STEM Careers and Technological Change

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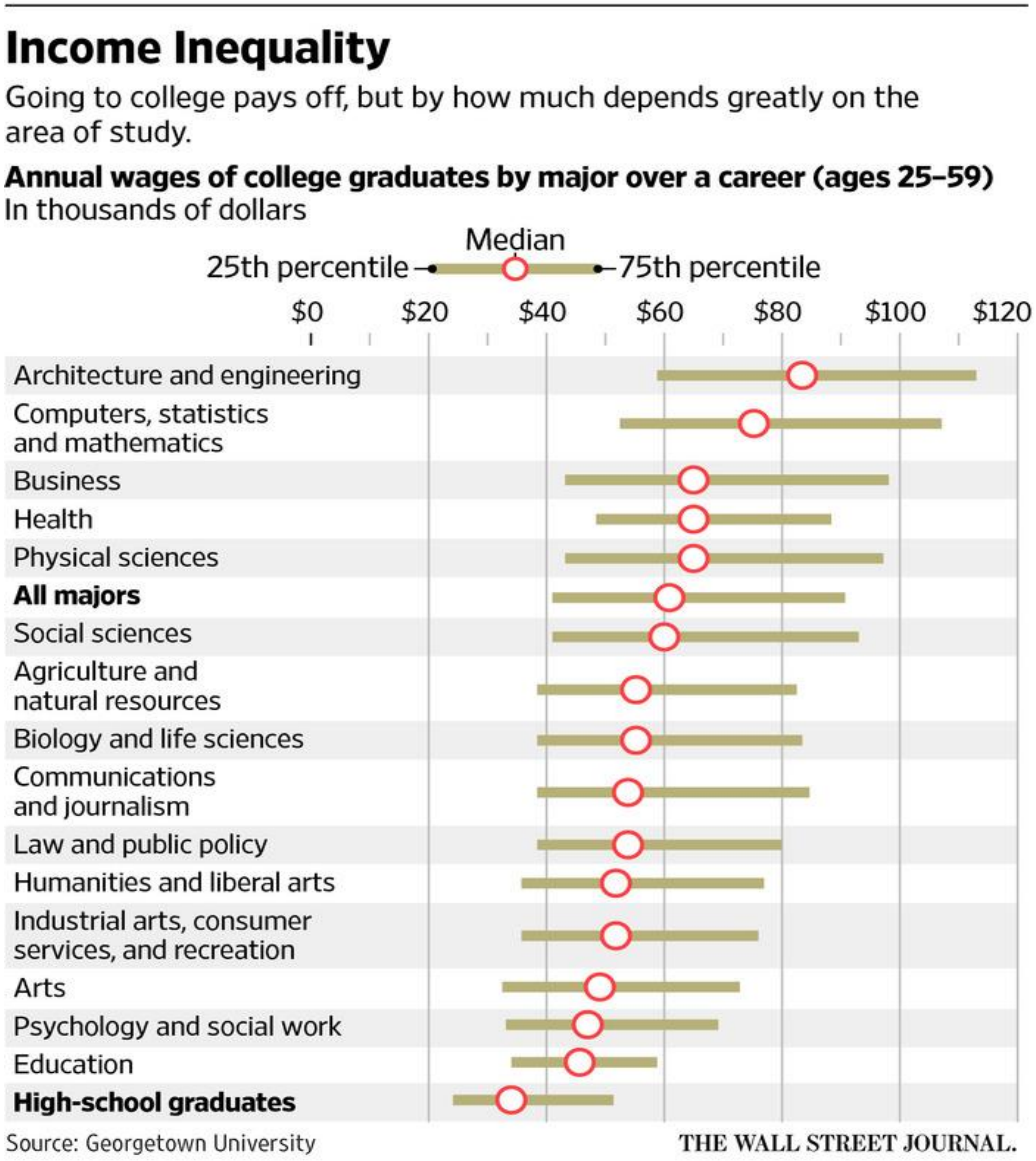
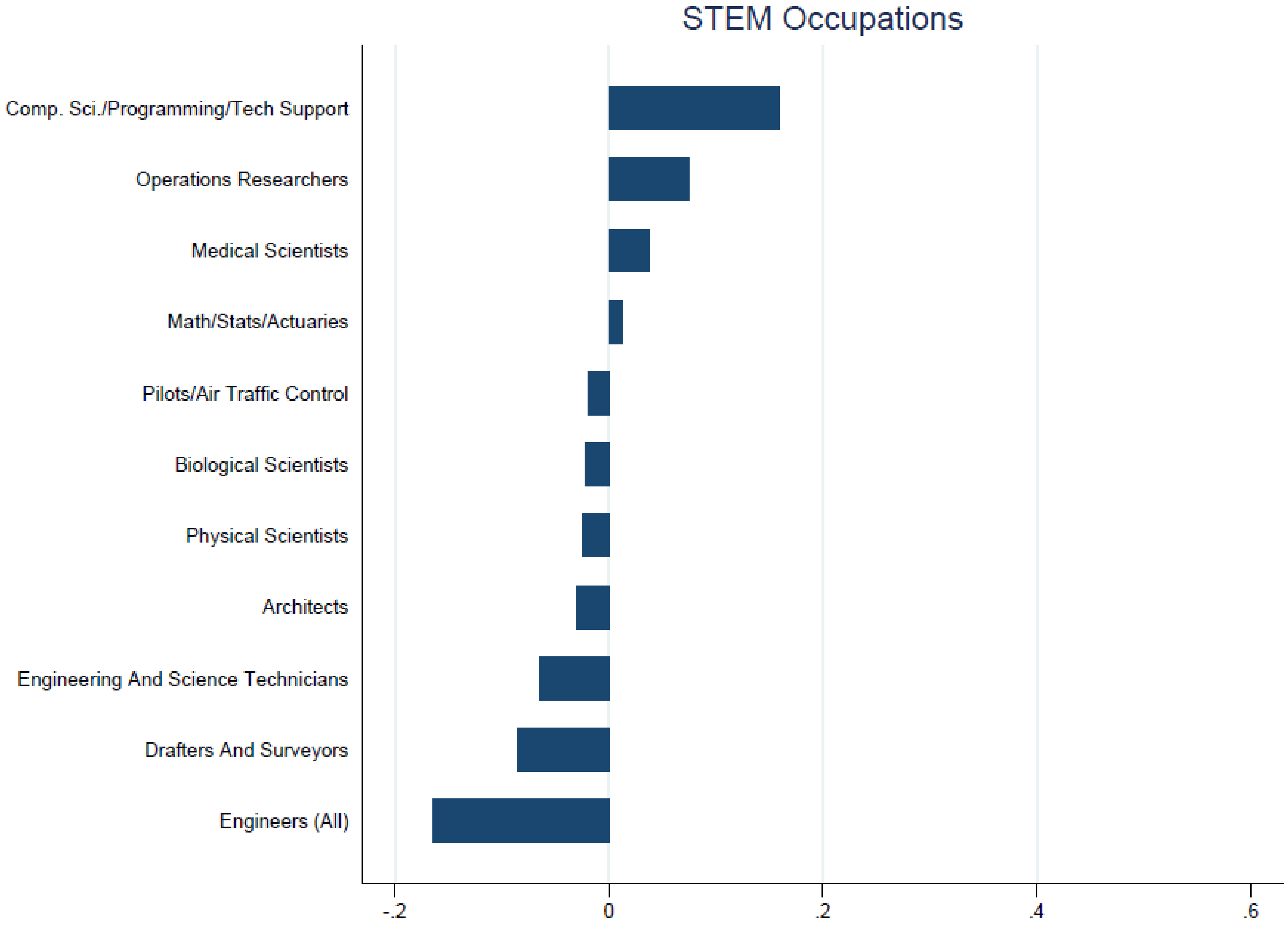
February 2019

