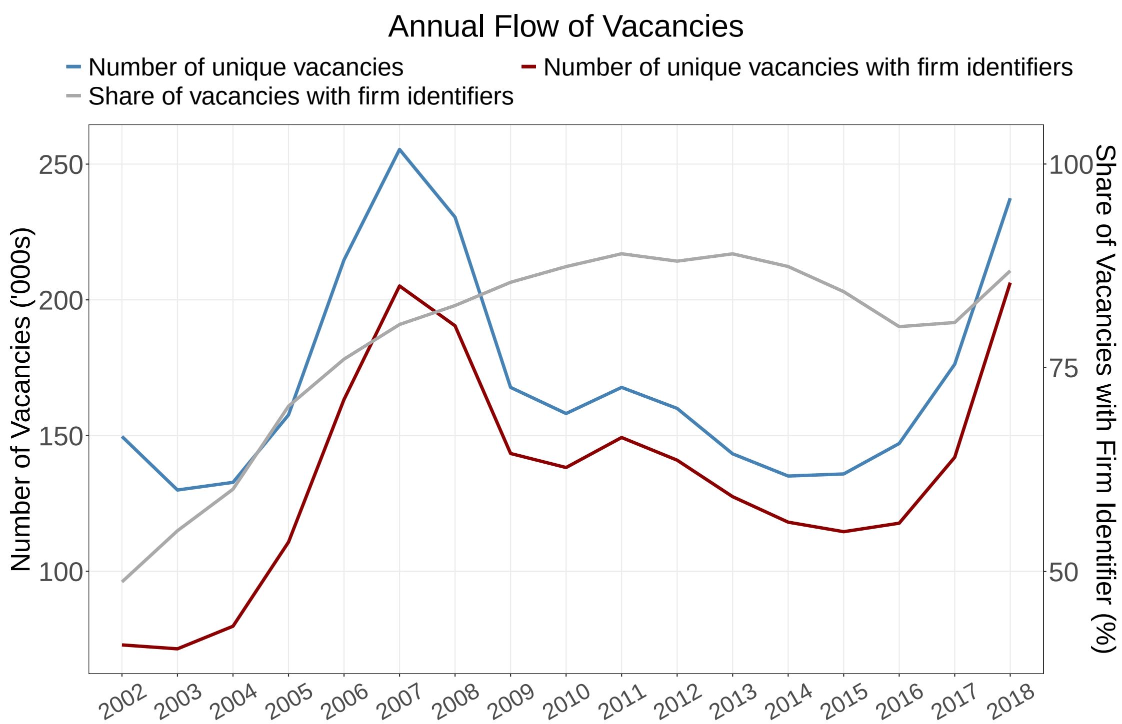
Major	Share of College Graduates			Log Hourly Wage		
	2002	2004	2007	2002	2004	2007
STEM	0.32	0.32	0.31	3.38	3.38	3.48
Law and Business	0.25	0.26	0.27	3.32	3.33	3.43
Humanities	0.14	0.13	0.13	3.05	3.09	3.17
Social Sciences	0.09	0.10	0.10	2.95	2.99	3.05
Health	0.08	0.08	0.09	3.02	3.04	3.11
Teaching	0.05	0.05	0.06	3.10	3.11	3.18
Other	0.05	0.05	0.05	3.18	3.21	3.33
Medicine	0.02	0.02	0.02	3.44	3.49	3.58

Note: Share of graduates and hourly wages by college major. Hourly wages come from Statistics Norway's Wage Statistics Survey. Data on college majors comes from the annual reports of educational establishments.

1.2.2 Vacancy Data

The Norwegian Labor and Welfare Administration (NAV) collected near-population of vacancy postings from 2002 to 2018. The agency aggregates direct firm reports and vacancies from printed and online sources. Each vacancy contains a unique identifier, occupational classification of the job, textual description, and posting source. Most vacancies come with the posting firm's identifier. However, some firms do not disclose their identifiers for privacy reasons. Figure 1.2 shows the total annual number of vacancies (blue), the number of vacancies with firm identifiers (red), and the share of vacancies with firm identifiers (gray, right axis). The share is just below 50 percent at the beginning of the reform and steadily increases to 80 percent by its end in 2007. I use firm identifiers to link vacancies with posting firm municipalities and broadband coverage expansion. I conduct empirical analysis on the subsample of vacancies from 2002 to 2008.

Figure 1.2: Vacancies Flows



Note: The total annual number of posted vacancies (blue), the number of vacancies with firm identifiers (red), and the share of vacancies with firm identifiers (gray, right axis). Vacancy postings come from the Norwegian Labor and Welfare Administration (NAV).

Definition 1. ***ICT skill*** *- software and hardware vintages or explicit textual descriptions of an ICT-related competencies*

I extract ICT skills from vacancies' textual descriptions in three steps. First, I search for all software and hardware vintages mentioned by their brand and version name. Second, I translate all textual descriptions from Norwegian to English and run word and phrase search for ICT-related competencies descriptions. Lastly, to make the sample of ICT skills as complete as possible, I manually read a 10 percent randomly chosen subsample of vacancies from each year. The third step never adds more than 5 percent of skills to the annual sample.

I classify ICT skills into five categories by their primary application listed on Wikipedia: General, Programming, Web Development, Enterprise Software, and Data Analysis. General ICT skills include basic office software applications, use of PC and internet, automated paperwork turnover, and information search. Programming skills contain all major general-purpose programming languages, handling of related hardware, software, and editing environments. Web Development skills are specific programming and hardware tools for website development and optimization. Enterprise Software skills cover applications for firm resource planning, secure communication, and specific languages developed for business usage. Finally, Data Analysis skills are statistical software packages, data centers and servers related hardware and software, and big data skills.

Table 1.3 shows the size and examples of skills for each ICT skill group. In total, I extract 2414 ICT skills from textual descriptions. Programming skill group is the most numerous, with 718 different ICT skills, while Enterprise Software is the least, with 249 skills.

Table 1.3: ICT Skills Classified by the Primary Application Listed in Wikipedia Description

Skill Group	Number of Skills	Examples
General	425	Excel, Power Point, Macbook, Windows
Programming	718	C++, CAD, Github, Pascal, Visual Basic
Web Development	580	Angular, PHP, Rails, SEO
Enterprise Software	249	Axapta, Biztalk, COBOL, Oracle EBS
Data Analysis	442	Geocoding, SPSS, SAS

Table 1.4 characterizes the distribution of posted vacancies per municipality from 2002 to

2008. On average, 398 vacancies are posted annually per municipality for this period. The distribution is heavily right-skewed, with a median of 122 vacancies and a max observation of 42,465 vacancies. Of all posted vacancies, 46.1 percent contain at least one ICT skill, and 39.0 percent have at least one General ICT skill. Notably, despite Programming being the most numerous skill group, it is only the third largest by mentions in vacancies.

Table 1.4: Posted Vacancies per Municipality in Norway in 2002-2008

	Mean	SD	Q1	Q2	Q3	Max
All Vacancies	398.0	1,667.9	59	122	277	42,465
At Least 1 ICT Skill	183.4	936.9	19	42	111	26,233
At Least 1 General ICT Skill	155.1	800.0	15	34	95	22,792
At Least 1 Web Dev Skill	55.0	348.2	3	9	27	10,038
At Least 1 Programming Skill	34.0	204.0	1	5	15	5,292
At Least 1 Data Skill	10.8	91.4	0	1	3	2,695
At Least 1 ES Skill	9.2	59.3	0	1	4	1,652

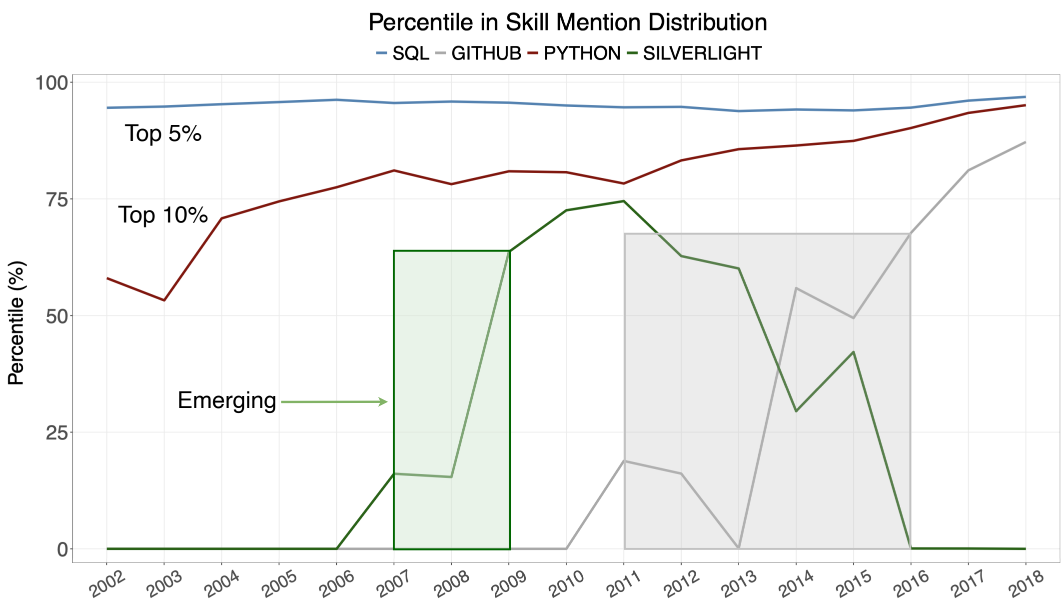
I emphasize two types of ICT skills: frequently mentioned skills (Top X% skill) and skills that have not been mentioned frequently before but are becoming such (Emerging skills). Following the literature, I assume that skill mentions in vacancies' descriptions reflect firms' current demand for skills. Frequently mentioned skills are in high demand and are widely utilized in the labor market, meaning that many workers are likely to be proficient in these skills. In contrast, emerging skills are new to the labor market, meaning that few workers are likely to be proficient in these skills. [5]

[5] Deming (2017), Deming and Noray (2020) and Deming (2021) use mentions of skills in the US vacancies as the measure of demand for skills. Bloom et al. (2021) used a similar classification of new ICT skills to study technology diffusion in the US labor market.

Definition 2. ***Top X% skill*** *- its rank in mentions distribution exceeds 100 - X percent at least once in the sample.*

Definition 3. ***Emerging in year*** t *- if* $t \in [t_1, t_2]$*, where* t_1 *is the first year when the skill's rank in mentions distribution exceeds 10 percent of its maximum rank over the entire sample, and* t_2 *is defined similarly for the 90 percent threshold.*

Figure 1.3: ICT Skills Mention Distribution Percentiles



Note: Percentile rank in the mention distribution for four ICT skills. SQL programming language for data queries has the highest percentile rank in the sample above 95 percent, making it a top 5% skill. Similarly, the general-purpose programming language Python is a top 10% skill. Web applications framework Microsoft Silverlight is an emerging skill in years 2007 through 2009, and software development and version control tool Github is an emerging skill in years 2011 through 2016.

Figure 1.3 illustrates both definitions with the time series of percentile ranks for four ICT skills. SQL programming language for data queries is consistently at the top of the skill mention distribution each year. Its highest percentile rank exceeds 95 percent, and by Definition 2, it is a top 5% skill. Similarly, the general-purpose programming language Python is a top 10% skill as its highest percentile rank exceeds 90 percent. According to

Definition 3 web applications framework Microsoft Silverlight is an emerging skill from 2007 to 2009 when its mention frequency rapidly increased. Software development and version control tool Github is an emerging skill from 2011 to 2016.[6] In subsequent analysis, I focus on the top 5%, 10%, and 25% skills and apply four threshold pairs for emerging skills definition: 10 to 75, 10 to 90, 25 to 75, and 25 to 90 percent. The longer time horizon of Figure 1.3 allows to show a variety of skill lifecycles in the mention distribution, while empirical analysis uses only the 2002-2008 sample with both Top X% skills and Emerging skills defined for the 2002-2008 period.

Appendix Figure C.1 shows the year when Top X% skills defined for the 2002-2008 vacancy sample crossed high percentile cutoffs in mention distribution. The majority of Top X% skills are in their respective Top category from the very beginning of the sample and almost the entire sample of Top 5% and Top 10% skills are in the the upper quartile of the mention distribution in 2002.

1.2.3 Firms ICT Usage Data

The Annual Community Survey on ICT Usage of Firms performed by Statistics Norway provides detailed data on ICT applications and technology usage. The survey uses stratified random sampling by industry and the number of employees from the population of joint-stock firms. This survey has a battery of questions to firms' managers about the adoption and use of ICT, including the type of internet connection: old analog or ISDN (telephone lines) and new broadband connection (optic fiber).[7]

Table 1.5 shows the means and the standard deviations for ICT usage outcomes in firms from the Annual Community Survey on ICT Usage of Firms. All outcomes except Analog or ISDN internet connection increase throughout the reform. The share of firms with Analog

[6] Github's rank in mention distribution declines from 2011 to 2013. However, according to Definition 3, it is still an emerging skill. I prefer this definition to labeling skills each year independently to safeguard against potential noise in the mention data.

[7] A small fraction of firms also uses wireless connection. It is also possible that firm has no internet connection at all or uses several types of internet connection.

or ISDN internet connection declines from 41 percent in 2002 to 19 percent in 2007. In contrast, the percentage of firms using broadband internet increases from 55 percent in 2002 to 89 percent in 2007.[8] Survey outcome variables cover major ICT applications: employee usage of PCs (with and without internet connection), firms purchasing goods on the internet, personnel recruitment and training using the internet, filing of basic paperwork, information search, firms having a website, and advanced applications such as establishing the separate capability to accept online orders and conduct full-scale market research.

Advanced ICT applications have fewer firms using them. For example, in 2002, only 35 percent of firms accepted online orders, while 87 percent had a website. The former application is much more likely to require specific technical knowledge and capital investment on the firm's side than the latter. The online store has to be constantly streamlined, functioning and up to date as the firm directly depends on it to generate profit. At the same time, a basic website requires lower maintenance or could be entirely outsourced.

1.3 Broadband Coverage Expansion Reform

As a source of exogenous variation in broadband internet coverage, I use a Norwegian public program aiming to ensure broadband access at a reasonable price throughout the country in 2001-2007. The broadband signal transmission operates through fiber-optic cables requiring local access points. Due to limited public funding, geographical size, and the low-density population of Norway, the infrastructure was installed in stages. The progressive rollout of the access points generates spatial and temporal variation in broadband coverage. The reform allows users to switch from the dial-up telephone line to the fiber-optic channel. This transition, on average, increases the available bit rate from 56 kbit/s to 256 kbit/s.

[8] A substantial share of Norwegian firms used broadband internet connection before the reform to expand broadband availability described below. Thus, estimates in this paper show the effect on the subpopulation of workers employed in firms with broadband adoption decisions affected by the subsequent reform.

