Are AI jobs driving up demand for STEM education? Yes, but not for women.

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January 2, 2025

Abstract

We combine data on degrees awarded across colleges and universities in the US with data on online job vacancies to study the impact of AI penetration in local labor markets on the demand for STEM education. We find that between 2014 and 2022 AI raised the demand for STEM in the US, overall and across all races. However, we also find that it raised the gender gap in STEM, as it raised the demand and number of degrees awarded for male-dominated STEM fields (e.g. engineering) by more than that of fields traditionally with a larger share of female students (e.g.health science). Finally, we find that for institutions with higher share of female faculty, the impact of AI on the STEM gender gap is attenuating.

Keywords: Artificial intelligence, Data analytics, Major Choice,Gender Gap

JEL Codes: J16,J24,O33

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1 Introduction

STEM education – the study of fields related to Science, Technology, Engineering, and Mathematics - plays a vital role in economic development, workforce readiness, technological innovation, and social equity. Stronger math and science education systems lead to higher levels of innovation, productivity, and economic development as these skills contribute to more robust innovation pipelines (Hanushek and Woessmann, 2020; Tytler, 2020). With technological advancements accelerating, particularly with the rise of artificial intelligence (AI), the importance of STEM skills is also growing rapidly.[1]

For educated workers, STEM degrees provide some of the highest returns in terms of employment opportunities and earnings, greater job stability and growth opportunities, and lower unemployment rates, particularly for those coming from low-income or underrepresented backgrounds. According to a study by the Pew Research Center in 2021, the median earnings for STEM workers are about 26% higher than for those in non-STEM fields, with some fields such as computer science and engineering offering even greater premiums. This wage differential is often attributed to the high demand for technical skills in an increasingly digitized economy, where STEM competencies are particularly valuable.

While STEM education is increasingly recognized as a powerful tool for economic development and increased earnings, little is known on the impact the rise of AI in the past decade has on its demand, and particularly on the gender gap in STEM.[2] Does AI lead to a higher uptake in STEM education, and if so, is the demand gender-biased? Studying this is important because women make up just 24% of the STEM workforce, even though women in

[1]For example, according to Standord's AI Index 2023, the number of jobs posted in the United States requiring AI skills have surged from 0.5% in 2014 to 2.05% in 2022 (Maslej et al., 2024). Similarly, by some estimates, 80% of the workforce could have at least 10% of their tasks affected by AI and large language models (LLMs) (Eloundou et al., 2023).

[2]According to a report by the National Science Board (National Science Board, 2015), ensuring that students acquire robust STEM skills is essential for maintaining the U.S.'s global competitiveness. The report argues that STEM skills are in high demand across multiple sectors, not just in traditional STEM industries.

STEM jobs earn 35% more than women in non-STEM (Noonan, 2017). The underrepresentation of women in high-paying STEM fields contributes to broader economic inequality and explains a large portion of the gender pay gap (Blau and Kahn, 2017). Closing the gap by enhancing gender diversity in STEM will help reduce inequality and boost innovation and creativity as it will foster diverse perspectives in problem-solving tasks (Díaz-García et al., 2013).

In this paper we present new evidence on the link between STEM education and AI by considering how the growth in the demand for AI-related skills in local labor markets has driven up the demand for stem degrees in the US between 2014 and 2021. We then analyze its impact on the STEM gender gap. While women have made significant strides in STEM fields overall, their representation varies drastically across specific disciplines. In 2014, in the U.S. women received 63% of all degrees awarded in biology but only 22% in the fields of engineering and computer science.

To study the impact of AI job openings on STEM education, we use data on nearly 200 million job vacancies posted online to measure the demand for AI-related jobs by US county each year between 2014 and 2022. To find the demand for AI we compile a list of thirty four skills that are important in the field of AI, such as *Artificial Intelligence*, *Supervised Learning*, and *Support Vector Machines*. The complete list is provided in Appendix A. We then compute the share of online job vacancies that contain at least one of these skills for each county-year corpus of online job vacancies. We refer to the derived share as the *AI intensity* of the local labor market, or simply as AI.

We then combine the constructed measure of local labor market *AI intensity* with records from the Integrated Postsecondary Education Data System on postsecondary education degrees awarded by 5,348 institutions in the US to examine if the documented increase in the demand for AI jobs has resulted in higher demand for stem education, and its effect on the gender gap.

By our calculations, in 2014 only 0.9% of all jobs posted required some AI skill and by 2022 that share rose to 2.2%. At same time, the share of graduate students with a STEM degree rose from 15.8% to 20.8%, whereas the gap between male and female STEM graduates - defined as the share of male graduates with STEM degree over all male graduates minus that of female – rose from 14.2% to 16.4%. Furthermore, during the same period the number of Bachelor's degrees awarded in non-STEM fields contracted by 2%, while it grew by 44% in STEM fields. We also show that the growth observed in the total number of degrees awarded is equally driven by growth in the intensive (more students pursuing existing STEM degrees) and extensive (students in 2021 pursuing STEM degrees that did not exist in 2014) margins of growth.

To minimize endogeneity issues that can arise between the level of STEM education in a county and AI intensity, we construct a shift-share instrument for AI intensity. Specifically, we use the national intensity of AI by occupation at the four-digit ONET classification level weighted by the pre-shock share of employment across occupations within a county to produce a Bartik-instrument for AI intensity that is exogenous to the level of STEM education within the county.

Our first finding is that higher AI-intensity in the local labor market results in higher share of STEM degrees awarded. When we decompose the data by degree type - Associate's, Bachelor's, and Master's – we find that the results are robust across all types, with the highest impact being on Master's degrees, followed by Bachelor's, and then by Associate's. We also explore whether the impact of AI on the demand for STEM education varies by race. We find that AI raises the demand for STEM education across all races, with the strongest impact on Asian students.

Next, we turn attention to the gender gap and ask whether the positive impact AI has on STEM education is equally shared across genders. Unfortunately, our analysis reveals that the rise of AI widens the STEM gender gap as the relation between the gap and AI is positive and statistically significant. This finding is robust for all degree types and across all gender gaps computed by race. We attribute this to the fact that AI raises the relative demand of STEM fields dominated by men (e.g. computer science and engineering) more than those dominated by women (e.g. psychology and health sciences) and as a result, the gender gap widens.