STEM graduates are in high demand, especially in "Applied" majors……

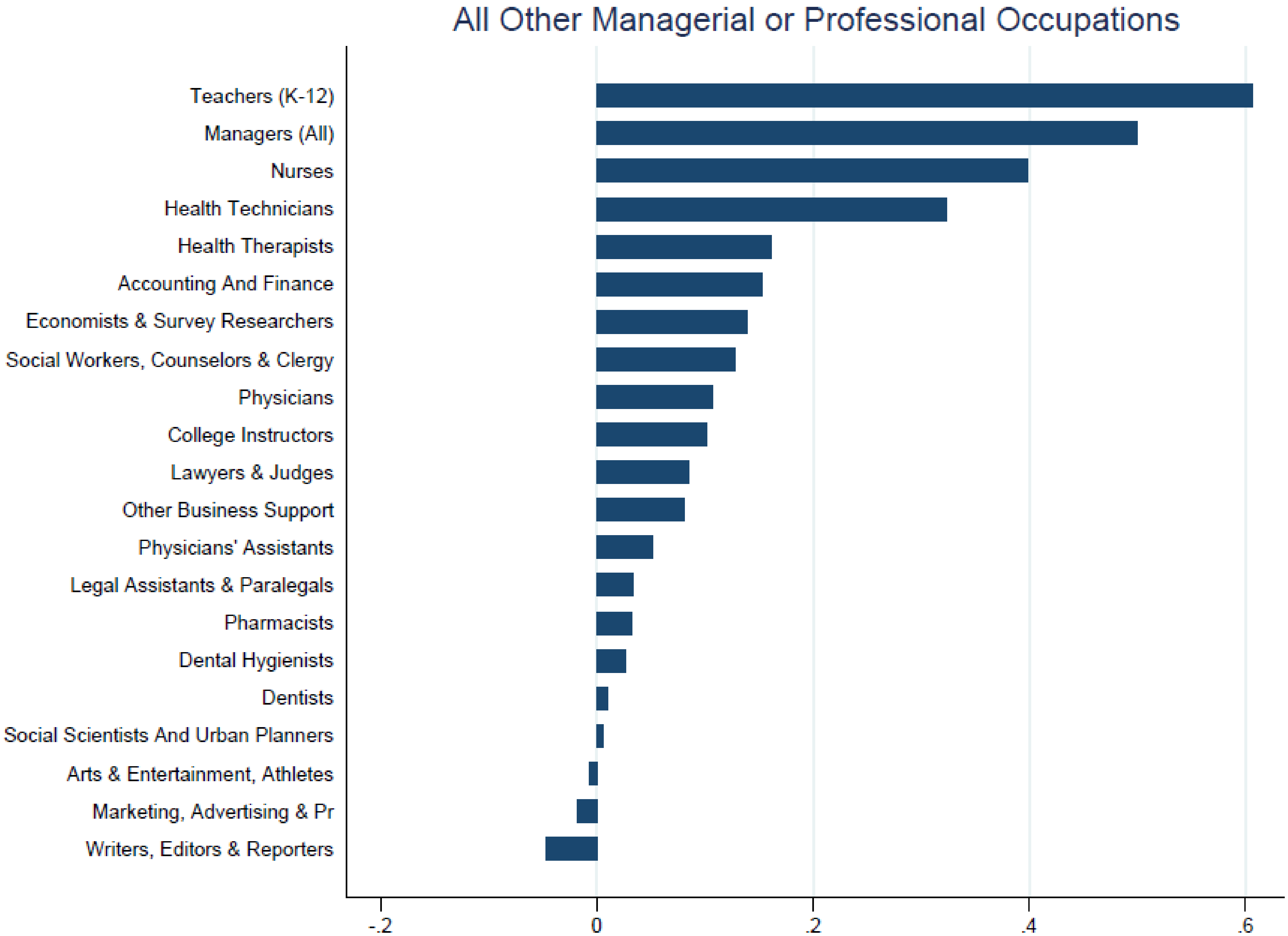


Yet slow employment growth in STEM jobs…

(Deming 2017)



Faster growth of other professional occs…..



30 Aug 2013 | 14:00 GMT

The STEM Crisis Is a Myth

Forget the dire predictions of a looming shortfall of scientists, technologists, engineers, and mathematicians

By **Robert N. Charette (/author/charette-robert-n)**

THE BLOG 09/11/2013 08:53 am ET | **Updated** Nov 11, 2013

The Truth Hurts: The STEM Crisis Is Not a Myth

By Linda Rosen

THE CHRONICLE
of Higher Education

FACULTY

The STEM Crisis: Reality or Myth?

ARTICLE

MAY 2015

STEM crisis or STEM surplus? Yes and yes

The last decade has seen considerable concern regarding a shortage of science, technology, engineering, and mathematics (STEM) workers to meet the demands of the labor market. At the same time, many experts have presented evidence of a STEM worker surplus. A comprehensive literature review, in conjunction with employment statistics, newspaper articles, and our own interviews with company recruiters, reveals a significant heterogeneity in the STEM labor market: the academic sector is generally oversupplied, while the government sector and private industry have shortages in specific areas.

STEM *skills* are scarce, not STEM workers.

- STEM graduates in CS/Engineering earn high initial wages because they learned job-relevant skills in school

- Yet job tasks change over time, especially in fields near the technology frontier