Table 1.5: ICT Outcomes from the Annual Community Survey on ICT Usage of Firms

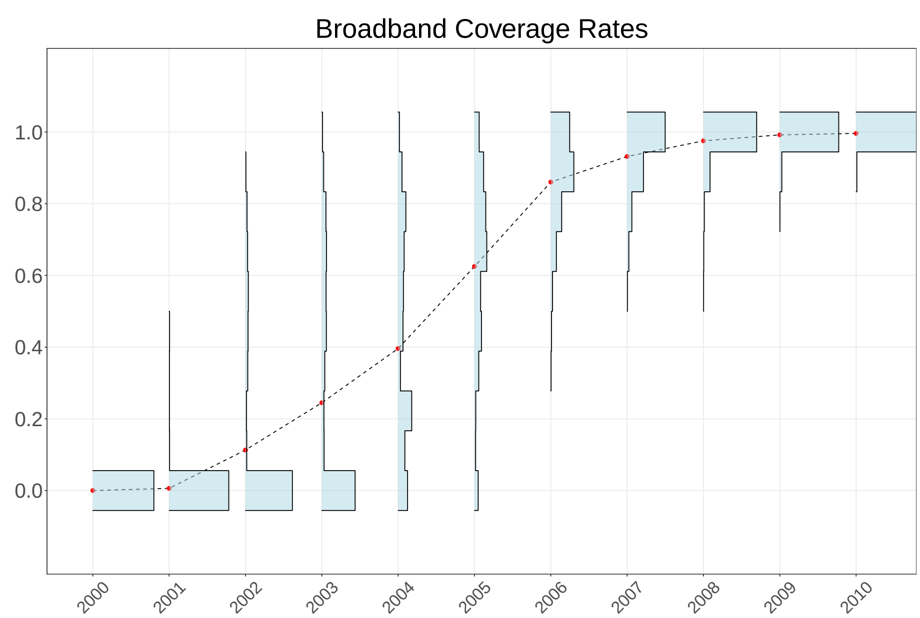
Survey Question	Outcome	Outcome Group	2002	2004	2007
Does this firm use ISDN or Analog connection?	ISDN or Analog		41.2	27.3	19.0
			(49.2)	(44.6)	(39.2)
Does this firm use broadband internet?	Broadband		54.8	81.5	87.9
			(49.8)	(38.8)	(32.6)
What percent of employees use PC?	%Empl Use PC		63.3	65.9	68.0
			(34.7)	(32.9)	(32.6)
What percent of employees use PC with Internet?	%Empl Use PC with Internet		58.6	59.4	64.7
			(37.1)	(34.6)	(33.4)
Does this firm make electronic transactions?	Transactions	Transactions	72.9	87.8	88.8
			(44.5)	(32.7)	(31.5)
Does this firm use Internet to make purchases?	Makes Internet Purchases		70.5	76.4	77.9
			(45.6)	(42.5)	(41.5)
Does this firm use Internet for recruitment?	Recruitment	Personnel	44.6	64.2	76.2
			(49.7)	(47.9)	(42.6)
Does this firm use Internet for personnel training?	Personnel Training		30.7	56.5	65.1
			(46.1)	(49.6)	(47.7)
Does this firm use Internet to file governmental forms?	File Gov Forms	Basic	78.8	94.9	88.1
			(40.9)	(22.0)	(32.4)
Does this firm use Internet for information search?	Information Search		92.1	96.7	97.1
			(27.0)	(17.9)	(16.9)
Does this firm have a website?	Has a Website		86.8	89.7	92.1
			(33.9)	(30.4)	(26.9)
Does this firm take Internet orders?	Takes Internet Orders	Advanced	34.7	32.1	49.7
			(47.6)	(46.7)	(50.0)
Does this firm use Internet for market monitoring?	Market Monitoring		51.1	72.0	76.0
			(50.0)	(44.9)	(42.7)
Number of firms in the survey			3364	3336	4611

Note: Share of firms with each ICT application in the Annual Community Survey on ICT Usage of Firms sample. Weights adjust for stratified random sampling by industry and number of employees. Standard deviations in parentheses.

The annual municipality-level data on broadband coverage comes from the Norwegian Ministry of Government Administration. The ministry monitors broadband coverage through the annual reports on coverage rates filed by broadband suppliers to the Norwegian Telecommunications Authority. The coverage rates are based on the area signal range and detailed information about the place of residence of households. In computing the coverage rates, it is taken into account that multiple suppliers may provide broadband coverage to households living in the same area to avoid double counting.

Figure 1.4 shows the mean and the distribution of broadband coverage rates across Norwegian municipalities from 2000 to 2010. There was no publicly provided coverage before the program. The coverage gradually increases within and across municipalities as access points roll out. This process generates a continuous measure of coverage rate with substantial temporal and spatial variation, even taking municipality and time fixed effects into account. By the end of the reform, the mean coverage rate exceeded 90 percent, with the majority of municipalities entirely covered by the signal.

Figure 1.4: Broadband Coverage Expansion



Note: The mean and the distribution of broadband internet coverage rates over municipalities for each year from 2000 to 2010.

I evaluate the effect of coverage expansion on broadband internet adoption in firms using the information about internet connection types from the Annual Community Survey on ICT Usage of Firms. I also consider the effect of coverage expansion on analog or ISDN connection usage. I estimate the following regression:

$$y_{jmt} = \alpha + z_{mt}\theta + \eta_m + \tau_t + u_{jmt}, \tag{1.1}$$

where y_{jmt} is an indicator variable for the type of internet connection used by firm j in municipality m in year t and z_{mt} is the broadband coverage level in municipality m in year t. The main coefficient of interest θ shows the effect of a one percent increase in broadband coverage on the probability of broadband (ISDN or Analog) usage. This interpretation relies on the coverage expansion reform providing exogenous variation in coverage conditional on municipality (η_m) and year (τ_t) fixed effects.[9]

Table 1.6 shows that broadband coverage expansion increases broadband adoption and decreases the usage of slower analog or ISDN connections. Estimates are highly statistically significant, similar in size, opposite in sign, and consistent across specifications with and without industry fixed effects. Both effects are economically significant, as a one percentage point increase in broadband coverage leads to a 0.24 percentage points increase in broadband adoption and to 0.19 percentage points reduction in analog or ISDN usage. The larger estimate for broadband internet adoption suggests that both substitution from the old connection types and first-time connection immediately to broadband likely take place.

[9] I cluster standard errors on the municipality level. Regression weights based on industry-specific firm distributions by the number of workers, total wage bill, and sales value account for the survey sampling design. Furthermore, I consider specification with and without industry fixed effects to account for industry-wise differences in broadband internet adoption.

Table 1.6: Estimates for the Effect of Coverage Expansion on the Type of Connection in Firms

	Connection Type:	
	ISDN or Analog	Broadband
No Industry FE	-0.184	0.234
	(0.047)	(0.042)
Industry FE	-0.186	0.235
	(0.045)	(0.041)
Dependent Mean	0.25	0.79
No. Observaions	21,739	21,739
No. Municipalities	427	427

Note: Regression specification is defined in Equation 1.1. Standard errors (in parentheses) are clustered on municipality level.

1.4 Effect of Coverage Expansion on Log Hourly Wages

1.4.1 Event Study Illustration

To illustrate the identification strategy and the effect of broadband coverage expansion on hourly wages, I start with an event-study interpretation. Figure 1.5 shows the average broadband coverage across municipalities from 2001 to 2007 (dashed line and right vertical axis). Time normalized to $T = 0$ in the year when municipalities experience the largest increase in broadband coverage (event). On average, broadband coverage is 3.9 and 13.2 percent two and one years before the event, respectively. Appendix Figure D.1 shows the distribution of the magnitude of the largest increase in coverage for all municipalities. There are no events with a magnitude below 20 percentage points, the median size is 50 percentage points, and the average event is 52.7 percentage points increase. Thus, on average, broadband coverage increases fivefold in the event year.

Figure 1.5: Event Study Illustration

Note: Hourly wage premia (left axis) over time for STEM (blue), Law and Business (red), and Medicine (green), and the average broadband coverage over municipalities (dashed line and right axis). The year of the largest coverage increase is normalized to T=0 (event year). Wage premia normalized to one at $T = -1$ for all majors.

Figure 1.5 shows hourly wage premia for three college majors: STEM (blue), Law and Business (red), and Medicine (green) for three periods before and after coverage expansion events. Separately for each period, I regress log hourly wage on the full set of college major dummies and the dummy for not having a college degree, gender, potential experience, year, and municipality fixed effects. To make estimates comparable across majors, I normalize all returns to be one at $T = -1$. Pre-trends for all majors are flat visually, and the joint test for every major does not reject zero.[10] Wage premia for all three majors increase substantially in the event year. The increase is the highest for Law and Business in all post-event periods,

[10]Pre-event coverage is five times lower than the coverage right after the event and has limited impact on pre-trends. One might notice a slight positive co-movement in coverage and wage premia for Law and Business and STEM majors between periods -2 and -1 when the coverage level increased from 3.9 to 13.2 percent. However, this co-movement is substantially smaller than the event effect.

while the effect is similar for Medicine and STEM at the event date and is larger for Medicine in the post-event periods. In the next section, I use the continuous measure of broadband coverage to obtain precise estimates and find similar results across two different approaches.

1.4.2 Empirical Strategy

The key problem in causally interpreting coefficients from regression of workers' wages on technology adoption is the potential correlation between unobserved productivity parameters of firms and workers and parameters determining the adoption of the new technology. For example, the most productive firms might be more likely to hire the most productive workers and are more likely to adopt the latest technology. Thus, higher hourly wages could not be attributed to technology adoption.

Randomization of technology adoption would break this dependence, but forcing firms to adopt or not adopt broadband internet is infeasible. The solution in this paper relies on exogenous variation in access to broadband infrastructure induced by Norwegian public reform. I assume that the staged nature of broadband coverage expansion generates spatial and temporal variation in coverage that is exogenous to unobserved determinants of productivity conditional on year and municipality fixed effects. Controlling for municipality and year fixed effects eliminates common changes over time and makes comparisons within municipalities. Thus, the exogeneity of broadband coverage variation could be interpreted as the common trends assumption: municipalities with early and late broadband coverage expansion would, on average, have had the same time trends in workers' wage outcomes. Event study interpretation in Section 1.4.1 helps to get evidence supporting the identification assumption. It shows flat pre-trends and allows to jointly test estimated pre-trend coefficients against zero (not rejected).

To estimate the effect of increased broadband coverage, I specify the following panel regression for all workers aged 18-65 recorded in the wage statistics survey:

$$y_{imt} = x'_{imt}\alpha + z_{mt}x'_{imt}\theta + w'_{imt}\delta + \eta_m + \tau_t + u_{imt}, \tag{1.2}$$

where y_{imt} is worker's i log of hourly wage in municipality m in year t and z_{mt} is the broadband coverage level in municipality m in year t. The set of mutually exclusive dummies for individual i's educational attainment x_{imt} is specified as either "College" and "No College"; or "No College" and a full set of dummies for college majors. Covariates w_{imt} include a dummy for gender, linear and quadratic potential experience terms, and industry fixed effects.[11] Unobserved determinants of production fixed at the municipality level are controlled by the municipality-level fixed effects η_m, while the common time shocks are controlled by the year fixed effects τ_t. Standard errors are clustered on the municipality level.

The main parameter of interest θ measures the effect of a one percentage point increase in broadband coverage rate on workers' log hourly wages for different education levels (college majors).

1.4.3 Results

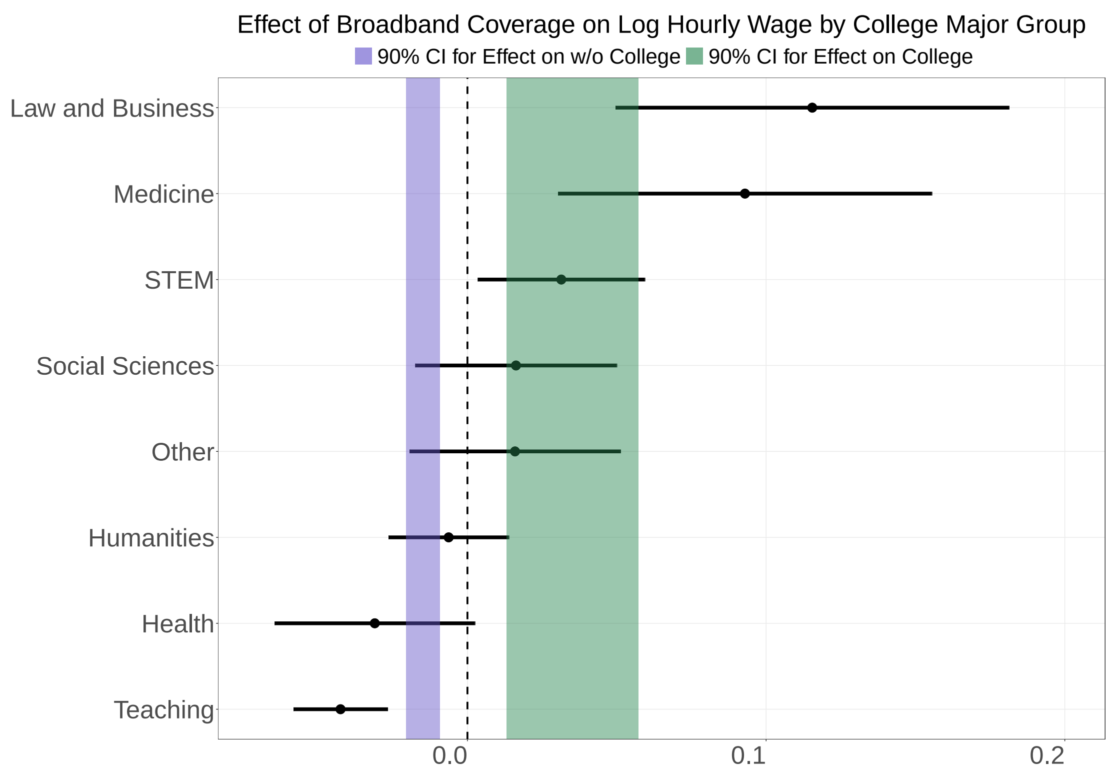
Figure 1.6 shows the estimates of θ for workers with and without a college degree, major-specific estimates, and 90% confidence intervals. Colored intervals summarize the results for all college-educated workers (green) and workers without a college degree (purple). Solid black intervals present the estimates for the specification with college majors.

The estimates show a positive (negative) effect of the broadband coverage expansion on the hourly wages of college-educated (not college-educated) workers. In particular, a one percentage point increase in broadband coverage leads to a 0.035 percent increase in the hourly wages of college-educated workers and a 0.014 percent decrease for workers without a college degree. These results are numerically similar to the results in Akerman et al. (2015),

[11] "No College" dummy includes all workers who do not have a college degree: did not finish college, only high school degree, and did not finish high school.

who also use the setup of the Norwegian broadband coverage expansion reform with a slightly different workers sample definition.

Figure 1.6: Estimates of the Effect of Coverage Expansion on Log Hourly Wages



Note: Estimates for the effect of broadband coverage expansion on log hourly wages of workers with different levels of educational attainment θ defined in Equation 1.2 with 90% confidence intervals. Colored intervals represent estimates for college-educated workers (green) and workers without college degrees (purple). Solid black lines show the results for the full set of college majors.

The estimates for the full set of college majors present a substantial heterogeneity in the effect of broadband coverage expansion on the hourly wages of college-educated workers. Figure 1.6 and Table 1.7 show that Law and Business graduates experience the highest increase in the hourly wage of 0.115 percent per one percentage point increase in broadband coverage, and the second largest estimate of 0.093 for Medicine major. Both estimates are economically larger than the average effect for all college-educated workers. The effect for Law and Business major is also statistically significantly larger at a 95% confidence level (one-sided). In contrast, Teaching graduates experience the most substantial decline in the hourly wage of 0.042 percent per one percentage point increase in broadband coverage. This decrease is economically larger than the estimate for workers without a college degree, and the difference is statistically significant at a 95% confidence level. However, it is important to keep in mind that my results are for workers with Teaching degrees employed in private firms rather than as teachers in public schools.

My results extend the literature on the positive effects of ICT for high-skill workers by showing college major-specific heterogeneity and by showing that college majors already define groups that benefit the most and the least from ICT access expansion. The broad pattern of heterogeneity confirms earlier findings that managerial workers' hourly wages increase the most from ICT adoption (Bartel et al. (2007); Bresnahan et al. (2002); Caroli and van Reenen (2001); Deming (2017,2); Kruger (1993)). In contrast to most of this literature, I compare managerial workers to other high-skill employees rather than lower-skill workers in the same industry or firm. Thus, managerial skills are complemented by ICT more favorably than other types of high-skill human capital and not just better than low-skill human capital. Furthermore, my estimates show the effect of the expanded access availability rather than the initial adoption.