This troubling finding suggests that as the demand for AI-skills rises and more jobs become available, the gender gap in the workforce will persist and the gender pay gap may start to rise again unless specific policies are enacted to reverse it. There are several factors and debates as to what drives the gender gap but one parameter that seems to play a role in reducing the gap is the availability of female faculty. Several studies have shown that high share of female faculty, especially in math and in sciences, results in better academic performance for female students, better grades, better post-graduation outcomes, and a higher share of female STEM students. This may be due to a plethora of reasons, such as differences in teaching style, in mentoring, in approachability, and in female faculty being role models for female students (as minority faculty are for minority students).[3]

Based on this observation we proceed to check if higher shares of female faculty mitigate the influence of AI on the STEM gender gap. We obtain data on the gender share of faculty by institution (and corresponding field) from SciSciNet, a large database of more than 270 million publications. For each publication, SciSciNet provides information on authors' name, affiliation, and gender, as well as information on citations, on publication location, and on keywords that characterize the subject matter. We use the author information to identify research faculty by institution, and keyword information to classify faculty to fields.

[3] Carrell et al. (2010) demonstrate that female students who have female instructors in STEM fields are more likely to pursue advanced coursework and careers in these areas. Umbach (2006) finds that the presence of minority faculty members is positively correlated with academic achievement and retention for minority students while Thomas et al. (2007) emphasize the importance of "same-race" and "same-gender" mentoring relationships in fostering student success. Similarly, Dee (2005) finds that minority students who were taught by minority teachers had better academic outcomes, particularly in subjects where these students have historically been marginalized. Hurtado et al. (2012) find that students are more likely to feel connected to their institutions when faculty members share their racial or gender identity.

Since gender is known, we then produce the gender share by institution and by field within institutions. To study if higher shares of female faculty matters, we split institutions into two bins, based on whether they have high female representation on their faculty body or not and then we test for the impact of AI on the STEM gender gap. We find that having a large number of female faculty mutes the adverse impact of AI on the STEM gender gap.

Our work contributes to three main strands of literature. First, we contribute to a new and growing literature the studies the impact of AI in the labor force and on the broader economy. Multiple recent papers use microdata to better assess the impact of in AI in various settings: Babina et al. (2024) focus on product entry and firm growth, Gofman and Jin (2024) on entrepreneurship, and Grennan and Michaely (2020) on entrepreneurship. More recent studies find that AI impacts labor productivity among college-educated workers. (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023; Noy and Zhang, 2023; Otis et al., 2023).

More recent scholarship, see Humlum and Meyer (2022), Humlum and Vestergaard (2024), Aldasoro et al. (2024), Carvajal et al. (2024), Otis et al. (2024) also focuses on the impact of AI on education. These papers explore gender differences in adoption of AI tools among students and recent graduates using experimental designs. Closer to our paper, in a large scale survey, Humlum and Meyer (2022) find that admission in AI related STEM degrees correlates with high AI-related earning gains and overall they find an increasing AI and Science skill association for STEM majors. These dynamics may have large implication for gender parity depending on the number of new STEM graduates by gender. Similarly, though, to our results on the increasing gender gap in STEM, recent surveys of AI adoption suggest that women are much less likely to use this new technology, see Aldasoro et al. (2024); Carvajal et al. (2024); Otis et al. (2024). We contribute to this literature by providing the first empirical national-wide investigation of the effect of labor investments in AI on the major choice of undergraduate and graduate students in the United States. Our result that AI technology leads to higher STEM uptake but also greater gender gap provides another dimension to the long debate put forth by many economists about the unequal distribution of automation and technology's economic benefits (see Acemoglu and Restrepo (2019); Autor (2015)).

Second, we contribute to the literature on the gender gap. Blau and Kahn (2017) examine the persistent gender pay gap and highlight that occupational segregation — particularly the underrepresentation of women in high-paying STEM fields — explains a large portion of this gap. According to National Science Board (2021), women made up just 34% of the STEM workforce in 2019, with significant variation across disciplines. While women are better represented in biological sciences (around 48%), they account for only about 16% of engineers and 26% of computer and mathematical scientists. Research, as a result, tries to explore whether this under-representation in STEM fields exacerbates major and occupational segregation. Using United States data, Goldin(2014) explores gender wage gaps across occupations and finds that technology and science occupations are among the most equal, and for younger workers the gap is not present in the sample considered. However, underepresentation of female workers across those occupations is reducing the overall effect of reduced inequity in STEM fields on the overall gender wage gap. Similarly, it has been observed, that these under-representation is due to female students major choices (e.g. Carrell et al., 2010). As a result, reducing the STEM gender gap is key for reducing overall inequity in the labor market. We provide direct evidence that AI related technological advantages that differentially affect demand for majors, can exacerbate these disparities, showing how AI in the past decade has increased the STEM gender gap across the United States.

Third, we contribute to the literature that studies the importance of having female and minority professors in academia. Explanations about gender disparities in STEM education and careers have been of significant focus in the economics literature. In particular, two important dimensions that help explain part of the STEM gender gap is the scarcity of female role models[4] and a gendered classroom environment in these fields. A study by Diekman et al. (2017) found that women in STEM often feel less "belonging" in these fields compared to their male counterparts, which can discourage them from continuing in STEM disciplines. Research by Carrell et al. (2010) demonstrates that female students who have female instructors in STEM fields are more likely to pursue advanced coursework and careers in these areas. This is particularly important in disciplines where women are traditionally underrepresented, such as engineering and computer science. Similarly, research by Porter and Serra (2020) show the importance of exposure to "same-gender" role models in the choice of major by doing a field experiment, showing a sizable increase in female enrollment in economics when exposed to female faculty in their first year of university. Similarly to the studies above, we observe that any negative effects of AI on gender imbalances can be alleviated in the presence of high representation of female faculty

The rest of the paper is as follows. In Section 2 we present the data and in Section 3 the methodology. Section 4 presents the results, while Sub-section 4.4 provides some robustness analysis. Section 5 concludes.

2 Data

2.1 STEM Degrees

Data on degrees awarded by U.S. colleges, universities, and technical and vocational institutions are collected by the National Center for Education Statistics and are available for download at the Postsecondary Education Data System (IPEDS) web portal. The information contains parameters such as degree type (e.g. Associate, Bachelor's, Masters), gender, type of student (e.g. full-time, part-time), race (e.g. Hispanic, black, white, Asian), Classification of Instructional Programs (CIP) code, and the location of the institution. We primary

[4]Female professors are significantly underrepresented across most disciplines, but more so in STEM fields.

use data from 2014 to 2022 as there is little AI content in job ads prior to 2014, although data from earlier years is used in a placebo exercise. Here we consider first degrees awarded to full-time students at three levels: Associate, Bachelor's, and Master's. Double majors, minors, certificates, and executive education courses are excluded. All data is aggregated at the county level.

To identify STEM degrees we use the STEM Designated Degree Program list provided by the Department of Homeland Security (DHS).[5] DHS maintains and updates the list as this information is required for the optional practical training (OPT) visa extension program application. By classifying degrees as STEM and non-STEM we are able to compute the STEM share – defined as the number of STEM degrees awarded over all degrees – by group of interest (e.g. Bachelor's degrees awarded to Black women in county c and year t).