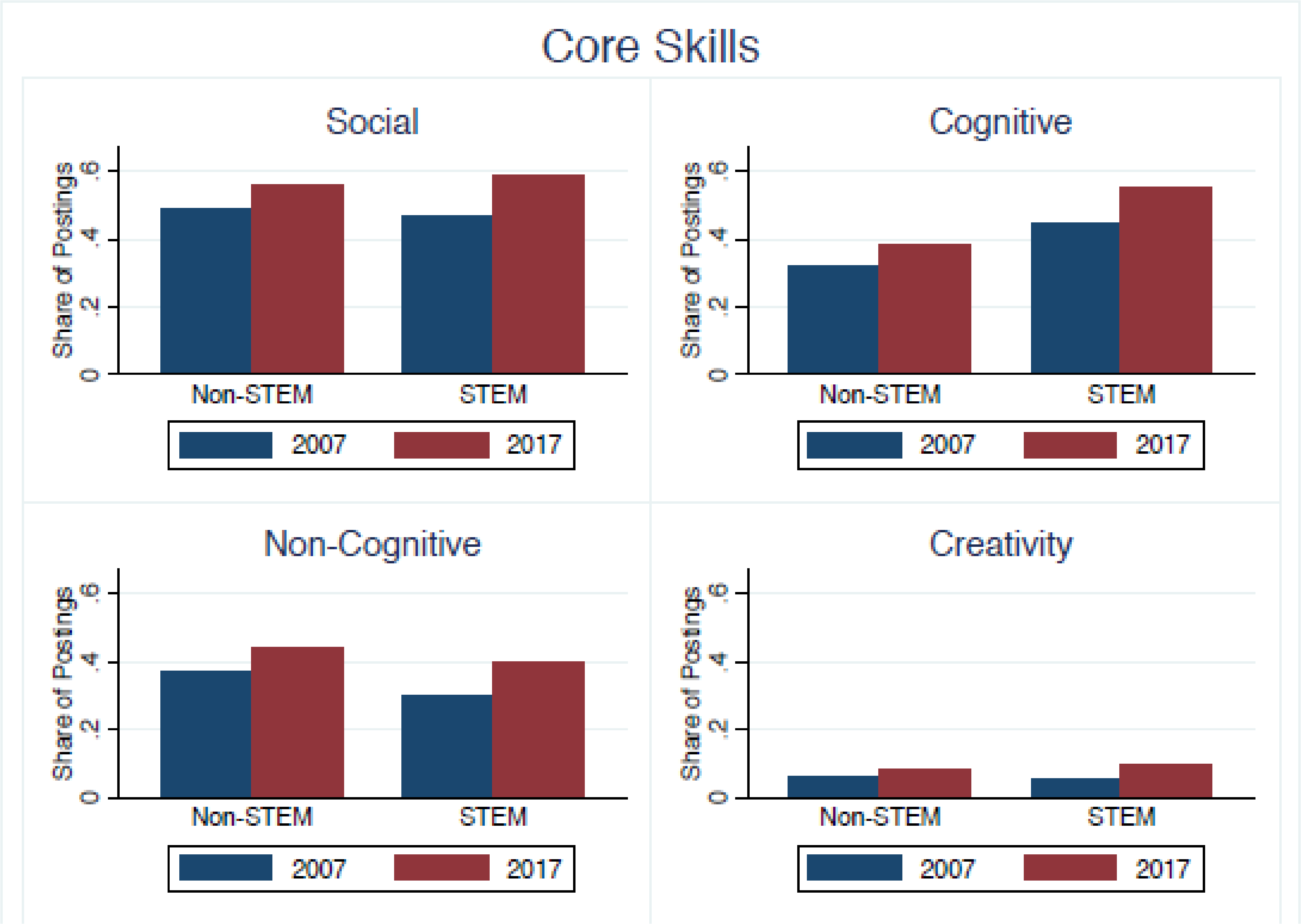
- Technological progress makes the skills of older STEM workers obsolete
  - Flatter wage growth, exit over time from STEM professions

- We show these patterns using ACS, NSCG, CPS, NLSY
  - Consistent under a wide variety of spec choices, samples, surveys
  - Cross-sectional and longitudinal surveys

Descriptive Patterns of Job Change

- Burning Glass job vacancy data – 2007-2017
  - Occupation, industry, firm, MSA, edu/exp, job skills (created with a text parsing algorithm)
- Create categories of similar job skills, following Deming and Kahn (2018)
  - Looking at professional occupations
- Compare decadal change, adjusting for changing sample composition
  - Vacancy-level regression of 2017 frequency of each skill on educ/experience requirements, # of total skills requested, and occ-MSA-employer fixed effects
  - Studies job skill change within same labor market and occupation, same firm