Particularly interesting is a relatively small estimate for STEM graduates. Its magnitude of 0.031 percent per one percentage point coverage increase is below the average effect for all college-educated workers and is substantially lower than the estimate for Law and Business graduates. Furthermore, a one-sided hypothesis that the effect for STEM major is greater or equal to the estimate for Law and Business major is rejected in favor of its one-sided alternative at a 95% confidence level. This finding contrasts with Humlum and Bjørnsson (2020), where STEM workers directly involved in the research and development of AI see the largest wage increase from AI's usage expansion. These two findings together illustrate how the hourly wages in the population of high-skill workers may reflect the diffusion of technology in the economy from localized technical hubs to a broad class of non-technical users (Bloom et al. (2021)).

Another angle to see my results is the effect of ICT access expansion on the evolution of returns to college majors. Causal evidence from college admission discontinuities in Chile (Hastings et al. (2013)) and Norway (Kirkeboen et al. (2016)) show substantial heterogeneity in college premia across college majors. In particular, high premia for Law, Business, Medicine, and STEM degrees and low premia for Humanities and Education/Teaching degrees. Interestingly, the effects of broadband coverage expansion on hourly wages follow a similar pattern with high effects for Law and Business, Medicine, and STEM. At the same time, Humanities, Health, and Teaching degrees have low estimates. The only caveat is the gap in estimates size between STEM and the top majors.

1.4.4 Threats to Interpretation

Appendix B shows that my results are not fully explained by the complementarity of ICT to workers in abstract occupations (Acemoglu and Autor (2011); Autor and Dorn (2003)). Table B.1 shows that the share of Law and Business graduates in abstract occupations is 8.8 percentage points lower than the share of STEM graduates and 14.6 percentage points lower than the share of Medicine graduates despite the former major having the highest increase in hourly wages. Similarly, the share of Teaching graduates in abstract occupations is 7.3 percentage points larger than that of Humanities graduates, while the estimate is substantially larger for Humanities. More generally, Appendix Figure B.1 shows that the correlation between major-specific estimates and shares of workers in abstract occupations is 0.52 and is not significant on any conventional significance level. To further explore the complementarity between managerial education and broadband internet in Section 1.6 I show the positive effect of coverage expansion on firms' demand for ICT skills and applications complementary to managerial skills.

Appendix F shows the estimates for the effect of broadband usage rate on log hourly wages by college major. I define municipality-level broadband usage rate as the survey-weighted average of firm-level broadband usage indicators in the municipality. While coverage expansion identifies the intention-to-treat effect on the population of workers affected by the reform, variation in municipality-level broadband usage rate identifies the effect on the workers affected by the selection in early broadband adoption in municipalities. Figure F.1 shows that the average usage rate substantially exceeds the coverage rate for almost the entire reform duration, meaning that many firms had broadband access before the reform. Figure F.2 shows that estimates for Law and Business and Medicine majors are similar for coverage and usage rates. In contrast, the estimate for STEM major is 2.45 larger for usage rate than for coverage rate. It suggests that workers with STEM major are likely to benefit more during early broadband adoption; however, the estimate is still lower than for Law and Business and Medicine majors.[12]

There is a valid threat that drastic differences in majors and gender composition between cohorts graduating from college and retiring during the reform may substantially influence my estimates. Section 1.2.1 shows that younger college-educated cohorts have several times larger share of women and have a much higher share of Law and Business graduates of both sexes. To alleviate concerns about the potential effect of composition changes on my estimates, Appendix E provides estimates for the effect of broadband coverage expansion on log hourly wages for three age groups: $18-34$ yo, $35-50$ yo, and $51-65$ yo. Reassuringly, the main findings survive in all three subsamples. In particular, the estimate for Law and Business is always the largest. In $35-50$ and $51-65$ subsamples, the effect for Law and Business is statistically significantly larger than the average for all college-educated workers on a 95% confidence level. In $35-50$ subsample, it is statistically significantly larger than the effect for STEM. The estimate for Teaching major is at the bottom in $18-34$ and $35-50$ subsamples and the second from the bottom in $51-65$ subsample. The estimate for STEM is always substantially smaller than estimates for Law and Business and Medicine majors.

[12] Similarly to the coverage expansion estimates, Appendix Figure F.3 shows that the correlation between major-specific estimates for the effect of broadband usage rate and share of workers in abstract occupations is 0.42 and is not significant on any conventional significance level.

1.5 Ranking of College Majors

The substantial heterogeneity in estimates of the effect of broadband coverage expansion on log hourly wages across college majors is incredibly relevant for policymakers and prospective college students. Understanding which college majors are affected in the best-/worst- way helps to identify workers that need policy support and helps students to adjust their college major choices given the effect of the new technology on hourly wages. In the Norwegian context, this heterogeneity is even more important as prospective students submit rank preferences of college majors in a centralized admission process. Such questions implicitly or explicitly require ranking college majors by the effect of broadband internet on log hourly wages. However, I observe estimates rather than the true values of the effect. Thus there is considerable uncertainty concerning the rank of each college major.[13]

I use the inference procedure developed in Mogstad et al. (2021) and Bazylik et al. (2021) to account for such uncertainty. The procedure shows how to construct three types of valid confidence sets for the ranks of college majors, each answering distinct economic questions. The first type, marginal confidence sets, answer whether a given college major has a relatively high or low effect of broadband internet coverage on log hourly wages. Thus, it is relevant if a student or a policymaker is interested in whether a particular major (say Law and Business) is among the best or the worst majors in terms of how its graduates' wages are affected by broadband coverage expansion. The second type, simultaneous confidence sets, allow such inferences to be drawn simultaneously across all majors. Thus, it is relevant if one is interested in broad patterns of the effect that coverage expansion has on the hourly wages of college majors. The third type, confidence sets for τ-best/-worst, answer the more specific question of which college majors cannot be ruled out as being among the most/least benefiting from

[13] Other examples of similar problems in the literature include ranking US counties and commuting zones by their intergenerational economic mobility (Chetty, Hendren, Kline and Saez (2014), Chetty, Friedman, Hendren, Jones and Porter (2018)), OECD countries by students' academic achievement (OECD (2017)), political parties and candidates by their popularity (Bazylik et al. (2021)) or journals and universities by their features (Mogstad, Romano, Shaikh and Wilhelm (2022)). See a more detailed discussion in Mogstad et al. (2021) and Bazylik et al. (2021).

broadband coverage expansion. It is relevant when one is interested in the top or bottom part of the ranking. I provide formal definitions and discussion in Appendix G.

Table 1.7 shows all three types of 90% confidence sets for the ranks of college majors by the effect of broadband coverage expansion on log hourly wages. Marginal CS shows that with 90% confidence Law and Business major is in the top three alternatives and that Teaching major is in the bottom two alternatives. At the same time, marginal CS for the rank of STEM major spans from one to six, and one can not guarantee that the effect for STEM major is even in the top half of the ranking. Figure 1.7 highlights that Law and Business major and Teaching major have the tightest marginal CS among all college majors. Thus, the statements about the best effect for Law and Business graduates and the worst effect for Teaching graduates have credibility when one takes multiple hypothesis testing issue of ranking into account.

Table 1.7: Confidence Sets for the Ranks of Majors

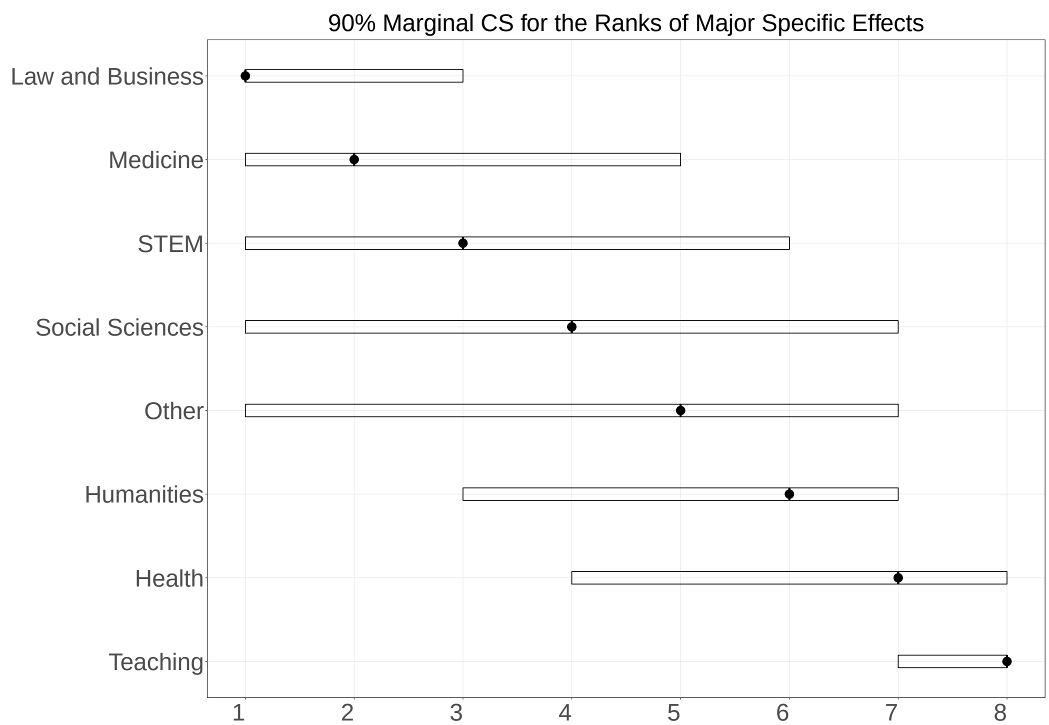
				90% CS			
Rank	Major	Est	SE	Marg	Simul	τ - best	τ - worst
1	Law and Business	0.115	0.040	[1,3]	[1,5]	5	8
2	Medicine	0.093	0.038	[1,5]	[1,6]	6	8
3	STEM	0.031	0.017	[1,6]	[1,7]	7	8
4	Social Sciences	0.016	0.021	[1,7]	[1,8]	8	8
5	Other	0.016	0.021	[1,7]	[1,8]	8	8
6	Humanities	-0.006	0.012	[3,7]	[2,8]	8	7
7	Health	-0.031	0.020	[4,8]	[3,8]	8	6
8	Teaching	-0.042	0.010	[7,8]	[4,8]	8	5

Note: The estimates and standard errors for the effect of broadband coverage expansion on log hourly wages by college major. 90% Marginal, Simultaneous and τ-best/-worst confidence sets for the ranks of college majors. Estimates and standard errors come from Specification 1.2.

The size of simultaneous and τ-best/-worst CS implies that my estimates are not precise enough to draw conclusions about broader patterns across college majors. For both Law and

Business and Teaching majors, 90% simultaneous confidence sets cover more than half of the ranking, and for majors in the middle the confidence set covers the entire ranking. The pattern of substantially wider simultaneous and τ-best/-worst confidence sets is natural as both objects require more pairwise comparisons than marginal confidence sets. For example, when one is interested only in Law and Business major, one has to compare it to 7 other majors. However, conclusions about the entire ranking require $C_2^8 = \frac{7\times 8}{2} = 28$ comparisons. Thus the adjustment for the multiple hypothesis testing inevitably leads to wider confidence sets.

Figure 1.7: 90% Marginal CS for the Ranks of College Majors



Note: 90% Marginal CS for the ranks of college majors by the effect of broadband coverage expansion on log hourly wages.

One way to achieve more informative conclusions about groups of majors is to restrict attention to majors within prospective students' choice sets. For policymakers and college applicants, the ranking of majors that are close substitutes is more relevant than the ranking of all majors. This framing is especially useful in the Norwegian college admission system, where prospective students submit rank preferences of majors through a centralized system and get admitted to their most preferred major available given their high school GPA.

Using administrative data on students' college majors ranking from the centralized admission system Kirkeboen et al. (2016) show how to construct relevant choice sets of college majors. They find that $\approx 40\%$ of applicants got admitted to their first ranked major and $\approx 80\%$ to one of their three highest-ranked choices. Furthermore, Law and Business, Social Sciences, Humanities, and Teaching majors are all among the most popular next-best alternatives for each other in students' rank preferences data. These four majors comprise the relevant choice set for prospective students.

Table 1.8 shows that within the relevant choice set, the best and the worst major have a single rank in both 90% marginal and simultaneous CS. One can be sure of their place in the entire ranking within this subset. Similarly, τ-best/-worst CS show that only a single college major could be at the top/bottom of the ranking. The Social Sciences and Humanities estimates are too close, meaning that both confidence sets include ranks two and three. However, we can be confident that both majors are not in the confidence sets for the best and the worst alternatives.

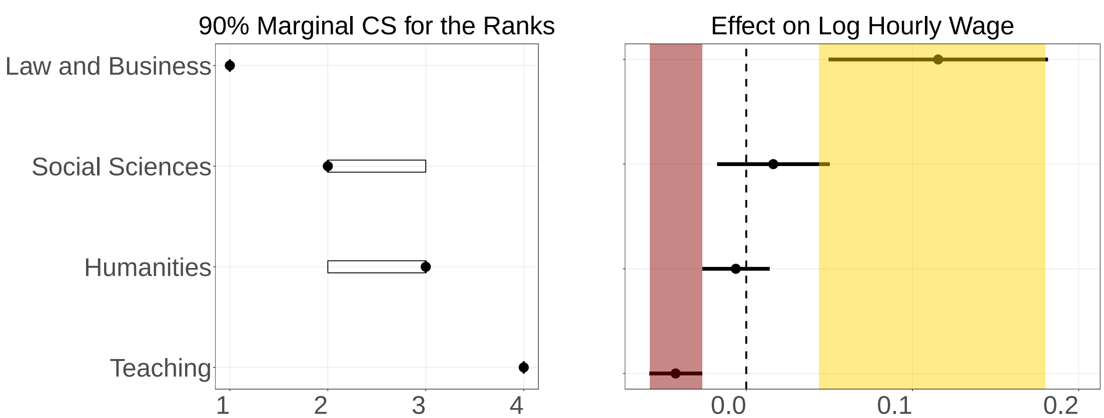
Table 1.8: Confidence Sets for the Ranks of Majors in the Choice-Relevant Subset

				90% CS			
Rank	Major	Est	SE	Marg	Simul	τ - best	τ - worst
1	Law and Business	0.115	0.040	[1,1]	[1,1]	1	4
2	Social Sciences	0.016	0.021	[2,3]	[2,3]	3	3
3	Humanities	-0.006	0.012	[2,3]	[2,3]	3	3
4	Teaching	-0.042	0.010	[4,4]	[4,4]	4	1

Note: The estimates and standard errors for the effect of broadband coverage expansion on log hourly wages and 90% CS for the ranks of Law and Business, Social Sciences, Humanities, and Teaching majors. These four majors are all in the set of the next best alternatives for each other in administrative student applicants data in Kirkeboen et al. (2016). Estimates and standard errors come from Specification 1.2.

The left panel of Figure 1.8 illustrates the lower uncertainty in 90% marginal CS for the ranks of majors in the restricted relevant choice set. The right panel shows the estimates with 90% confidence intervals and Andrews, Kitagawa and McCloskey (2019) 90% conditional confidence intervals for best and worst majors. The approach of Andrews et al. (2019) constructs valid confidence intervals for best and worst taking into account the "winners curse" arising from using the same sample for selection and inference. In practice, this implies wider confidence intervals than for the raw point estimates and a shift closer to the mean effect. The confidence intervals for the best and the worst effect in the choice-relevant set are tight, confirming the informative characterization of the confidence sets for the ranks. Appendix Figure G.1 shows that 90% conditional confidence intervals for the best and the worst effect are not informative in the full sample of majors. In contrast, the approach of Mogstad et al. (2021) and Bazylik et al. (2021) still allows for an informative characterization of the top and the bottom of the ranking of college majors in Figure 1.7.

Figure 1.8: Majors Ranking in the Choice-Relevant Subset



Note: **Left:** 90% Marginal CS for the ranks of college majors by the effect of broadband coverage expansion on log hourly wages. **Right:** estimates with 90% confidence intervals, and Andrews et al. (2019) conditional 90% confidence intervals for "winner" and "loser".