The STEM gender gap for a given group g is then defined as the gap between the STEM share of male degrees awarded minus the STEM share of female, or

$$STEM\ Gender\ Gap_{gt} = \frac{S^{mgt}}{N^{mgt}} - \frac{S^{fgt}}{N^{fgt}} \tag{1}$$

where N^{kgt} and S^{kgt} are the total degrees and STEM degrees, respectively, awarded to group g, time t, and gender $k = (m : \text{male}, f : \text{female})$.

Summary statistics of the IPEDS data are provided in Table 1 and plots of key variables over the sample period are available in Figure 1. In 2014, 3,292 institutions in the U.S. awarded 3,104,432 Associate, Bachelor's, and Master's degrees. Of these degrees, 15.8% were in STEM fields and 59.1% of all degrees were awarded to women. Among STEM degrees, 37.4% were awarded to women. This is equivalent to a ratio of 1.68 male students for every female student in STEM. The gender gap, defined in Equation 1 above was 14.2%.

[5] https://www.ice.gov/sevis/schools#dhs-stem-designated-degree-program-list-and-cip-code-nomination-process

Year	Institutions	Total Degrees Awarded	STEM Degrees (as share of total)	Female share of total degrees	Female share of STEM degrees	STEM m/f ratio	STEM gender gap
2014	3,292	3,104,432	0.158	0.591	0.374	1.68	0.142
2015	3,291	3,150,329	0.164	0.591	0.376	1.66	0.146
2016	3,293	3,211,624	0.170	0.593	0.381	1.62	0.149
2017	3,293	3,266,327	0.176	0.594	0.384	1.60	0.153
2018	3,293	3,335,138	0.183	0.596	0.390	1.56	0.156
2019	3,293	3,415,021	0.188	0.598	0.395	1.53	0.159
2020	3,293	3,454,406	0.197	0.603	0.407	1.46	0.161
2021	3,293	3,530,600	0.201	0.611	0.419	1.39	0.162
2022	3,293	3,491,432	0.208	0.612	0.425	1.35	0.164

Table 1: Summary Statistics of Degrees Awarded in the US, 2014–2022

Notes: ...

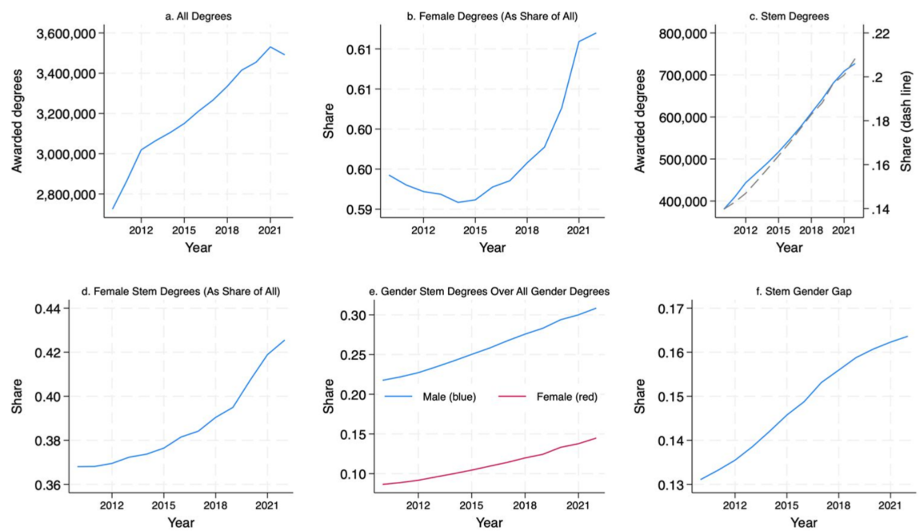

Figure 1: Plots of awarded degrees variables over time. 2014 - 2022

Notes: ...

Over time, the number of degrees awarded rose to over 3.5 million degrees (Figure 1a), and the share of those degrees awarded to women rose to 61.2% (Figure 1b). By 2022, 20.8% of these degrees were in STEM designated fields, up from 15.8% in 2014 (Figure 1c). The share of STEM degrees awarded to women also rose from 37.4% in 2014 to 42.5% in 2022. However, the gender gap in STEM also rose over the same period (Figure 1f) as the share of female STEM degrees over all female degrees rose at a slower pace than that of men (Figure 1e).

Within fields there is substantial heterogeneity in gender preferences. To highlight this, we present in Table 2 more detailed data on the share of majors (defined here as a 6-digit cipcode) within fields (defined as 2-digit cipcodes) that are STEM-designated and the share of female STEM graduates in each field. In 2022, there were 19 fields that contained at least one STEM-designated Bachelor's major. Combined, these fields awarded 1.7 million degrees (Col 1) across 913 majors (Col 3), 39% of which were STEM-designated (Col 4). In total, 32% of all degrees awarded in these 19 fields were in STEM (Col 5). Within these STEM-designated degrees awarded, 43% were received by women (Col 6).

Splicing now the data by CIP2 field — ranked from the field with the highest share of STEM degrees awarded to female to the field with the lowest share (Col 6) — we observe that women have a significantly higher representation in *Psychology, Health Professions, Biological and Biomedical Sciences,* and *Multi/Interdisciplinary Studies*, while men have higher representation in fields such as *Computer and Information Sciences, Military Technology, Engineering,* and *Transportation and Materials Moving*. Within these fields we see substantial variation in the share of majors that are STEM-designated, and the share of STEM degrees awarded. For example, within the field of Psychology there are 24 majors (Col 3), but only 33% of these majors are STEM-designated, and only 12% of all graduates in Psychology (CIP2 = 42) receive the STEM-designated degrees. In contrast, in Engineering (CIP2=14), out of the 54 available majors across the US, all are STEM-designated, which implies that 100% of Engineering graduates have STEM-designated degrees. Looking at the female share, in Psychology 78% of all STEM graduates are women, whereas in Engineering women comprise only 25% of all STEM graduates. This finding is important because if the impact of AI on the demand across CIP2 fields differs, then its impact on the gender gap in STEM will be significant. We come back to this point later in the analysis section.