Figure 1: Changing Skill Profiles for Professional Occupations, 2007-2017

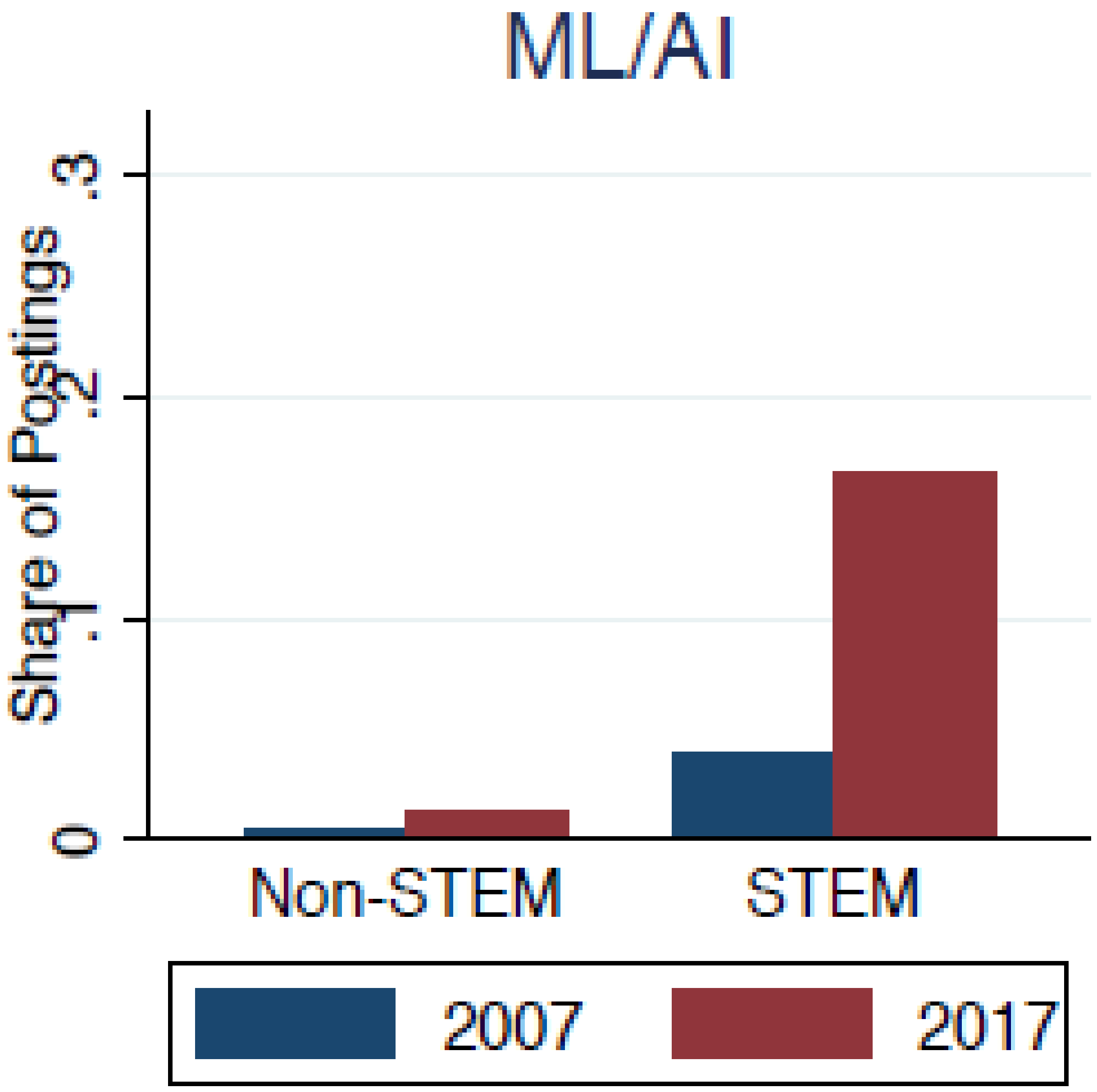


Skill Requirements in Professional Occupations by Category, 2007

	Management	Finance	Customer Service	Office Software	Other Software
Management	0.362	0.436	0.328	0.301	0.222
STEM	0.157	0.159	0.194	0.248	0.651
Business	0.172	0.551	0.244	0.452	0.323
Social Service	0.143	0.099	0.156	0.201	0.110
Art/Design/Media	0.133	0.154	0.174	0.346	0.456
Health	0.148	0.066	0.368	0.167	0.057
Sales and Admin	0.178	0.250	0.734	0.365	0.182
Total	0.210	0.298	0.318	0.309	0.369

Each cell is the share of jobs in the occupation category in 2007 that require at least one skill in the indicated category. The sample is all vacancies that require at least a bachelor's degree and have nonmissing experience requirements.