1.6 Event Study of ICT Vacancies

Results of Section 1.4.3 show that broadband internet coverage expansion leads to a particularly large increase in the hourly wages of workers with Law and Business college major. In contrast, the estimates for STEM majors are substantially lower. This section presents evidence for one of the explanations behind this heterogeneity. Broadband coverage expansion increases the demand for ICT skills complementary to managerial skills and has no effect on the demand for advanced and technical ICT skills.

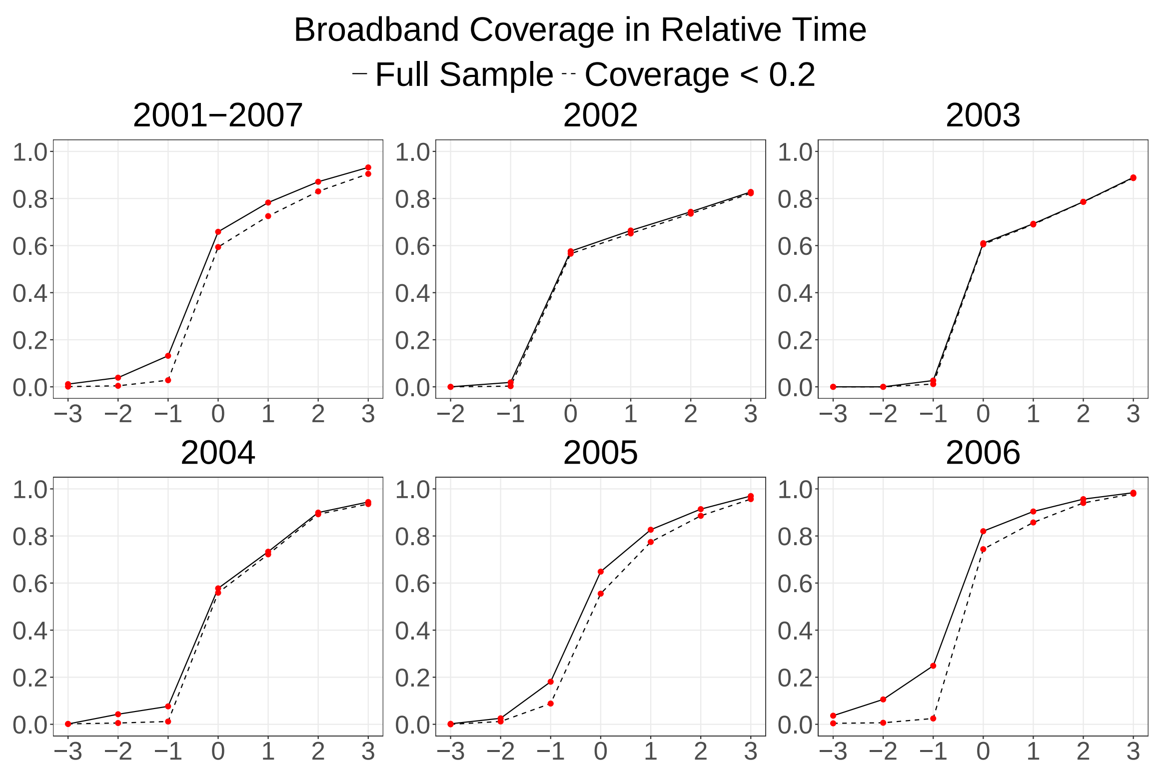
1.6.1 Event Definition

This section shows event study estimates for the dynamic effect of broadband coverage expansion events in Norwegian municipalities on firms' demand for ICT skills. My main estimates in Section 1.4.3 use the total continuous variation in municipality-level broadband coverage for increased precision of estimates. Vacancy data provides me with enough statistical power to analyze the event study setting with discretized treatment events and allows me to see the dynamic effect of broadband coverage expansion events on vacancy postings.

I define the treatment event in each municipality as the largest increase in broadband internet coverage in a year. The sample contains seven treatment cohorts with event dates from 2001 to 2007. The top left panel of Figure 1.9 plots the average over 2001-2007 treated cohorts broadband coverage in time relative to the event year. The remaining panels show broadband coverage for the [2002,. . . , 2006] treated cohorts. Appendix Figure D.1 shows that the average event corresponds to a 52.7 percentage points increase in broadband coverage, and Figure 1.9 shows that the average event size is consistent across the treatment cohorts reassuring consistent event definition for the entire reform period.

For treatment cohorts after 2004 there is a noticeable pre-event coverage that might contaminate the not-yet-treated controls and bias the event study estimates. To decrease the influence of pre-event coverage contamination, I define subsamples with pre-event broadband coverage restrictions. Figure 1.9 shows that a 20 percent pre-event coverage restriction substantially reduces pre-event contamination across all later treated cohorts (dashed line). Table 1.9 highlights the tradeoff between the sample size in later treated cohorts and the pre-event coverage restriction in municipalities. Decreasing the cutoff from 20 to 10 percent reduces the eligible sample in the 2005 treated cohort from 60 to 28 municipalities. Even a 20 percent coverage restriction decreases 2006 eligible treated cohort from 90 to 34 municipalities. To strike a balance between estimates precision and contamination of the control group, I present the results for the unrestricted sample in the main text and for the subsample with 20 percent restriction in Appendix H. It is reassuring that estimates do not materially change with sample restrictions.

Figure 1.9: Coverage Expansion Events by Cohort



Note: **Top Left:** the average broadband coverage for 2001-2007 treated cohorts relative the event year. **Other Panels:** the average broadband coverage for each of the [2002,. . . , 2006] treated cohorts relative to the event year. Solid lines - full sample of municipalities. Dashed lines - subsample with a 20 percent pre-event coverage restriction.

Table 1.9: Treatment Cohorts Sample Size with and without Pre-Event Coverage Restrictions

Pre-Treatment Coverage:	2001	2002	2003	2004	2005	2006	2007	Total
No Restrictions	2	71	74	50	135	90	5	427
< 0.20	2	67	70	38	60	34	0	271
< 0.10	2	66	65	35	28	27	0	223
$= 0$	2	65	63	34	21	26	0	211

Eliminating municipalities with high pre-event broadband coverage may produce selection bias in my estimates. One way to alleviate this concern is to ensure that the identification assumption of parallel trends in vacancy outcomes holds in restricted subsamples. The results with a 20 percent coverage restriction in Appendix H show that pre-trends remain flat.

1.6.2 Empirical Strategy

Section 1.2.2 shows drastic differences in the number of vacancies with each type of ICT skill. On average, the number of vacancies mentioning General ICT skills is three times larger than the number of vacancies with Web Development skills, five times larger than the number of vacancies with Programming skills, and fifteen times larger than the number of vacancies with Data or Enterprise Software skills. Thus, I standardize vacancy mention outcomes for each ICT skill type to scale the effects to comparable units. For each skill type, vacancy outcomes are demeaned and normalized by standard deviation.[14]

To estimate the average treatment on the treated effect for each treated cohort $g \in \{2002, \ldots, 2006\}$ and for time $\tau \in \{-3, \ldots, 2\} \setminus \{-1\}$ relative to the event date, I specify the following regression:

$$Y_{mt} = \alpha_0^{g,\tau} + \alpha_1^{g,\tau} G_{mg} + \alpha_2^{g,\tau} \mathbb{I}[T = t] + \alpha_3^{g,\tau} \mathbb{I}[T = t] G_{mg} + \gamma^{g,\tau} X_m + \epsilon_{mt}, \tag{1.3}$$

[14]The mean and the std. dev. are defined for each ICT skill group separately.

where Y_{mt} is standardized municipality-level vacancy outcome in year t, G_{mg} is an indicator that municipality m is in the treatment cohort g, $t \in \{g-1, g+\tau\}$ are the base period one year before the coverage expansion event and the period of interest τ years away from the treatment event, and X_m are controls for municipality level industry composition and firm size and labor market fixed effects[15] in the last pre-reform year 2000.

Specification 1.3 is estimated using a sample of municipalities treated in year g and control municipalities not-yet-treated at the time $g+\tau$ (treatment effects when $\tau \geq 0$) or g (pre-trends when $\tau < -1$).[16] The entire model is estimated in a single fully interacted step to get a joint variance-covariance matrix. Standard errors are clustered at the municipality level and are robust to heteroskedasticity.

The main coefficient of interest $\alpha_3^{g,\tau}$ is the 2×2 DID parameter for the base period $g-1$ and the period of interest τ years from the coverage expansion event $g+\tau$:[17]

$$\underbrace{\mathbb{E}[Y_{m,g+\tau} - Y_{m,g-1} | m \text{ treated at } g]}_{\text{difference over time for treated group}} - \underbrace{\mathbb{E}[Y_{m,g+\tau} - Y_{m,g-1} | m \text{ has not been treated by } g+\tau]}_{\text{difference over time for control group}} \tag{1.4}$$

Unobserved time-invariant municipality heterogeneity is eliminated by comparing treated municipalities before and after broadband coverage expansion event while using not-yet-treated municipalities as a control group to account for the year and event-time effects. This parameter recovers the average effect of the broadband coverage expansion event for treated cohort g in year $g+\tau$ under the assumption that in the absence of the broadband coverage expansion event, the municipalities in the treated and not-yet-treated control groups would have had a common trend in the vacancy outcomes between dates $g-1$ and $g+\tau$.

The parameter $\alpha_3^{g,\tau}$ allows flexible aggregation to dynamic event study effect α_3^{τ} and to overall post-treatment average effect α_3. Event study parameter α_3^{τ} is recovered by aggregating $\alpha_3^{g,\tau}$ over treated cohorts τ periods after treatment and weighting by cohort's

[15] A set of municipalities where people commute to work defines a labor market.

[16] Every municipality is treated by the year 2007, meaning there are no untreated controls for correct comparisons and, thus, no treatment effect estimates for $g = 2007$ cohort.

[17] When $\tau \in \{-3, -2\}$ the parameter shows pre-trend coefficients for the treatment cohort g.

share:

$$\alpha_3^{\tau} = \frac{1}{N}\sum_{g} N_g \alpha_3^{g,\tau} \tag{1.5}$$

where N_g is the amount of workers in treatment cohort g and $N = \sum_g N_g$. Averaging event study parameter over $\tau \geq 0$ recovers the average treatment effect α_3:

$$\alpha_3 = \frac{1}{3}\sum_{\tau=0}^{\tau=2} \alpha_3^{\tau} \tag{1.6}$$

Standard errors for aggregated parameters use the joint variance-covariance matrix from the estimation step. The estimation procedure and aggregate parameters definition follow Callaway and Sant'Anna (2021) and ensure that parameters of interest are positively weighted sums of causal parameters under the parallel trends assumption.[18]

1.6.3 Results

The top left panel of Figure 1.10 plots point estimates with 90% confidence intervals for the event study parameters α_3^{τ} for all vacancy postings, vacancies with at least one ICT skill and vacancies with at least one General ICT skill. Pre-trends for all three outcomes are zero in both pre-periods providing more confidence in the parallel trends identification assumption.[19] The estimates for the total amount of posted vacancies become positive and statistically significant only in the third post-treatment year. In contrast, the estimates for vacancies with at least one ICT skill and at least one General ICT skill become positive in the second post-treatment period and are economically and statistically significantly larger than the estimates for the total number of vacancies in the second and third periods. It is essential to establish that broadband expansion has a larger effect on ICT-related vacancies than on all

[18] This estimation procedure avoids the problems discussed in de Chaisemartin and D'Haultfœuille (2020), Sun and Abraham (2021), and Callaway and Sant'Anna (2021), and Borusyak, Jaravel and Spiess (2022). Furthermore, pre-event coefficients allow for valid pre-trends testing.

[19] Joint test also does not reject zero value for the pre-trends.

vacancies as the proxy for higher demand for ICT skills.[20]

The first three rows of Table 1.10 confirm event study findings with estimates for the overall post-treatment effect α_3 consistently across four specifications with and without controls and labor market fixed effects. The estimates show that broadband coverage expansion events have no statistically significant effect on the number of posted vacancies. The estimates for vacancies with at least one ICT skill or one General ICT skill are from 2 to 3 percent of standard deviation and are highly statistically significant. Using the standard deviation from Table 1.4, the estimates for vacancies with at least one ICT skill translate to the range from $0.022 \times 936.9 \approx 20.6$ to $0.031 \times 936.9 \approx 29.0$ compared to the mean of 183.4 vacancies with at least one ICT skill per municipality, meaning that the estimates are economically significant.

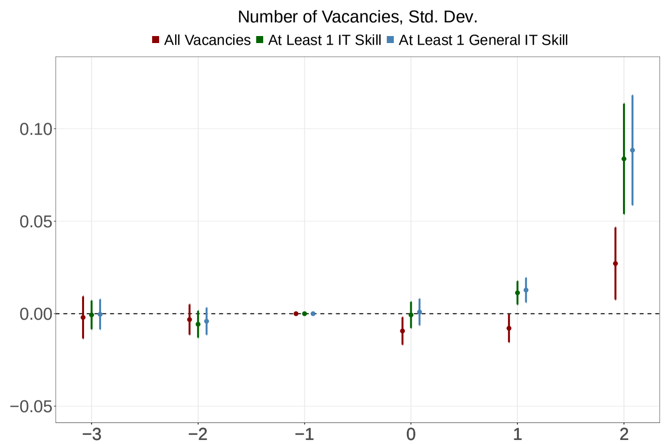
The top right panel of Figure 1.10 plots point estimates for α_3^{τ} with 90% confidence intervals for all five categories of ICT skills. Consistently in all post-treatment periods, estimates for vacancies with General ICT skills are larger than estimates for other ICT skills. In the third post-treatment period, the differences between the General ICT and Enterprise Software and Data skills estimates are significant at a 95% confidence level. Rows three through seven in Table 1.10 support these findings with estimates of the overall post-treatment α_3. In my preferred specifications (3) and (4) with municipality-level industry structure controls, one-sided hypotheses of estimates for vacancies with General ICT skills being smaller than estimates for any other type of ICT vacancies are rejected in favor of their one-sided alternatives at a 90% confidence level. The difference in magnitudes is stark when converted from standard deviations into vacancies amount. For vacancies with at least one General ICT skill, the increase post-treatment is $0.034 \times 800 \approx 27.2$ vacancies, for vacancies with at least one Programming skill - $0.019 \times 204 \approx 3.9$, with at least one Web Development skill - $0.018 \times 348.2 \approx 6.3$, with at least one Enterprise Software skill - $0.007 \times 59.3 \approx 0.4$, and with at least one Data skill - $0.003 \times 91.4 \approx 0.3$.

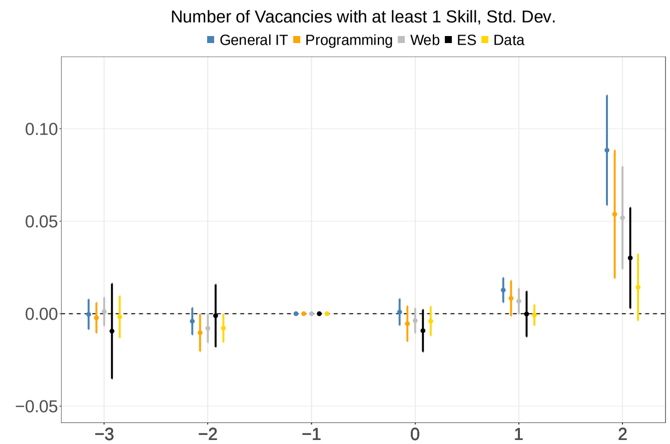
[20]Section 1.7 shows that broadband coverage expansion substantially increases the usage of online recruitment practices. Thus, higher visibility or efficiency of online vacancy postings could cause an increase in the number of posted vacancies.