CIP2 Field Name	Total	%	CIP2 Majors	% of CIP2 majors that are STEM-designated	% of CIP2 degrees awarded to STEM-designated programs	Share of STEM degrees awarded to women
	(1)	(2)	(3)	(4)	(5)	(6)
All degrees awarded across CIP2 fields (see below) with designated STEM majors	1,700,427	–	913	39%	32%	0.43
42 Psychology	130,795	7.7%	24	33%	12%	0.78
51 Health Professions and Related Programs	268,032	15.8%	163	7%	2%	0.73
01 Agricultural/Animal/Plant/Veterinary Science and Related Fields	20,615	1.2%	63	35%	51%	0.72
26 Biological and Biomedical Sciences	133,837	7.9%	72	100%	100%	0.66
30 Multi/Interdisciplinary Studies	52,968	3.1%	52	25%	32%	0.66
43 Homeland Security, Law Enforcement, Firefighting and Related Protective Services	58,013	3.4%	30	7%	4%	0.64
03 Natural Resources and Conservation	20,456	1.2%	22	41%	88%	0.60
10 Communications Technologies/Technicians and Support Services	5,077	0.3%	13	8%	60%	0.54
41 Science Technologies/Technicians	445	0.0%	5	100%	100%	0.51
13 Education	90,444	5.3%	90	1%	0%	0.50
04 Architecture and Related Services	9,555	0.6%	15	7%	30%	0.48
40 Physical Sciences	28,158	1.7%	38	100%	100%	0.45
27 Mathematics and Statistics	26,285	1.5%	16	100%	100%	0.41
52 Business, Management, Marketing, and Related Support Services	378,764	22.3%	88	5%	3%	0.40
14 Engineering	124,278	7.3%	54	100%	100%	0.25
11 Computer and Information Sciences and Support Services	109,589	6.4%	31	84%	99%	0.23
29 Military Technologies and Applied Sciences	1,619	0.1%	11	91%	98%	0.21
15 Engineering/Engineering-Related Technologies/Technicians	18,185	1.1%	59	92%	99%	0.15
49 Transportation and Materials Moving	6,562	0.4%	9	11%	64%	0.13

Table 2: Male to Female Ratio by STEM Field

Notes: ...

2.2 AI-Intensity

We measure the AI content of local labor markets by computing the share of online job ads in a given county and a given year that mention at least one skill from a group of predetermined AI-related skills. In total, we have selected 34 skills that we think are important in the field of AI, such as *Artificial Intelligence, Supervised Learning, and Support Vector Machines*. We selected these skills after consulting various reports and talking to professionals in the fields of computer science and AI. For robustness, we also consider a broader definition of AI that includes additional skills related to Data Analytics. The list of skills is available in Appendix A.

Data on online job vacancies (OJVs) are provided by Lightcast (formerly known as Burning Glass Technologies) between 2014 and 2022 Q1. Each day, Lightcast mines online job vacancies across 40,000 to 50,000 different web boards, company websites, forums, and other directories. Each OJV contains typically information on the job (job title, description, requirements), on the ideal candidate (qualifications, experience, education), on the company (name of company, industry), and the location (address). Lightcast then processes the unstructured text and creates a structured dataset with more than 70 different parameters available for each post, including the skill content, company, location, industry, and occupation.[6]

We provide a summary of the OJV data and the computed AI intensities in Table 3 below. In 2014, the number of job ads available is 21.4 million and by 2021 it doubles to 41.5 million (Columns 3 and 4). A decomposition of how these jobs are allocated across SOC occupations is provided as well. The top five occupations based on the number of job openings are *"Sales and Related"*, *"Management"*, *"Computer and Mathematics"*, *"Office and Administrative Support"*, and *"Healthcare Practitioners and Technical"*.

Occupations		**Online Job Vacancies**			**Occupational Characteristics**			
		(in thousands, 000s)			2. AI Intensity			1. High nonroutine cognitive
SOC 2	SOC2 Name	2014 Q1-Q4	2021 Q1-Q4	2022 Q1	2014 Q1-Q4	2021 Q1-Q4	2022 Q1	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
23 Total occupation groups (SOC 2)		21,439	41,544	12,631	0.9%	2.0%	2.2%	0.45
SOC2 occupation group								
11	Management	2,554	4,879	1,556	0.6%	1.8%	1.9%	0.90
13	Business and Financial Operations	1,449	2,497	788	0.5%	1.4%	1.4%	0.78
15	Computer and Mathematical	2,468	3,846	1,185	5.5%	14.9%	15.6%	1.00
17	Architecture and Engineering	705	1,067	343	1.2%	4.8%	4.7%	0.86
19	Life, Physical, and Social Science	243	436	137	0.8%	2.0%	2.2%	0.95
21	Community and Social Service	261	564	174	0.1%	0.2%	0.2%	0.79
23	Legal	187	272	90	0.2%	0.7%	0.6%	0.71
25	Educational Instruction and Library	567	1,136	334	0.2%	0.5%	0.4%	0.93
27	Arts, Design, Entertainment, Sports, and Media	586	962	287	0.2%	0.8%	0.7%	0.72
29	Healthcare Practitioners and Technical	2,188	4,727	1,480	0.1%	0.1%	0.1%	0.73
31	Healthcare Support	473	1,257	340	0.0%	0.1%	0.1%	0.13
33	Protective Service	235	572	172	0.1%	0.6%	0.5%	0.53
35	Food Preparation and Serving Related	892	2,153	699	0.0%	0.0%	0.0%	0.00
37	Building and Grounds Cleaning and Maintenance	287	960	279	0.0%	0.0%	0.0%	0.00
39	Personal Care and Service	492	966	311	0.0%	0.0%	0.0%	0.10
41	Sales and Related	2,890	4,455	1,275	0.1%	0.4%	1.0%	0.38
43	Office and Administrative Support	2,434	4,655	1,386	0.1%	0.2%	0.2%	0.14
45	Farming, Fishing, and Forestry	16	45	13	0.1%	0.3%	0.2%	0.00
47	Construction and Extraction	253	668	172	0.2%	0.2%	0.4%	0.08
49	Installation, Maintenance, and Repair	730	1,569	445	0.6%	0.7%	0.8%	0.12
51	Production	632	1,362	401	0.2%	0.3%	0.3%	0.10
53	Transportation and Material Moving	871	2,487	761	0.0%	0.1%	0.1%	0.11
55	Military Specific	27	12	4	0.4%	2.2%	1.5%	-

Table 3: AI Intensity by SOC Occupation Classification

Notes: ...

[6]Lightcast data have been extensively used over the past decade by scholars working in the fields of labor economics (see for example Deming and Kahn (2018), Acemoglu et al. (2022),Antoniades et al. (2024), and the references within). While the data starts in 2007, it has been recommended to use the data starting from 2014 as the quality is substantially lower in prior years (Cammeraat and Squicciarini, 2021). Moreover, by our calculations, there was little to no content of AI-related skills in the job posts prior to 2014. For these two reasons, we begin the analysis from 2014.