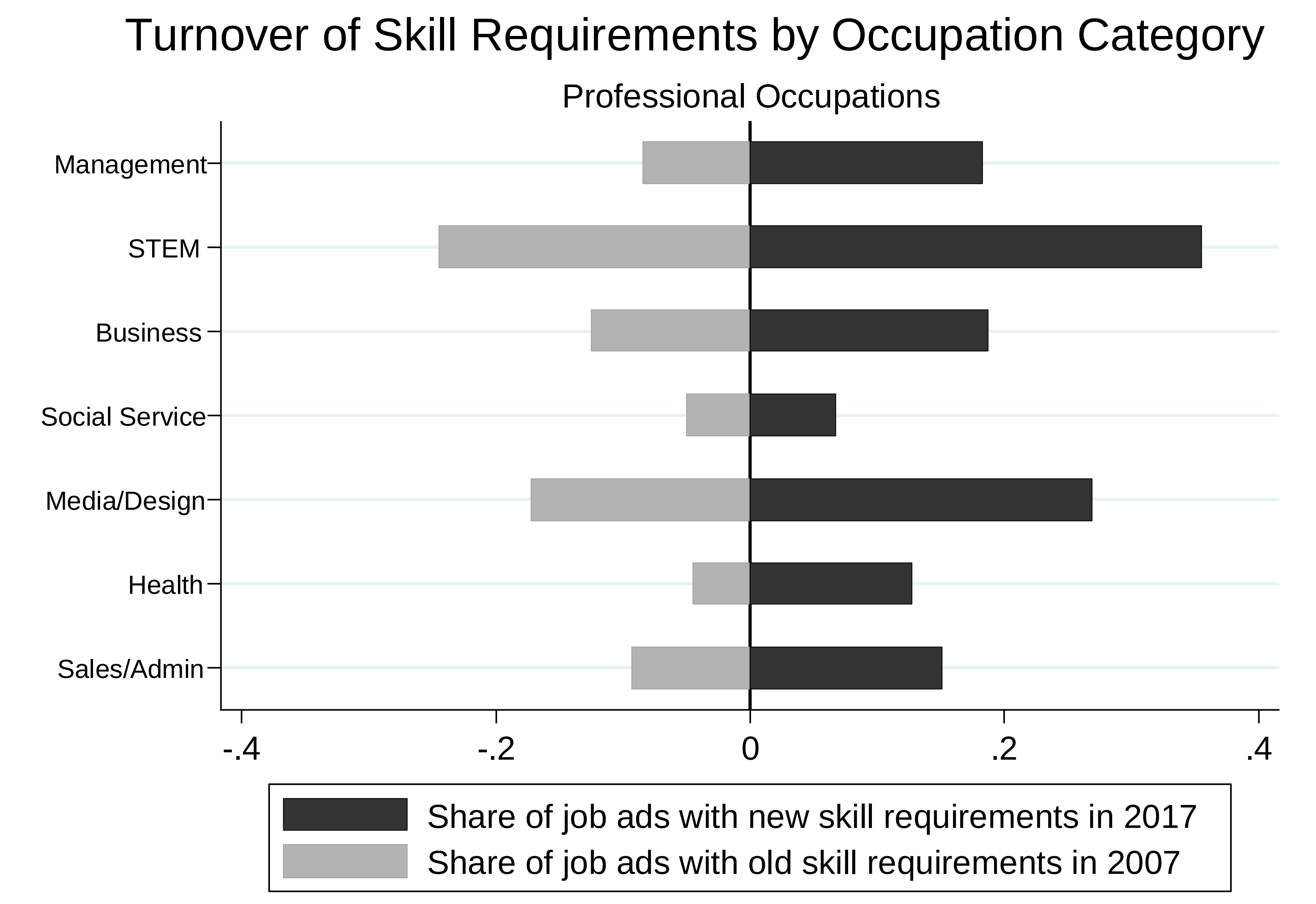
Between 2007 and 2017, the share of STEM vacancies requiring skills related to machine learning / AI increased by 370 percent.