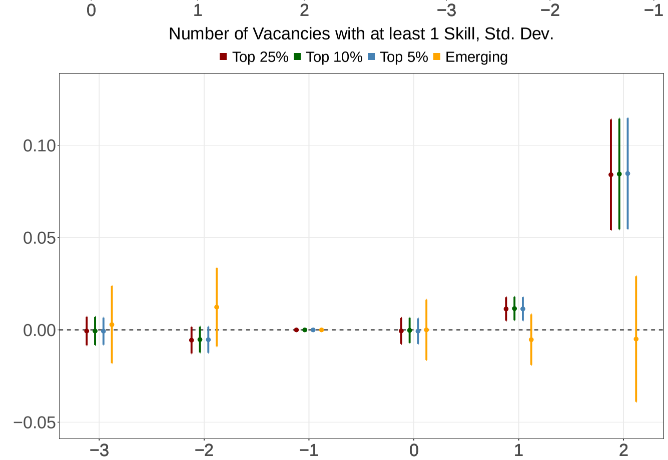
Finally, the bottom panel of Figure 1.10 plots point estimates for α_3^τ with 90% confidence intervals for vacancies with a least one top 25%, top 10%, top 5%, or emerging ICT skill. Starting from the second post-treatment period, the estimates for outcomes with all three cutoffs for popular skills are positive and statistically significant. The estimates for vacancies with emerging skills are close to zero and statistically insignificant at all conventional levels. In the third post-treatment period, the difference between the estimates for any top and emerging skills cutoff is highly statistically significant on all common confidence levels. Notably, the estimates for all three top skills cutoffs are the same in size, meaning that broadband expansion events predominantly affect the demand for widely used ICT skills. Rows eight through eleven in Table 1.10 show the consistency of these results across all specifications in the overall post-treatment period.

Taken together, these findings show that broadband expansion events have the most sizable effect on the vacancies with General ICT skills and widely used ICT skills. General ICT skills simplify information collection, storage, and communication, complementing managerial skills. The prevalence of the increase in General ICT skills provides a plausible explanation for the large effect of broadband coverage expansion on the hourly wages of workers with Law and Business major. Similarly, the low effect of coverage expansion events on the number of vacancies with advanced technical and new ICT skills points to small estimates for STEM graduates. These patterns in the effect of the expansion of the established technology are in contrast with studies of the initial adoption of the more recent ICTs, such as AI., where the importance of research and development skews positive wage effects in favor of STEM graduates with advanced ICT skills (Deming and Noray (2020)). Appendix H shows that similar results hold in the subsample of municipalities with 20 percent pre-treatment coverage restriction.

Figure 1.10: Event Study Estimates for the Effect of Coverage Expansion on Vacancies







Note: Event study estimates for the full sample of Norwegian municipalities defined in Equation 1.5 and components estimated in Specification 1.3 for standardized vacancy outcomes Y_{mt}: All Posted Vacancies, Vacancies with At Least 1 IT Skill and with At Least 1 General IT Skill (**Top Left**); for Vacancies with At Least 1 General IT Skill, At Least 1 Programming Skill, At Least 1 Web Development Skill, At Least 1 Enterprise Software Skill and At Least 1 Data Skill (**Top Right**); for Vacancies with At Least 1 Top 25% IT Skill, At Least 1 Top 10% IT Skill, At Least 1 Top 5% IT Skill and At Least 1 Emerging IT Skill (**Bottom**). All estimates are presented with 90% confidence intervals.

Table 1.10: Aggregate Post-Treatment Effect α_3

Vacancy outcome:	(1)	(2)	(3)	(4)
All Vacancies	-0.001 (0.003)	0.007 (0.004)	-0.002 (0.004)	0.003 (0.004)
Any ICT Skill	0.023 (0.003)	0.027 (0.004)	0.022 (0.005)	0.031 (0.006)
General ICT	0.024 (0.003)	0.028 (0.004)	0.025 (0.005)	0.034 (0.006)
Programming	0.017 (0.004)	0.021 (0.005)	0.011 (0.006)	0.019 (0.008)
Web Development	0.019 (0.003)	0.022 (0.004)	0.013 (0.005)	0.018 (0.006)
Enterprise Software	0.007 (0.004)	0.008 (0.004)	0.004 (0.006)	0.007 (0.006)
Data Skills	0.006 (0.002)	0.007 (0.002)	0.002 (0.004)	0.003 (0.004)
Top 25%	0.023 (0.003)	0.027 (0.004)	0.023 (0.005)	0.032 (0.006)
Top 10%	0.023 (0.003)	0.027 (0.004)	0.023 (0.005)	0.032 (0.006)
Top 5%	0.023 (0.003)	0.027 (0.004)	0.023 (0.005)	0.032 (0.006)
Emerging	-0.004 (0.005)	0 (0.005)	0 (0.008)	-0.004 (0.008)
Controls			✓	✓
Labor Market FEs		✓		✓

Note: Aggregate treatment effect α_3 for post-treatment periods $\{0, 1, 2\}$ for the full sample of Norwegian vacancies defined in Equation 1.6 and components estimated in Specification 1.3 . Each vacancy outcome variable is standardized. Standard errors in parenthesis. Specifications (3) and (4) include municipality level industry composition controls for the last pre-reform year 2000. Specifications (2) and (4) include labor market fixed effects. Top X% skills and Emerging skills are defined in Definitions 2 and 3 respectively.

A noteworthy feature of event study estimates for all vacancy outcomes is the initial slow growth that becomes more pronounced in the last post-treatment period. Figure 1.11 shows that there is no lack of personnel with ICT skills and no resistance to learning ICT skills among the current employees at the beginning of the coverage expansion reform in 2002. Both factors are likely to be more pronounced for General ICT skills. Thus, firms' initial reliance on internal skill capital can explain the lag between broadband coverage expansion events and increased mentions of ICT skills. Bloom et al. (2021) observe a similar dynamic pattern in the US for a change in mentions of technology in vacancy postings and in firms' earning calls after its emergence in patent data.

1.7 ICT Usage in Firms

In this section, I use the Annual Community Survey on ICT Usage of Firms to show that broadband coverage expansion leads to higher usage of ICT applications complementary to managerial skills but have a substantially lower effect on more advanced ICT applications requiring advanced ICT skills. These results further justify why the largest effect of broadband coverage expansion on hourly wages occurs to Law and Business rather than STEM graduates.

1.7.1 Empirical Strategy

I use the entire continuous variation of broadband coverage over municipalities and time z_{mt} to estimate the regression specification:

$$y_{jmt} = \alpha + z_{mt}\theta + ind_j + \eta_m + \tau_t + u_{jmt}, \tag{1.7}$$

where y_{jmt} is an ICT usage outcome for a firm j in municipality m at period t, ind_j are industry fixed effects, and the main parameter of interest θ shows the effect of one percentage point increase in broadband coverage z_{mt} on firms' ICT outcomes. To account for the survey sampling design, the regression is weighted, with weights designed to match firm population distribution in each industry by the number of workers, total wage bill, and the value of sales. I cluster standard errors on the municipality level.

1.7.2 Results

Rows one and two in Table 1.11 show the estimates for the effect of broadband coverage expansion on the share of employees using PC in their workplace and on the share of employees who use PC with internet connection in their workplace. Each percentage point increase in coverage leads to ≈ 0.03 percentage points increase in PC usage and ≈ 0.05 percentage points increase in PC usage with the internet. The latter estimate is substantially more statistically significant than the former. Naturally, PC usage with the internet may arise purely from the higher connection quality and increased bandwidth, while the increase in PC usage requires extra capital investment in new computers. It is also evidence that improved access to broadband internet drives the effect rather than additional capital investment. Furthermore, this finding supports the previous result of higher demand for General ICT skills as many of them are more accessible on PC with an internet connection (email, information search, online purchases, etc.).

Rows three to five show the estimates for internet usage for online purchases, personnel recruiting and training, filing governmental forms, and information search. For each percentage point increase in broadband coverage firms are ≈ 0.05 percentage points more likely to use the internet for information search and filing governmental forms (Basic), are ≈ 0.08 percentage points more likely to use the internet for transactions and purchases (Transactions), and are ≈ 0.15 percentage points more likely to use the internet for personnel recruitment and training (Personnel). The estimates are highly statistically significant and consistent over specifications with and without industry fixed effects.[21] These applications require only General ICT skills from employees and complement managerial work. Thus, the estimates

[21] The estimate for the effect of coverage expansion on using the internet for personnel recruiting is particularly large. Thus, it was crucial to show in Section 1.6 that the increase in the number of vacancies with ICT skills goes beyond the increase in the total number of posted vacancies driven by possibly lower costs of posting on the internet.

are consistent with the increase in demand for General and widely used ICT skills and the high increase in hourly wages of workers with managerial degrees.

Table 1.11: Estimates for the Effect of Coverage Expansion on ICT Usage Outcomes

Outcome	(1)	(2)
%Empl Use PC	0.032	0.030
	(0.026)	(0.019)
%Empl Use PC with Internet	0.050	0.047
	(0.030)	(0.023)
Transactions	0.079	0.080
	(0.037)	(0.037)
Personnel	0.149	0.152
	(0.057)	(0.054)
Basic	0.050	0.050
	(0.025)	(0.025)
Has a Website	0.072	0.075
	(0.030)	(0.029)
Advanced	0.010	0.012
	(0.043)	(0.041)
Industry FEs		✓
No. Observaions	21,739	21,739
No. Municipalities	427	427

Note: ICT usage outcomes come from Table 1.5. Regression specification is defined in Equation 1.7. Standard errors in parentheses and are clustered on municipality level.

Finally, rows six and seven of Table 1.11 show the estimates for the effect of broadband coverage expansion on having a website and on using advanced ICT applications, such as taking internet orders and conducting market monitoring and research. The estimate for having a website is 0.075 percentage points per one percentage point increase in broadband coverage and is highly statistically significant, while the estimate for advanced ICT applications is small 0.012 and not statistically significant. This contrast supports the story about the increased demand for basic ICT skills and no change in demand for advanced ICT skills. Website for a firm and its maintenance could be purchased from an outside vendor and requires only General ICT skills from the firm's employees to use it. In comparison, an online store needs constant updates and maintenance as the firm's profit directly depends on the store's streamlined operation requiring the presence of employees with advanced Web Development and Programming ICT skills. Similarly, concerted online market research effort requires Data and Programming ICT skills. Thus, the lack of effect on the usage of advanced ICT applications in firms is consistent with the lack of effect on demand for advanced ICT skills.

1.7.3 Supportive Survey Evidence

The estimates in Section 1.6 and Section 1.7 show that broadband coverage expansion leads to an increase in demand for General and widely used ICT skills and to an increase in usage of basic ICT applications requiring these skills while there is no effect on the demand for advanced and novel ICT skills and advanced ICT applications. In this section, I show survey evidence on obstacles to ICT adoption in firms where the difficulties in recruiting or lack of personnel with required ICT skills and employees' resistance to ICT adoption are all among the least important obstacles. This evidence confirms that firms did not require employees with advanced and novel ICT skills; in that case, hiring new personnel or teaching existing employees new ICT skills would have been more challenging.

The Annual Community Survey on ICT Usage of Firms for 2002 contains a battery of questions on obstacles to ICT adoption in firms. Firms classify obstacles by their level of importance to impeding ICT adoption: Low, Medium, or High importance. Table 1.12 shows three groups of obstacles from the survey. Workers-related obstacles include the lack of personnel with required ICT skills, difficulties in hiring employees with required ICT skills, and employees' resistance to ICT adoption. Management obstacles consist of the lack of ICT adoption strategy and underestimation of required expenses. Access obstacles are difficulties in finding ICT suppliers and malfunctioning of purchased software.

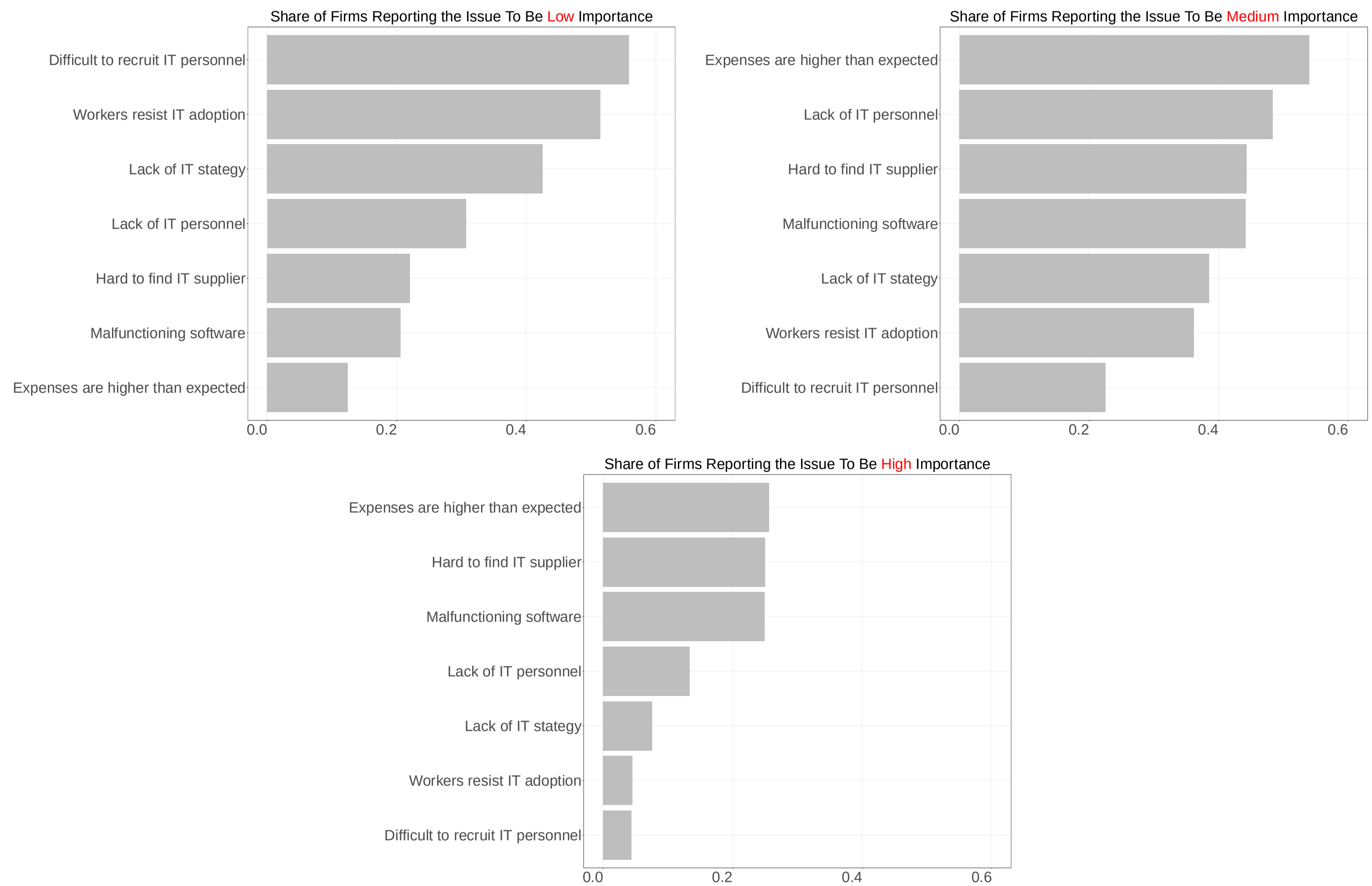
Figure 1.11 shows for each obstacle the share of firms classifying it as Low, Medium, or High importance. The top left panel shows that more than half of firms assign Low importance to difficulties in hiring personnel with required ICT skills and to employees' resistance to ICT adoption, while the bottom panel shows that less than five percent of firms assign High importance to these obstacles. Similarly, the lack of personnel with ICT skills is listed as only Low or Medium importance by more than 85 percent of firms. In contrast, more than a quarter of firms classify higher-than-expected expenses, malfunctioning software, and trouble finding IT suppliers as High importance obstacles. At the same time, these three obstacles are least frequently assigned to Low importance group. These results show that firms did not face shortages of ICT skills, at least at the beginning of the coverage expansion reform. With the evidence on the kinds of ICT adopted by firms, it is highly plausible that firms only required General and widely used ICT skills from their employees. Thus, they did not face obstacles in finding employees with the required skills.