We calculate the AI intensity across online jobs posts in 2014 to be 0.9% (Column 6). That is, about 1 in every 100 job posts mentioned at least one of the AI-related skills on our list. By 2021, the share rose to 2% (Column 7), and by 2022 Q1 (Column 8) to 2.2%. In terms of occupations, *Computer and Mathematical Operations* (15.6%), *Architecture and Engineering* (4.7%), and *Management* (1.9%) exhibit the highest penetration of AI in 2022.[7]

We also present the share of high non-routine cognitive (HNRC) tasks within each occupation group (Column 9). This share, which measures job activities requiring complex problem-solving and analytical skills, has been highlighted in studies examining labor market shifts due to technological change. For example, Acemoglu and Autor (2011) demonstrate that technological advancements increase the demand for jobs with a high share of HNRC tasks, leading to wage polarization and greater economic returns for those in cognitively demanding roles.

Broadly, we observe that AI penetration is higher in occupations that score high on the share of HNRC tasks, although some exceptions exist. For example, *Community and Social Service* occupations has an HNRC score of 0.79 and AI intensity of only 0.2% in 2021, while *Installation, Maintenance, and Repair* has an HNRC score of 0.12 but AI intensity of 0.7%.

We complement the control variables in the regression analysis with county-level data on income, unemployment, and immigration taken by the American Consumer Survey (ACS), as well as data on the level of offshoring activity. Specifically, we construct a measure of offshoring activity by leveraging data from the U.S. Direct Investment Abroad (USDIA) database provided by the Bureau of Economic Analysis (BEA), which contains insights into industry employment of U.S. multinational activities abroad. By dividing industry employment abroad to domestic industry employment of US firms, we create a proxy for the national

[7] Antoniades et al. (2024) use the same data to introduce a measure of distance across occupations that can vary across time and space. The authors show that between 2014 and 2022 occupations have converged, and this helps explain the observations that across-occupations wages are converging and mobility is rising post 2014.

level of offshoring by industry. We then calculate the weighted average of this national offshoring index, where weights are the industry employment shares in each county, and create a local labor market index of offshoring. Relevant studies, such as those by Feenstra and Hanson (1999), have shown that offshoring leads to shifts in domestic labor demand, particularly affecting regions with high exposure to industries prone to relocating jobs overseas.

3 Methodology

We want to estimate the effect of AI-intensity in local labor markets on the demand for STEM education and on the STEM gender gap. We specify the following model:

$$y_{ct} = \gamma AI_{ct} + \alpha \mathbf{X}_{ct} + \xi_{st} + \epsilon_{ct} \tag{2}$$

The dependent variable refers to either the STEM major field demand or the level of STEM field segregation as described in detail in the Results section. AI_{ct} is the level of AI intensity at the county level as measured by the presence of job posts with AI-specific skill requirements. In order to capture the demand for AI and not the broader increase in demand for IT specific occupations, we create a subset of the job posts data by deleting observations associated with Computer Specific occupations.[8] For robustness, in Sub-section 4.4, we also include observations including the universe of the job posts data across all occupations and counties. Results remain largely unchanged. County-level controls include the level of unemployment, and immigration, the log-level of income and an index of offshoring at the county level to capture the effect in the dynamics of trade and multinational firms, that may be impacted at the same time, e.g. due to the trade war. State-by-year fixed effects are included to control for unobserved factors, such as state-specific tax and other policy changes or labor market conditions, that vary across states and years and could influence both the

[8] These are occupation wit 2-digit SOC equal to 15.

level AI exposure and major choice. We first show using the OLS specification above that AI labor demand and STEM major demand correlate positively, and in addition the recent increase in AI posts has increased the major segregation observed in many STEM fields.

Because the demand for AI skills by companies may be endogenous to the availability of STEM graduates in a particular county, and despite the fact that we incorporate several control variables that could affect the education choices at the local level, omitted variable bias and reverse causality can still lead to biased estimates in our specification. For example, given the low availability of STEM talent in the US, there is the risk of capturing the reverse causal effect: incentives to hire high-demand STEM majors in local labor markets can lead to increased AI job posting activity in counties with many degrees awarded, due to faster fulfillment of AI job posts.

To address these issues, we create a Bartik instrument that uses each county's pre-exposure to the national increase in AI labor demand. Specifically, we construct the following Bartik-like measure:

$$\text{BARTIK}_{ct} = \sum_{j} \left(\frac{\text{Emp}_{c,j,t_0}}{\text{Emp}_{c,t_0}} \right) \times AI_{jt} \tag{3}$$

The first term in the summation represents the share of employment in county c for occupation j in the period 2005-2009, following the common by now technique of fixing the "exposure" variable before the period of the increase in the national shock, to ensure exogeneity of the instrument due to the exogeneity of the weights (see for example Goldsmith-Pinkham et al. (2020)). The second captures variation in annual AI job postings at the national level for each occupation, representing changes in aggregate demand for AI related skills. This measure then serves as an instrument for the share of AI job postings in a two-stage least squares (2SLS) regression:

$$AI_{ct} = \zeta \text{BARTIK}_{ct} + \beta \mathbf{X}_{ct} + \phi_{st} + \epsilon_{ct} \tag{4}$$

$$y_{ct} = \gamma \widehat{AI_{ct}} + \alpha \mathbf{X}_{ct} + \xi_{st} + \epsilon_{ct} \tag{5}$$

The primary identification assumption is that shocks to county-level major demand other than those associated with AI are uncorrelated with the preexisting occupation weights, conditional on the inclusion of relevant controls and after removing common shocks within the same state-year. In all of our specifications, standard errors are clustered at the county level.

4 Results

4.1 AI and STEM Share

We begin our analysis by estimating the impact of AI on the demand for STEM education. Demand is defined as the share of degrees awarded in STEM-designated majors (cipcodes) in a given county over all degrees. The results are reported in Table 4. First, we estimate the impact of AI by pooling together all data across degree types and race (Column 1). The coefficient is positive and statistically significant, indicating that higher content of AI skills in local (county) labor markets results in higher demand for STEM education. To control for other parameters that may also affect the demand we include state-year fixed effects, as well as controls for the level of unemployment, median household income, immigration, and offshoring.