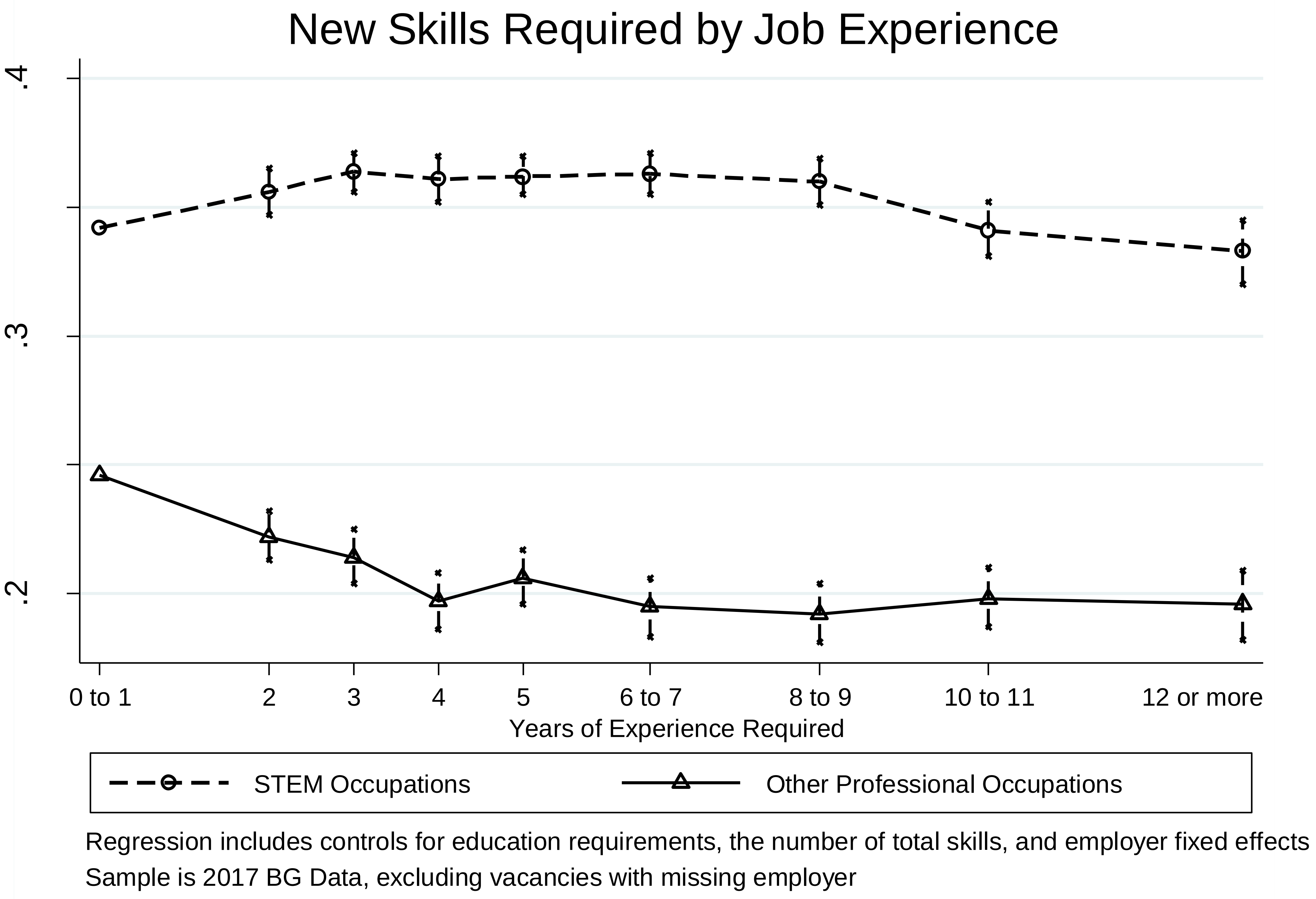


Skill Turnover

- What about “new skills”?
  - We define a new skill as one that either didn’t exist at all in 2007, or was 20x more common in 2017 than 2007
  - “Old” skills defined as 5x less common

- This is arbitrary, but illustrative


Turnover of Skill Requirements by Occupation Category
Professional Occupations
Management
STEM
Business
Social Service
Media/Design
Health
Sales/Admin
-.4
-.2
0
.2
.4
Share of job ads with new skill requirements in 2017
Share of job ads with old skill requirements in 2007



New Skills Required by Job Experience
.4
.3
.2
0 to 1
2
3
4
5
6 to 7
8 to 9
10 to 11
12 or more
Years of Experience Required
STEM Occupations
Other Professional Occupations
Regression includes controls for education requirements, the number of total skills, and employer fixed effects
Sample is 2017 BG Data, excluding vacancies with missing employer

Measuring Job Skill Change

- Calculate shares for each unique skill, in each occupation
  - Can be zero if the task is new or has disappeared

- Compute the absolute value of the decadal difference in task shares

$$SkillChange_o = \sum_{s=1}^{S} \left\{ Abs \left[\left(\frac{Skill_o^s}{JobAds_o} \right)_{2017} - \left(\frac{Skill_o^s}{JobAds_o} \right)_{2007} \right] \right\}$$

Panel A: Fastest-Changing Professional Occupations (3-digit)

SOC code	Occupation Title	Rate of Task Change
172	Engineers	3.53
192	Physical Scientists	3.48
191	Life Scientists	3.25
151	Computer Occupations	3.24
113	Operations Specialties Managers	3.20
152	Mathematical Scientists	3.19
171	Architects and Surveyors	3.13
112	Advertising, Marketing and Sales Managers	3.00
132	Financial Specialists	2.71
173	Drafters and Engineering Technicians	2.61

Panel B: Fastest-Changing Professional Occupations (6-digit)