Table 1.12: Obstacles to ICT Adoption

Group	Obstacle
Workers related	Workers resist ICT adoption
	Lack of IT personnel
	Difficult to recruit IT personnel
Management related	Lack of IT strategy
	Expenses are higher than expected
Access to ICT	Hard to find ICT supplier
	Malfunctioning software

Note: Survey questions on obstacles to ICT adoption from 2002 Annual Community Survey on ICT Usage of Firms in Norway. Each obstacle could be classified as Low, Middle or High importance by firms' managers.

Figure 1.11: Obstacles to ICT Adoption from 2002 Annual Community Survey on ICT Usage in Firms



Note: Answer shares in 2002 Annual Community Survey on ICT Usage of Firms questions on obstacles to ICT adoption. **Top Left:** share of firms that classified obstacles as Low importance; **Top Right:** share of firms that classified obstacles as Medium importance; **Bottom:** share of firms that classified obstacles as High importance.

1.8 Conclusion

Federal Communications Commission projects transition to an even faster generation of internet connection in the coming decade (FCC (2020)). It is crucial to understand how workers with different education are affected by the expansion of access to faster internet connection. Despite robust evidence that college-educated workers benefit from access to faster internet, there is little research on the heterogeneity of this effect across college majors.

In this paper, I use the Norwegian public program with limited funding that rolled out broadband internet access points and provided plausibly exogenous variation in broadband coverage. My results show substantial heterogeneity in the effect of broadband coverage expansion on hourly wages by college major. The hourly wages of workers with Law and Business major increase the most, in particular, more than those of workers with STEM degrees. Furthermore, this heterogeneity allows for an informative ranking of college majors by the effect of broadband coverage expansion on hourly wages and helps inform prospective students' college major choices.

I explore two plausible explanations for the larger increase in hourly wages of workers with managerial degrees than those with STEM majors. First, broadband expansion events increase demand for General and widely used ICT skills complementary to managerial skills. At the same time, there was no such effect on the advanced and novel ICT skills. Second, broadband coverage expansion leads to wider usage of ICT applications for information search, electronic communications and transactions, automated paperwork, and personnel recruitment. All these applications enhance the productivity of managerial workers. These findings suggest that improvements in internet speed and quality benefit the users rather than the developers of ICT applications.

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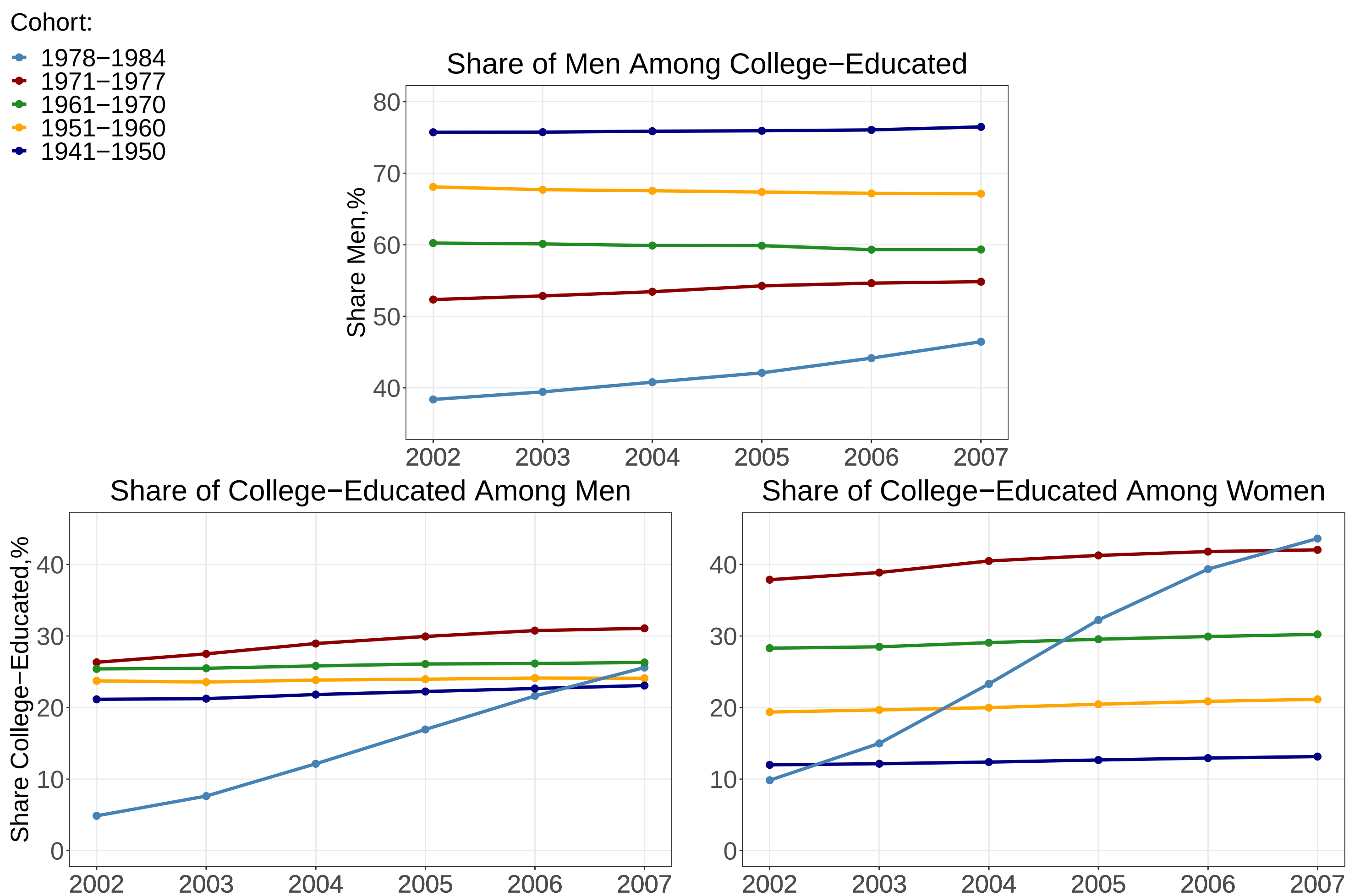
APPENDIX A

COLLEGE MAJORS DESCRIPTIVE STATISTICS

Table A.1: Composition of College Majors Groups

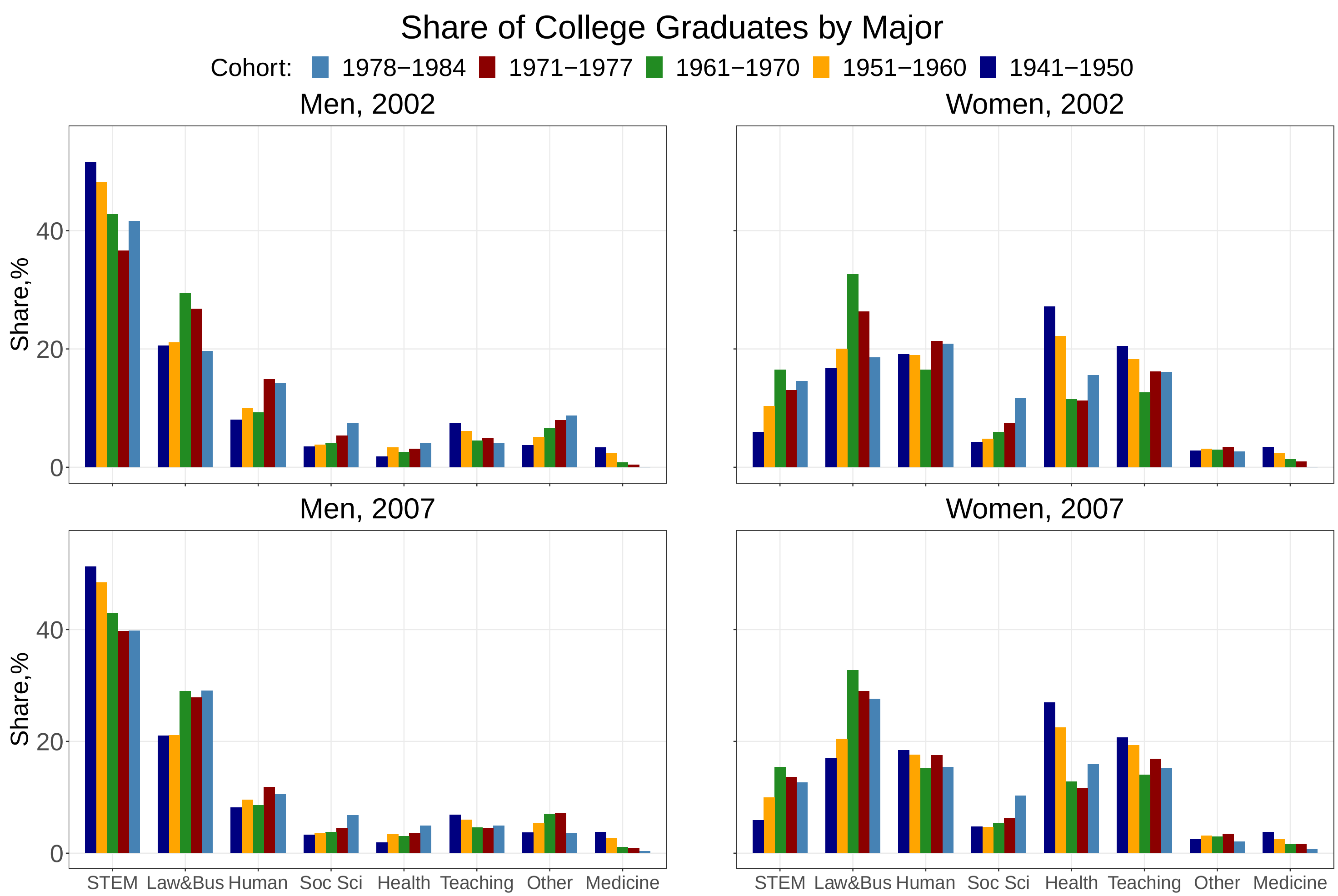
Majors Group	Majors
STEM	Biology, Chemistry, Mathematics, Physics, Electrical Eng,
	Mechanical Eng, Computer Science, Construction Eng, Industry Eng
Law and Business	Law, Administration, Accounting, Business Studies
Humanities	History, Philosophy, Languages, Media, Architecture, Art
Social Sciences	Sociology, Political Science, Anthropology, Economics, Psychology
Health	Nursing, Social Work, Physical Therapy
Teaching	Kindergarten Teacher, School Teacher
Other	Transport and Communications, Safety and Security, Other Services, Unknown
Medicine	Medicine, Dentistry, Pharmacology, Veterinary

Figure A.1: Gender Composition of College-Educated Population



Note: **Top:** Share of men among college-educated workers by birth cohort. **Bottom Left:** Share of college-educated among male workers by birth cohort. **Bottom Right:** Share of college-educated among female workers by birth cohort. Sample of workers from private firms in Statistics Norway's Wage Statistics Survey.

Figure A.2: College Majors Shares by Gender



Note: Share of each major among college-educated men (left) and women (right) by birth cohort in 2002 (top) and 2007 (bottom). Sample of workers from private firms in Statistics Norway's Wage Statistics Survey.

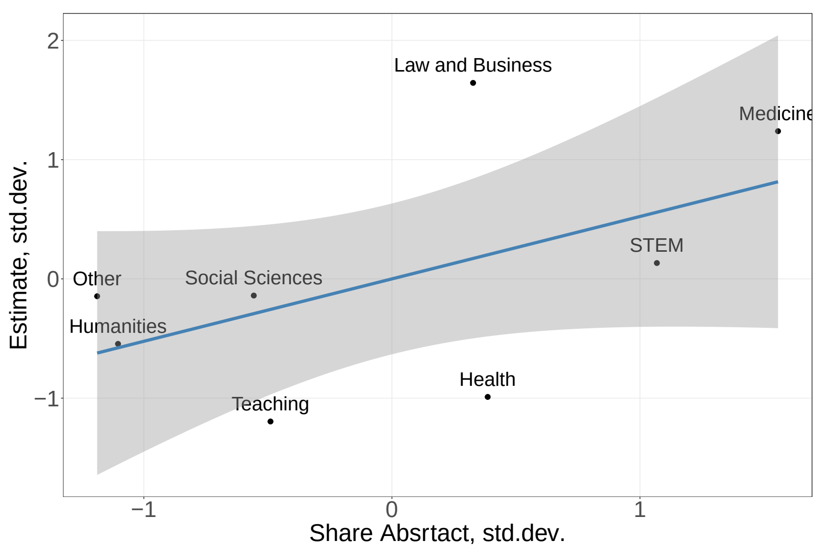
APPENDIX B

COLLEGE MAJORS AND OCCUPATIONS GROUPS

Table B.1: Shares of Abstract, Routine and Manual Occupations by College Major

Major	Abstract	Routine	Manual
STEM	88.8	6.9	4.2
Law and Business	80.0	17.7	2.3
Humanities	63.0	31.7	5.3
Social Sciences	69.5	26.4	4.2
Health	80.7	17.1	2.2
Teaching	70.3	25.3	4.3
Other	62.0	27.2	10.8
Medicine	94.6	3.8	1.7
No College	25.4	51.9	22.8

Figure B.1: Major-Specific Shares in Abstract Occupations and Coverage Expansion Estimates

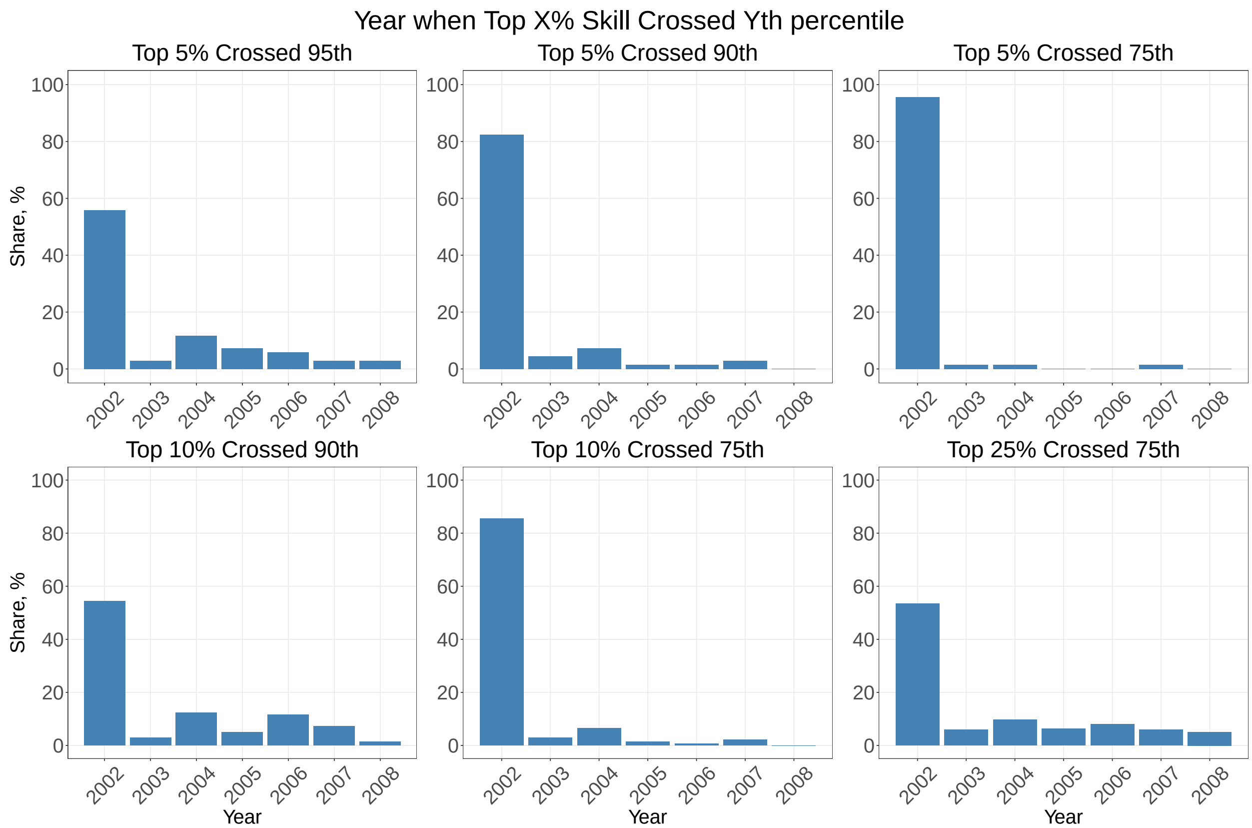


Note: Correlation between the estimates for the effect of broadband internet coverage expansion on hourly wages and the shares of graduates working in abstract occupations by college major. The correlation coefficient is 0.52 and the regression line is shown with 90% confidence interval.