A potential concern with the OLS estimation above is the presence of omitted variable bias and reverse causality. This may arise for example, if counties with higher shares of STEM graduates attract more tech companies, hence having higher AI intensity. Including state-year fixed effects mitigates some of the concern but not all. To address this, we report

VARIABLES	All Data		By Degree Type			By Race				
	All Degrees	All Degrees	Associate's	Bachelor's	Master's	Asian	Black	Hispanic	White	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of AI in OJVs	5.241***	17.17***	2.898	25.63***	23.44***	27.34***	9.860***	16.74***	16.74***	18.48***
	(0.900)	(2.694)	(2.755)	(4.988)	(5.605)	(3.951)	(2.498)	(3.076)	(3.018)	(3.219)
Immigration	0.00748	-0.166***	-0.0993*	-0.234**	-0.232**	-0.150*	-0.0552	-0.201***	-0.193***	-0.166**
	(0.0485)	(0.0595)	(0.0544)	(0.109)	(0.114)	(0.0870)	(0.0549)	(0.0630)	(0.0669)	(0.0681)
Offshoring	-0.0391	-0.147**	-0.0423	-0.234**	-0.235	-0.130	-0.156**	-0.0602	-0.132*	-0.155**
	(0.0724)	(0.0725)	(0.0808)	(0.0918)	(0.296)	(0.107)	(0.0662)	(0.0773)	(0.0754)	(0.0760)
Ln(Income)	-0.0324	-0.0785***	0.0225	-0.103***	-0.160***	-0.0828**	-0.0513**	-0.0765***	-0.0847***	-0.0750***
	(0.0201)	(0.0230)	(0.0285)	(0.0329)	(0.0411)	(0.0334)	(0.0232)	(0.0268)	(0.0258)	(0.0254)
Unemployment Rate	-0.00584***	-0.00757***	-0.000693	-0.00805***	-0.0116**	-0.00293	-0.00419*	-0.00566**	-0.00794***	-0.00581***
	(0.00188)	(0.00196)	(0.00179)	(0.00299)	(0.00518)	(0.00293)	(0.00224)	(0.00243)	(0.00212)	(0.00216)
Constant	0.534**									
	-0,227									
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV Approach	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,871	16,871	6,905	6,373	3,550	15,447	16,295	16,232	16,818	16,559
R-squared	0.079	-0.079	0.003	-0.157	-0.031	-0.045	-0.010	-0.053	-0.067	-0.071

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: The Effect of AI in Online Job Vacancies on Demand for STEM Degrees

Notes: This table presents regression estimates of the impact of AI intensity on students' major choice using cross-county variation in the United States. The sample is all counties with higher education institutions having degrees awarded between 2014-2022. AI intensity using posted vacancies is measured using data from 2014–22 except from SOC with first four digits: 15-10 or 15-11 (computer occupations). The dependent variable, constructed from IPEDS data, is the number of degrees awarded to STEM students relative to Non-STEM students. The main regressor, county AI intensity each year, is the number of vacancies with AI skills required across all the non-computer occupation vacancies. The instrumental variable, is an annual Bartik-style predicted county AI intensity each year, where the construction is based on pre-2014 occupation shares and national shifts in AI intensity by occupation each year in 2014-2022. In the first two columns, using the full sample of degrees awarded, the first column presents the OLS results and the second the IV results. Columns 3-5 include the results when we only consider subsamples by degree type. Columns 6–11 include results when we only consider subsamples by students' race. Every regression includes state-year fixed effects and county controls. Standard errors are clustered at the county level.

regression estimates using the shift-share instrument for AI introduced in the section above (Column 2). Replacing AI intensity with the instrument does not change the results: higher AI intensity leads to higher demand for STEM education (measured as the share over all degrees awarded).

Next, we estimate the impact of AI across degree types (Columns 3 to 5) and race (Columns 6-10) using the instrumental variable approach. For brevity, we use the instrumental variable approach when looking at subsamples. In all subsamples, AI drives up the demand for STEM education. Across degrees, the impact is higher for Master's, followed by Bachelor's and then Associate's, although for Associate's degrees the coefficient is not statistically significant. AI also raises the demand for STEM education across students of all races, with the highest impact found on Asian students and the lowest on Black students.

4.2 AI and the STEM Gender Gap

Next, we turn our attention to the gender gap and ask whether the increase in STEM education, as a result of rising shares of jobs requiring AI-related skills, affects male and female students the same.

To investigate this, we repeat the regression analysis, but this time instead of identifying the impact of AI on the share of STEM degrees awarded, we do it on the STEM gender gap defined in Equation 1 above. The results are reported in Table 5.

VARIABLES	All Data		By Degree Type			By Race				
	All Degrees	All Degrees	Associate's	Bachelor's	Master's	Asian	Black	Hispanic	White	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of AI in OJVs	2.943***	9.466***	5.887**	11.29***	16.79***	7.855***	7.449***	8.977***	10.49***	7.802***
	(0.562)	(1.930)	(2.593)	(2.842)	(3.698)	(2.447)	(1.859)	(2.017)	(2.064)	(2.143)
Immigration	0.0460	-0.0484	-0.116**	0.0696	-0.161*	-0.0489	0.0246	0.0287	-0.139***	-0.0218
	(0.0410)	(0.0434)	(0.0559)	(0.0646)	(0.0880)	(0.0518)	(0.0416)	(0.0461)	(0.0476)	(0.0499)
Offshoring	0.0490	-0.0100	0.104	-0.0512	-0.276	0.0274	-0.00191	0.0428	-0.0160	-0.00235
	(0.0669)	(0.0669)	(0.0889)	(0.0857)	(0.172)	(0.130)	(0.0636)	(0.0701)	(0.0684)	(0.0808)
Ln(Income)	-0.0177	-0.0429**	-0.0218	-0.0569**	-0.0539*	-0.00770	0.0210	-0.0420**	-0.0429**	-0.0101
	(0.0157)	(0.0174)	(0.0260)	(0.0234)	(0.0278)	(0.0232)	(0.0164)	(0.0190)	(0.0183)	(0.0175)
Unemployment Rate	0.000661	-0.000274	-0.00237	0.00108	0.00207	0.00799***	0.00496***	0.000959	0.000283	0.00167
	(0.00131)	(0.00133)	(0.00172)	(0.00205)	(0.00303)	(0.00237)	(0.00152)	(0.00172)	(0.00151)	(0.00155)
Constant	0.301*									
	(0.173)									
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV Approach	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,826	16,826	6,893	6,344	3,544	12,836	15,192	15,119	16,651	15,700
R-squared	0.051	-0.027	-0.020	0.009	-0.088	-0.001	-0.000	-0.007	-0.033	-0.003

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Regression Results: The Effect of AI in Online Job Vacancies on STEM Gender Gap

First, we report regression estimates with all data pooled together using the AI intensity variable (Column 1) and the instrumental variable approach for AI (Column 2). Then, we report estimates for various subsamples (using the instrumental variable approach) by isolating the impact of AI on the gender gap by degree type (Columns 3 to 5) and by race

(Columns 6 to 10).

Regardless of which specification and sub-sample we use, we find that AI raises the female gender gap in STEM. This occurs because AI is driving the demand of STEM fields that are predominately male dominated (e.g. Computer Science, Engineering, and Math) over those that are not (e.g. Psychology and Biology). This is a troubling finding because it suggests that the underrepresentation of women in high-paying STEM fields will persist, leading potentially to broader economic inequality and the widening of the gender pay gap.