APPENDIX C

TOP SKILLS CROSSING PERCENTILE CUTOFFS

Figure C.1: Timing of Top Skills Crossing Percentile Cutoffs

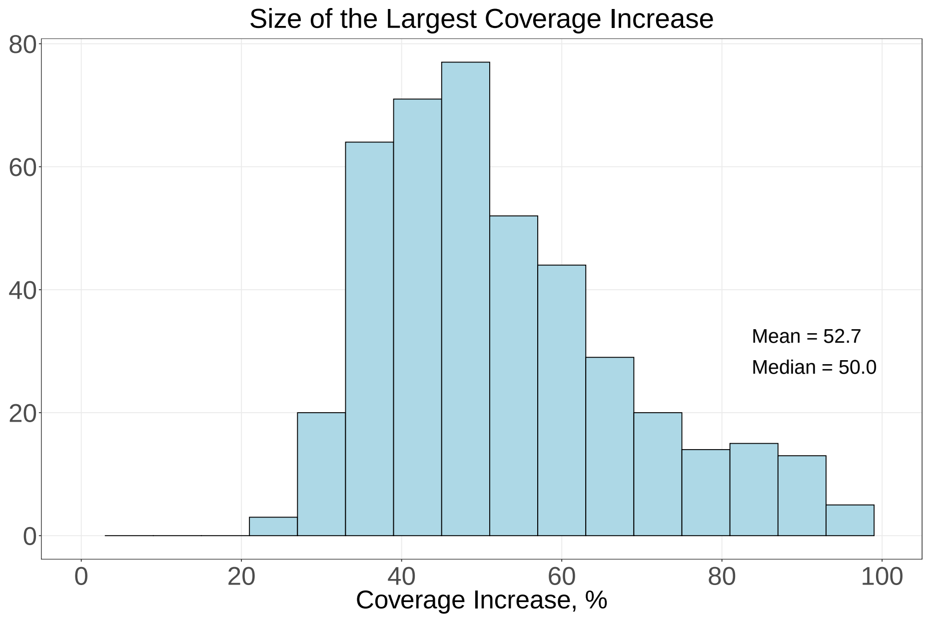


Note: Year when Top X% skill crossed Yth percentile in the skill mention distribution. Definition of Top X% percentile skill based on 2002-2008 vacancy sample. **Top:** Top 5% skill with 95th, 90th, and 75th percentile cutoffs. **Bottom:** Top 10% skill with 90th and 75th percentile cutoffs, and Top 25% skill with 75 percentile cutoff.

APPENDIX D

LARGEST COVERAGE EXPANSION EVENTS

Figure D.1: Coverage Expansion Events Magnitude

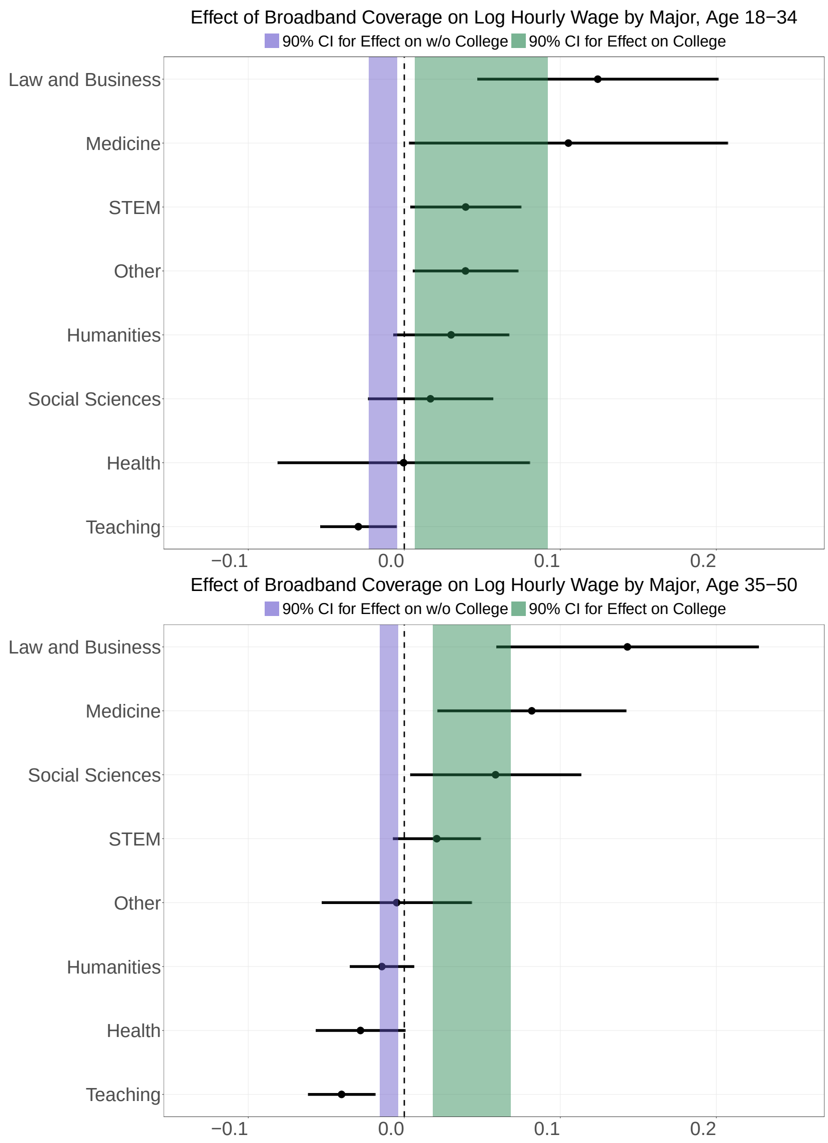


Note: Distribution of the magnitude of the largest broadband coverage increases in Norwegian municipalities from 2001 to 2007.

APPENDIX E

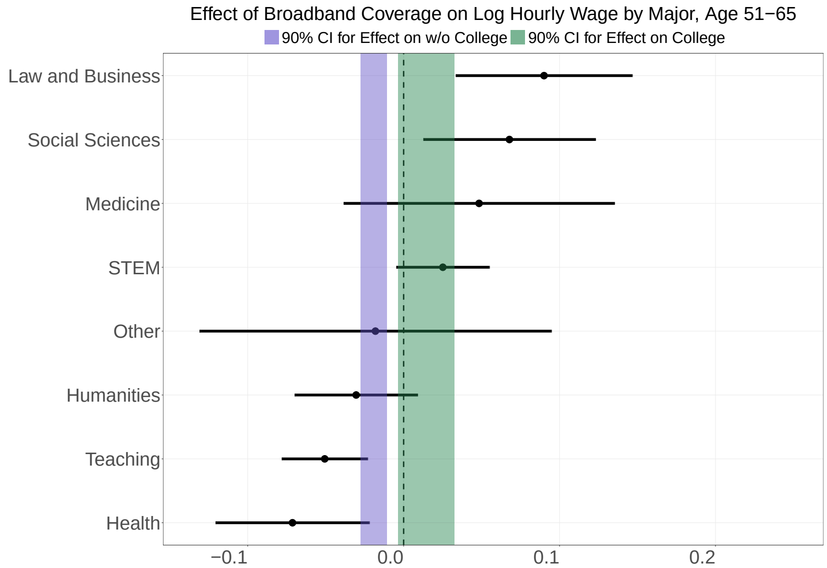
EFFECT OF COVERAGE EXPANSION ON LOG HOURLY WAGES BY AGE GROUP

Figure E.1: Estimates for the Effect of Coverage Expansion on Log Hourly Wages for 18-34 and 35-50 Age Groups



Note: Estimates for the effect of broadband coverage expansion on log hourly wages of workers 18-34 yo (top) and 35-50 yo (bottom) with different levels of educational attainment θ defined in Equation 1.2 with 90% confidence intervals. Colored intervals represent estimates for college-educated workers (green) and workers without college degrees (purple). Solid black lines show the results for the full set of college majors.

Figure E.2: Estimates for the Effect of Coverage Expansion on Log Hourly Wages for 51-65 Age Group



Note: Estimates for the effect of broadband coverage expansion on log hourly wages of workers 51-65 yo with different levels of educational attainment θ defined in Equation 1.2 with 90% confidence intervals. Colored intervals represent estimates for college-educated workers (green) and workers without college degrees (purple). Solid black lines show the results for the full set of college majors.

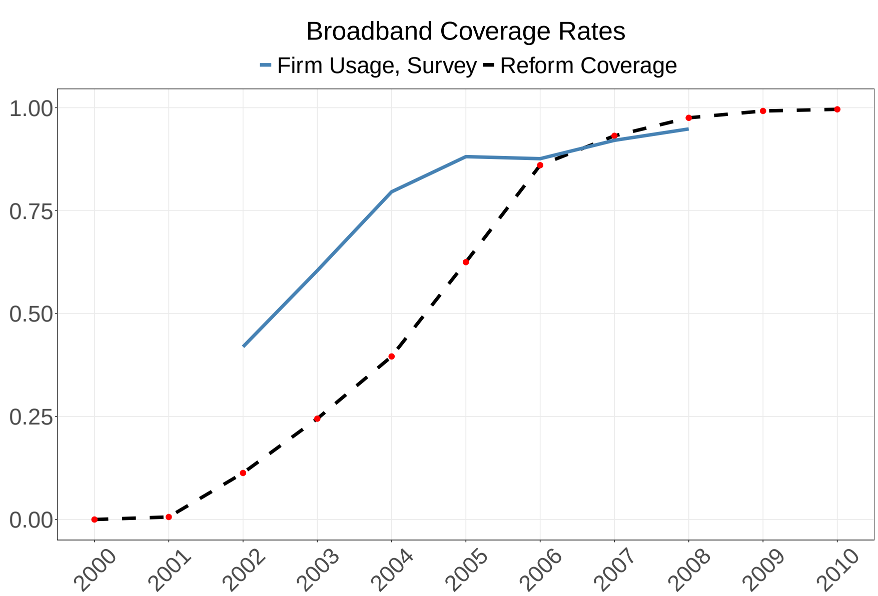
APPENDIX F

EFFECT OF BROADBAND USAGE ON LOG HOURLY WAGES

Municipality-level firms' broadband usage rate is a weighted mean of broadband usage indicators for all firms from the Annual Community Survey on ICT Usage of Firms. Figure F.1 compares the average across all municipalities broadband usage and coverage rates. The usage rate substantially exceeds the coverage rate provided by the public program until 2006. Thus, many firms were early broadband adopters without the infrastructure provided by the reform.

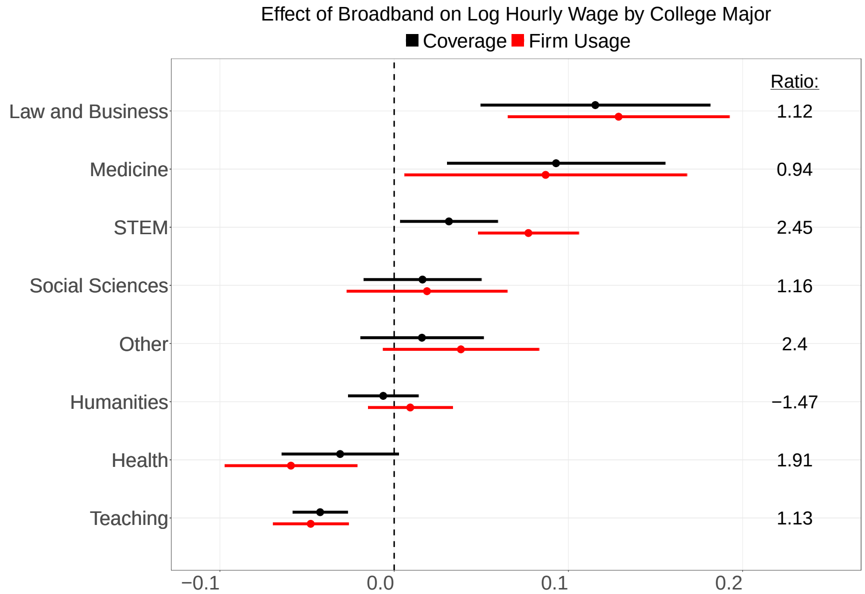
I run regression in Specification 1.2 with municipality-level broadband usage rate to estimate its effect on log hourly wages . Figure F.2 compares the estimates for coverage (black) and usage (red) rates by college major. The estimate for STEM is 2.45 times larger for usage rate than for coverage rate, while the estimates for Law and Business and Medicine majors are similar in both specifications. Thus, the effect of broadband adoption is substantially more favorable for STEM graduates.

Figure F.1: Broadband Usage Rate



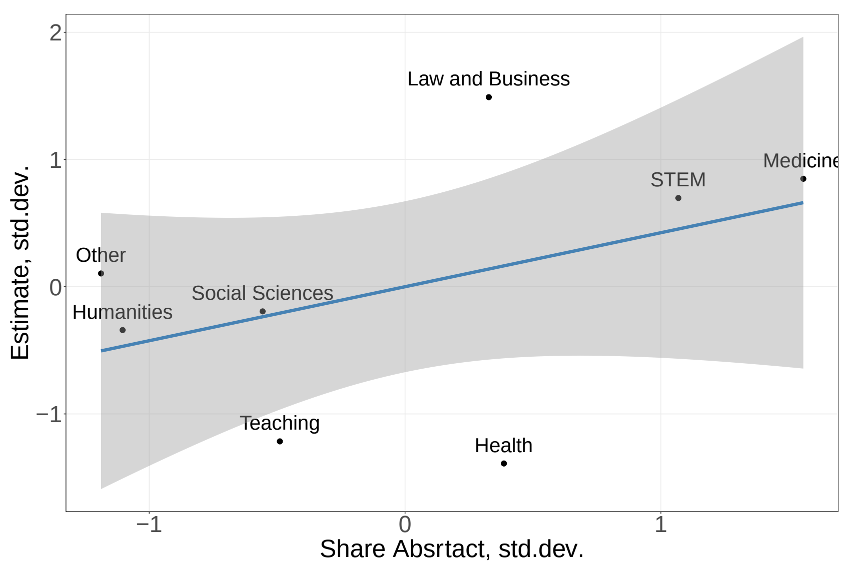
Note: Mean broadband coverage rate (black) and mean firms' broadband usage rate (blue) across municipalities.

Figure F.2: Estimates for the Effect of Coverage Expansion and Broadband Usage on Log Hourly Wages



Note: Estimates for the effect of broadband coverage expansion (black) and usage in firms (red) on log hourly wages by college major. The ratio of estimates shows $\frac{\text{usage est}}{\text{coverage est}}$.

Figure F.3: Major-Specific Shares in Abstract Occupations and Broadband Usage Estimates



Note: Correlation between the estimates for the effect of firms' broadband usage on hourly wages and the shares of graduates working in abstract occupations by college major. The correlation coefficient is 0.42 and the regression line is shown with 90% confidence interval.