4.3 AI, STEM Gender Gap, and Female Faculty

Motivated by the observation that female faculty act as role models for female students and their presence leads to better academic outcomes among female students and a higher likelihood that they pursue STEM education and careers, we proceed to check if higher shares of female faculty affect the impact of AI on the STEM gender gap. This is important, because finding attenuating factors can help inform the right policies to close both the gender gap in STEM education and in wages.

To study this hypothesis, we construct data on male and female faculty by institution, year, and field (CIP2 code). The initial data comes from SciSciNet, a large database of science research that uses the Microsoft Academic Graph (MAG) dataset to collect records for over 270 million publications. The information includes author information (including gender), affiliation, citations, and keywords.[9] We use publication keywords to identify the academic field of each author at the CIP2 level.[10]

Next, we use the constructed dataset on faculty gender to create a dummy variable that

[9]https://www.nature.com/articles/s41597-023-02198-9

[10]Using AI and manual checking accuracy, we are able to match keywords to CIP2 categories, therefore we can identify research faculty by their academic field. We also populate data for individual affiliation in between publication years. That is, if a scholar from affiliation A appears with a publication in year t and then again in year $t+T$, if the affiliation remains the same we assume that in all periods between t and t+T the affiliation has not changed.

takes the value 1 if the county has high female faculty share (defined as shares above the median across counties) or 0 otherwise. To go from institutional affiliation to county-level data we aggregate up the data. We then interact the AI-intensity (using the IV approach) with the dummy variable to check if high female faculty share affects the impact of AI intensity of the STEM gender gap.

The results are available in Table 6. Across all specifications high shares of female faculty significantly reduces the adverse impact AI has on the STEM gender gap. This finding is consistent with earlier work on the importance of female faculty, and it offers one more channel through which their presence has a positive impact.

VARIABLES		By Degree Type			By Race				
	All Degrees	Associate's	Bachelor's	Master's	Asian	Black	Hispanic	White	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of AI in OJVs	11.65***	4.922*	11.95***	18.95***	9.251***	9.004***	10.28***	12.64***	11.01***
	(1.944)	(2.752)	(2.738)	(3.434)	(2.452)	(1.902)	(1.999)	(2.055)	(2.104)
AI Share * High Fem Share	-6.425***	-4.459***	-6.791***	-7.092***	-5.455***	-2.664***	-5.371***	-6.917***	-5.825***
	(1.023)	(1.515)	(1.400)	(1.730)	(1.485)	(1.021)	(1.236)	(1.076)	(1.191)
Immigration	-0.0264	-0.0656	0.0743	-0.134	-0.0355	0.00878	0.0342	-0.108**	-0.0282
	(0.0429)	(0.0562)	(0.0606)	(0.0823)	(0.0517)	(0.0422)	(0.0507)	(0.0457)	(0.0490)
Offshoring	0.0251	0.00849	0.0378	-0.222	0.0959	0.0155	0.0704	0.0370	0.0453
	(0.0813)	(0.121)	(0.113)	(0.166)	(0.153)	(0.0858)	(0.0880)	(0.0824)	(0.0945)
Ln(Income)	-0.0412**	-0.0546	-0.0470*	-0.0374	-0.00387	0.0207	-0.0429**	-0.0433**	-0.00540
	(0.0177)	(0.0345)	(0.0241)	(0.0261)	(0.0243)	(0.0167)	(0.0191)	(0.0183)	(0.0184)
Unemployment Rate	0.00229	-0.00414	0.00364	0.00435	0.0102***	0.00715***	0.00389*	0.00239	0.00528***
	(0.00170)	(0.00294)	(0.00234)	(0.00291)	(0.00267)	(0.00170)	(0.00206)	(0.00182)	(0.00197)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV Approach	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,805	3,505	5,021	3,224	9,989	11,095	11,007	11,757	11,287
R-squared	0.002	0.005	0.026	-0.043	0.004	0.002	0.006	-0.001	0.002

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Regression Results: The Effect of AI in Online Job Vacancies Interacted with Female Faculty Share on STEM Gender Gap

4.4 Robustness

To ensure that our results are not sensitive to alternative parameter or sample specifications, we consider a series of robustness tests on the impact of AI on the demand for STEM education and on the STEM gender gap. We present results from alternative specifications on the level and the gap in Table 7, *panels A* and *B*, respectively. In Column 1 we reproduce the coefficients from the regressions above using all data pooled together as benchmark. In Column 2, we present results when the IV parameter is lagged by one period. In Column 3, we present results from the second half of the estimation sample (post 2017) when the prevalence of AI is higher. In Column 4, we present results when the shift-share instrument of AI is calculated using levels and not shares. In Column 5, we repeat the baseline analysis but this time, as in Acemoglu et al. (2022), we consider a broader definition of AI that includes additional skills related to data analysis (see Appendix C). Finally, in Column 6 we consider a shift-share instrument that does not exclude occupation 1510 (Computer Science) in its construction. Regardless of specification, we observe that AI has a positive and statistically effect on both the STEM share and the STEM gender gap.

5 Conclusion

Using variation from local labor markets in the United States, this article contributes to the discussion of how artificial intelligence will affect labor markets and especially white collar jobs. First, we use comprehensive online job posts data to measure the exposure of students to the AI revolution by looking at the demand for different skills across labor markets and study how uptake for STEM fields is impacted by AI-skills demand. Second, we provide causal estimates of the effects of AI demand on the STEM gender gap.

An important finding from our study is that AI has increased students' enrollment in STEM majors and especially AI-related majors, but it did not alter the gender segregation of these majors as a result increasing the STEM gender gap in the aggregate. We explore one important characteristic of education, the presence of female faculty overall in a university and in STEM fields in particular. We find that a higher share of female faculty in higher education can attenuate the increase in the STEM gender gap, providing evidence towards the importance of female faculty as role models that can alter gendered views towards specific