APPENDIX G

RANKING OF COLLEGE MAJORS

G.1 Formal Definitions

Let $j \in \{1, \ldots, p\}$ index college majors. Denote by P_j distributions of the effect of broadband coverage expansion on major j and by $\theta(P_j)$ means of these effects by which the majors are ranked. The rank of major j is defined as

$$r_j(P) \equiv 1 + \sum_{k \neq j} \mathbb{I}[\theta(P_k) > \theta(P_j)],$$

where P is a distribution with marginals P_j or $j \in J$. Let $\theta(P) \equiv \Big(\theta(P_1), \ldots, \theta(P_p)\Big)'$ and $r(P) \equiv \Big(r(P_1), \ldots, r(P_p)\Big)'$. Mogstad et al. (2021) and Bazylik et al. (2021) show how to construct three types of valid confidence sets for the ranks of college majors, each answering distinct economic questions. The first type, marginal confidence sets, answer the question about the rank of a particular major. More precisely, for a given value of $\alpha \in (0, 1)$, using a sample of observations from P the procedure constructs (random) sets $R_{n,j}$ such that

$$\liminf_{n \to \infty} \inf_{P \in \mathbf{P}} Pr\{r_j(P) \in R_{n,j}\} \geq 1 - \alpha,$$

for a pre-specified major $j \in J$, where n is a measure of sample size and P denotes a “large" nonparametric family of distributions. The second type, simultaneous confidence sets, allow such inferences to be drawn simultaneously across all college majors. The procedure constructs (random) sets $R_n^{\text{joint}} \equiv \Pi_{j \in J} R_{n,j}^{\text{joint}}$ such that

$$\liminf_{n \to \infty} \inf_{P \in \mathbf{P}} Pr\{r(P) \in R_n^{\text{joint}}\} \geq 1 - \alpha.$$

In both construction $R_{n,j}$ and $R_{n,j}^{\text{joint}}$ are subsets of J. The third type, confidence sets for τ-best/-worst, answer the more specific question of which college majors cannot be ruled out as being among the most/least benefiting from broadband coverage expansion. For a pre-specified value of $\tau \in J$ and for a given value of $\alpha \in (0,1)$, the procedure constructs (random) sets $J_n^{\tau-\text{best}}$ that are subsets of J and satisfy

$$\liminf_{n\to\infty} \inf_{P\in\mathbf{P}} Pr\{J_0^{\tau-\text{best}}(P) \subseteq J_n^{\tau-\text{best}}\} \geq 1-\alpha,$$

where

$$J_0^{\tau-\text{best}}(P) \equiv \{j \in J : r_j(P) \leq \tau\}.$$

The confidence set for τ − worst is constructed as a the confidence set for τ − best among $-\theta(P_1), \ldots, -\theta(P_p)$.

Construction of all three confidence sets relies on simultaneous confidence sets for the differences in effects on majors. For marginal confidence set for the rank of major j consider

$$C_{symm,n,j,k} \equiv \left[\hat{\theta}_j - \hat{\theta}_k \pm \hat{se}_{j,k} c^{1-\alpha}_{symm,n,j}\right],$$

where $\hat{se}_{j,k}$ is an estimate of the variance of $\hat{\theta}_j - \hat{\theta}_k$ and $c^{1-\alpha}_{symm,n,j}$ is the $(1-\alpha)$ - quantile of

$$\max_{k:k\neq j} \frac{|\hat{\theta}_j - \hat{\theta}_k - (\theta(P_j) - \theta(P_k))|}{\hat{se}_{j,k}},$$

which can be approximated by bootstrap. Let N_j^- be the set of all majors with significantly higher effect than for major j

$$N_j^- \equiv \{k : k \neq j \text{ and } C_{symm,n,j,k} \subseteq \mathbf{R}_-\},$$

and let N_j^+ be the set of all majors with significantly lower effect than for major j

$$N_j^+ \equiv \{k : k \neq j \text{ and } C_{symm,n,j,k} \subseteq \mathbf{R}_+\}$$

Mogstad et al. (2021) show that under weak conditions

$$\liminf_{n\to\infty} \inf_{P\in\mathbf{P}} Pr\{\theta(P_j)-\theta(P_k)\in C_{symm,n,j,k}, \text{for all } k \text{ with } k\neq j\}\geq 1-\alpha,$$

which implies that the marginal confidence set for the rank of major j is

$$R_{n,j}\equiv\{|N_j^-|+1,\ldots,p-|N_j^+|\}.$$

Mogstad et al. (2021) show that to get simultaneous confidence set for the ranks, we construct $R_{n,j}$ in the same way except for substituting $c^{1-\alpha}_{symm,n,j}$ with $c^{1-\alpha}_{symm,n}$ defined as the $(1-\alpha)$ - quantile of

$$\max_{(\mathbf{j},\ \mathbf{k}):k\neq j}\frac{|\hat{\theta}_j-\hat{\theta}_k-(\theta(P_j)-\theta(P_k))|}{\hat{se}_{j,k}},$$

where the max is now taken over all pairs of distinct majors and is the same for all majors. Similarly to $c^{1-\alpha}_{symm,n,j}$, $c^{1-\alpha}_{symm,n}$ is computed by bootstrap.

For $J_n^{\tau-\text{best}}$ define a one sided set

$$C_{upper,n,j,k}\equiv\left(-\infty,\hat{\theta}_j-\hat{\theta}_k+\hat{se}_{j,k}c^{1-\alpha}_{upper,n,j}\right],$$

where $c^{1-\alpha}_{upper,n,j}$ is the $(1-\alpha)$ - quantile of

$$\max_{(j,k):k\neq j}\frac{\hat{\theta}_j-\hat{\theta}_k-(\theta(P_j)-\theta(P_k))}{\hat{se}_{j,k}}.$$

Finally, adjusting the definitions

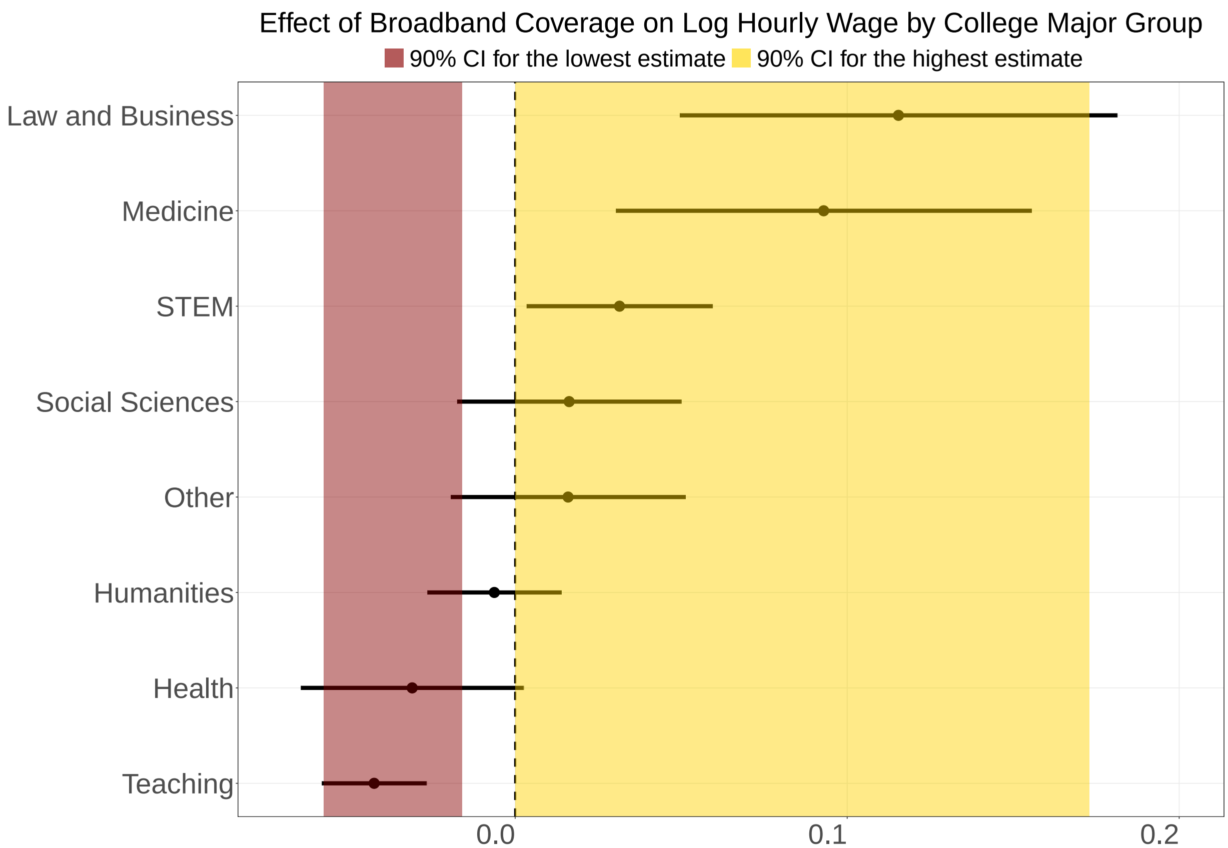
$$R_{n,j}\equiv\{|N_j^-|+1,\ldots,p\}$$

$$R_n^{\tau-best}\equiv\{j\in J:\tau\in R_{n,j}\}.$$

Mogstad et al. (2021) and Bazylik et al. (2021) also propose alternative constructions for the confidence sets.

G.2 Figures

Figure G.1: Majors Ranking and Andrews et al. (2019) CI for “Winner" and “Loser"



Note: **Left:** 90% Marginal CS for the ranks of college majors by the effect of broadband Internet coverage expansion on log hourly wages. **Right:** estimates with 90% confidence intervals, and Andrews et al. (2019) conditional 90% confidence intervals for “winner" and “loser" majors.

APPENDIX H

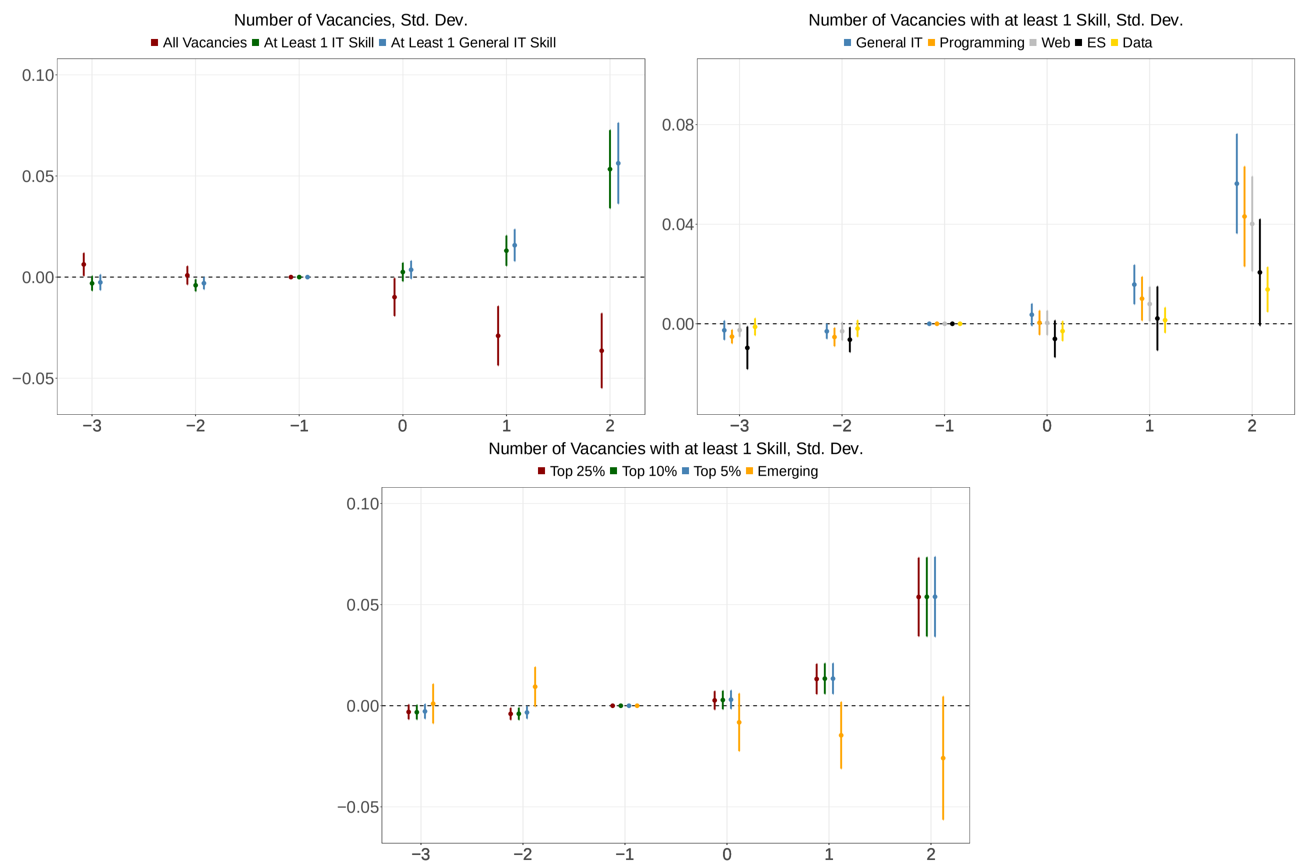
EVENT STUDY OF ICT VACANCIES: MUNICIPALITIES WITH PRE-TREATMENT COVERAGE BELOW 20 PERCENT

Table H.1: Aggregate Post-Treatment Effect α_3 with a 20 Percent Pre-Event Coverage Restriction

Vacancy outcome:	(1)	(2)	(3)	(4)
All Vacancies	-0.025 (0.005)	-0.023 (0.012)	-0.018 (0.006)	-0.018 (0.006)
Any ICT Skill	0.023 (0.004)	0.022 (0.009)	0.031 (0.008)	0.031 (0.008)
General ICT	0.025 (0.004)	0.024 (0.009)	0.032 (0.008)	0.032 (0.008)
Programming	0.018 (0.005)	0.019 (0.007)	0.036 (0.015)	0.036 (0.015)
Web Development	0.016 (0.004)	0.016 (0.008)	0.018 (0.009)	0.018 (0.009)
Enterprise Soft	0.006 (0.005)	0.007 (0.007)	0.008 (0.018)	0.008 (0.018)
Data Skills	0.004 (0.002)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)
Top 25%	0.023 (0.004)	0.023 (0.009)	0.031 (0.008)	0.031 (0.008)
Top 10%	0.023 (0.004)	0.023 (0.009)	0.032 (0.008)	0.032 (0.008)
Top 5%	0.023 (0.004)	0.023 (0.009)	0.029 (0.008)	0.029 (0.008)
Emerging	-0.017 (0.008)	-0.019 (0.01)	-0.015 (0.015)	-0.015 (0.015)
Controls			✓	✓
Labor Market FEs		✓		✓

Note: Aggregate treatment effect α_3 for post-treatment periods $\{0, 1, 2\}$ for the restricted subsample of Norwegian vacancies with pre-treatment broadband coverage below 20 percent defined in Equation 1.6 and components estimated in Specification 1.3 . Each vacancy outcome variable is standardized. Standard errors in parenthesis. Specifications (3) and (4) include municipality level industry composition controls for the last pre-reform year 2000. Specifications (2) and (4) include labor market fixed effects. Top X% skills and Emerging skills are defined in Definitions 2 and 3 respectively.

Figure H.1: Event Study Estimates for the Effect of Coverage Expansion on Vacancies with a 20 Percent Pre-Event Coverage Restriction



Note: Event study estimates for the restricted subsample of Norwegian municipalities with pre-treatment broadband coverage below 20 percent defined in Equation 1.5 and components estimated in Specification 1.3 for standardized vacancy outcomes Y_{mt}: All Posted Vacancies, Vacancies with At Least 1 IT Skill and with At Least 1 General IT Skill (**Top Left**); for Vacancies with At Least 1 General IT Skill, At Least 1 Programming Skill, At Least 1 Web Development Skill, At Least 1 Enterprise Software Skill and At Least 1 Data Skill (**Top Right**); for Vacancies with At Least 1 Top 25% IT Skill, At Least 1 Top 10% IT Skill, At Least 1 Top 5% IT Skill and At Least 1 Emerging IT Skill (**Bottom**). All estimates are presented with 90% confidence intervals.