VARIABLES	All Degrees					
	Benchmark specification	Lag IV by one period	Use data post 2017	Use IV in levels, not share	Use broader definition of AI	Include CS (Occ 1510) in the construction of the IV
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Stem Share			
Share of AI in OJVs	17.17***	20.57***	16.64***	12.56***	11.66***	13.43***
	(2.694)	(3.100)	(2.646)	(2.088)	(1.938)	(1.989)
Immigration	-0.166***	-0.174***	-0.166**	-0.0987*	-0.0856*	-0.111**
	(0.0595)	(0.0618)	(0.0693)	(0.0515)	(0.0490)	(0.0523)
Offshoring	-0.147**	-0.185**	-0.171**	-0.105	-0.0972	-0.113
	(0.0725)	(0.0774)	(0.0819)	(0.0701)	(0.0703)	(0.0700)
Ln(Income)	-0.0785***	-0.0791***	-0.0786***	-0.0607***	-0.0572***	-0.0640***
	(0.0230)	(0.0243)	(0.0259)	(0.0208)	(0.0210)	(0.0206)
Unemployment Rate	-0.00757***	-0.00837***	-0.00736***	-0.00690***	-0.00677***	-0.00702***
	(0.00196)	(0.00232)	(0.00249)	(0.00190)	(0.00190)	(0.00191)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV Approach	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,871	12,915	9,417	16,871	16,871	16,871
R-squared	-0.079	-0.06	-0.106	-0.014	-0.005	-0.024
			Panel B: Stem Gender Gap			
Share of AI in OJVs	9.466***	11.21***	8.394***	6.899***	7.282***	7.933***
	(1.930)	(2.208)	(1.879)	(1.586)	(1.445)	(1.328)
Immigration	-0.0484	-0.0503	-0.0310	-0.0113	-0.0168	-0.0262
	(0.0434)	(0.0447)	(0.0482)	(0.0405)	(0.0400)	(0.0398)
Offshoring	-0.0100	-0.0212	0.0112	0.0132	0.00972	0.00383
	(0.0669)	(0.0728)	(0.0816)	(0.0664)	(0.0660)	(0.0656)
Ln(Income)	-0.0429**	-0.0423**	-0.0416**	-0.0329*	-0.0344**	-0.0369**
	(0.0174)	(0.0182)	(0.0189)	(0.0170)	(0.0164)	(0.0163)
Unemployment Rate	-0.000274	-0.000436	0.000322	9.39e-05	3.91e-05	-5.41e-05
	(0.00133)	(0.00156)	(0.00171)	(0.00132)	(0.00130)	(0.00131)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV Approach	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,826	12,882	9,392	16,826	16,826	16,826
R-squared	-0.027	-0.018	-0.028	-0.003	-0.006	-0.011

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Regression Results: Robustness Checks

fields. Given the increasing interest in the AI revolution, it is important to identify the reasons that can drive unequal benefits of the expected productivity gains. The importance of major choice on career trajectories for men and women implies that greater attention should be paid to understand the STEM gender gap.

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Appendix A

AI- and DA- Related Skills

We use the definitions of skills provided by LIghtcast to identify skills related to AI. In total, there are about 16,000 skills definitions in Lightcast, and from these we have selected 34 that we consider to be related to AI. For robustness, we have repeated the analysis with a shorter (24 definitions) and a longer (60) list of skills, but the results do not change.

AI Keywords	**DA Keywords**
Apache Ant	Apache Hadoop
Apache Spark	Apache Hive
Artificial Intelligence	Apache Kafka
Automated Testing	Bayesian Inference
Automation Consulting	Bayesian Modeling
Automation Systems	Bayesian Networks
Automation Techniques	Big Data
Automation Tools	Big Data Analytics
AWS Elastic MapReduce (EMR)	Data Analysis
BigQuery	Data Analytics
Boosting (Machine Learning)	Data Conversion
Caffe Deep Learning Framework	Data Engineering
Cluster Analysis	Data Management
Clustering	Data Modeling
Clustering Algorithms	Data Science
Computer Vision	Data Visualization
Convolutional Neural Network (CNN)	Extraction Transformation and Loading (ETL)
Decision Trees	Microsoft Power BI
Deep Learning	Microsoft SQL
Deeplearning4j	MongoDB
Machine Learning	MySQL
Machine Vision	NoSQL
MapReduce	Oracle PL/SQL
Kubernetes	PostgreSQL
Natural Language Processing	Predictive Analytics
Natural Language Toolkit (NLTK)	Predictive Models
Neural Networks	Prepare Spreadsheets
Splunk	Spreadsheets
Supervised Learning (Machine Learning)	SQL
Support Vector Machines (SVM)	SQL Injection
TensorFlow	SQL Plus
Torch (Machine Learning)	SQL Server
	SQL Server Analysis Services (SSAS)
	SQL Server Reporting Services (SSRS)
	SQL'Loader
	SQLAlchemy
	SQLite
	Tableau
	Transact-SQL

Table 8: Selected AI- and DA-Related Lightcast Skills

Appendix B

Intensive and Extensive Margins of Growth

Before we analyze the impact of AI on STEM education, we study how the demand for majors has changed between 2014 and 2022. For each field, we decompose the growth in degrees awarded between 2014 and 2022 into growth that came from students in same majors between the two periods, and growth that came from students in majors that were not present in 2014. We call the former the intensive margin of growth and the latter the extensive.

	Degree Growth: 2014 - 2022		
	Total	Intensive	Extensive
i. All Degrees			
Associate's	0.00	0.01	-0.01
Bachelor's	0.08	0.00	0.07
Master's	0.17	-0.03	0.20
ii. Bachelor's: STEM vs Non-STEM degrees			
Non-STEM	-0.02	-0.05	0.04
STEM	0.44	0.23	0.22
iii. Bachelor's degrees by STEM field (CIP2 classification)			
Agricultural/Animal/Plant/Veterinary Science and Related Fields	0.13	0.02	0.11
Natural Resources and Conservation	0.19	0.06	0.13
Architecture and Related Services	0.04	-0.17	0.20
Communication, Journalism, and Related Programs	-0.02	-0.13	0.11
Communications Technologies/Technicians and Support Services	-0.01	0.10	-0.10
Computer and Information Sciences and Support Services	0.95	0.74	0.22
Education	-0.10	-0.19	0.08
Engineering	0.33	0.24	0.09
Engineering/Engineering-Related Technologies/Technicians	0.11	0.01	0.09
Biological and Biomedical Sciences	0.26	0.16	0.10
Mathematics and Statistics	0.25	0.17	0.07
Military Technologies and Applied Sciences	7.75	1.18	6.57
Multi/Interdisciplinary Studies	0.09	-0.16	0.25
Physical Sciences	-0.03	-0.05	0.02
Science Technologies/Technicians	-0.11	-0.06	-0.05
Psychology	0.10	0.06	0.04
Homeland Security, Law Enforcement, Firefighting and Related Protective Services	-0.09	-0.10	0.01
Social Sciences	-0.09	-0.17	0.08
Transportation and Materials Moving	0.42	0.19	0.23
Health Professions and Related Programs	0.32	0.17	0.15
Business, Management, Marketing, and Related Support Services	0.05	0.03	0.02

Notes: ...

Table 9: Intensive and Extensive Margins of Growth in Degrees: 2014 - 2022

Appendix C