SOC code	Occupation Title	Rate of Task Change
151131	Computer Programmers	6.69
151133	Software Developers, Systems Software	5.99
172081	Environmental Engineers	5.49
151142	Network / Computer Systems Administrators	4.71
173013	Mechanical Drafters	4.49
172041	Chemical Engineers	4.37
152041	Statisticians	4.29
151141	Database Administrators	3.98
151134	Web Developers	3.96
151152	Computer Network Support Specialists	3.77

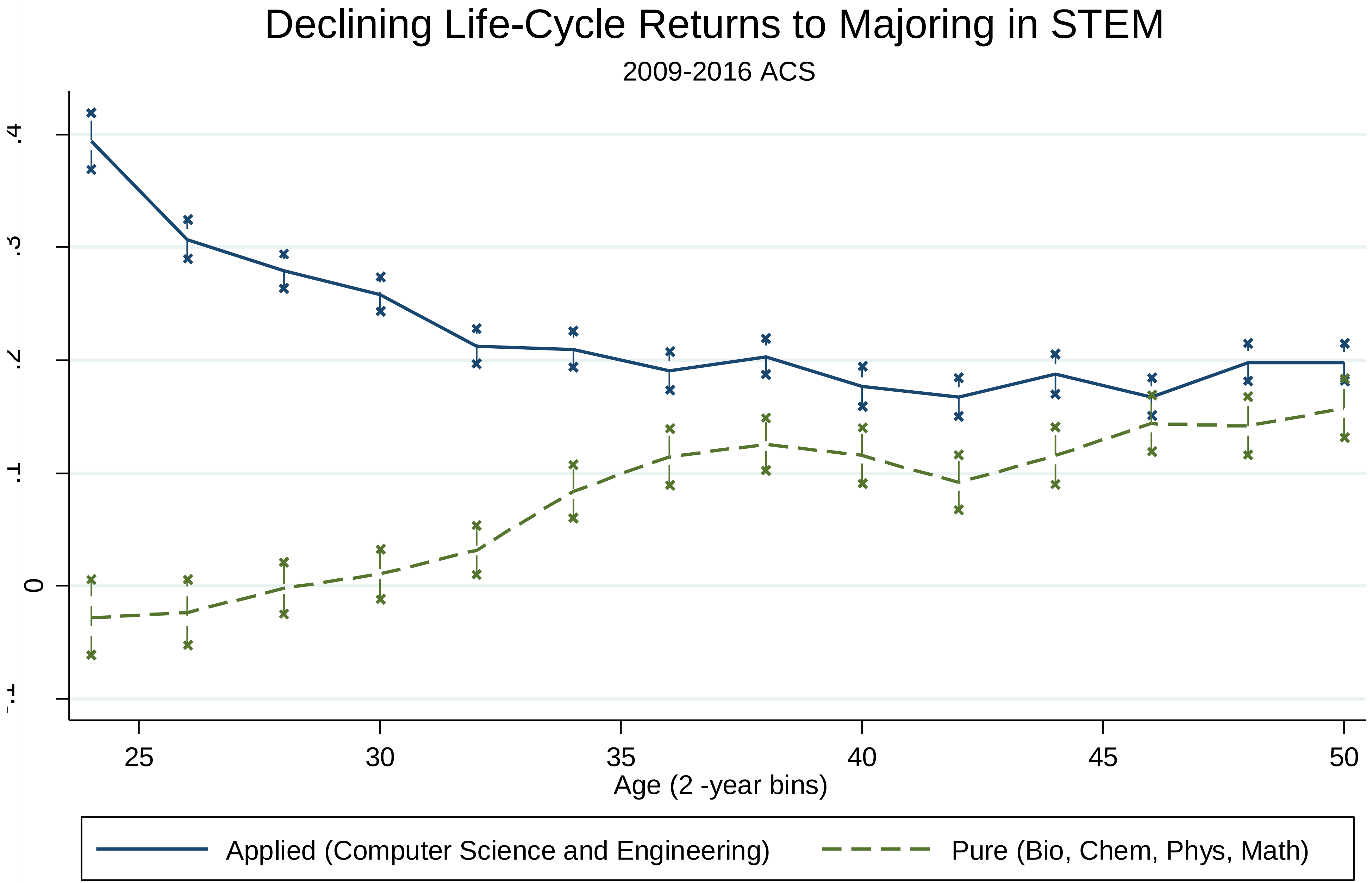
Panel C: Slowest-Changing Professional Occupations (3-digit)

SOC code	Occupation Title	Rate of Task Change
252	Pre-K, Primary and Secondary School Teachers	0.74
253	Other Teachers and Instructors	0.79
291	Health Diagnosing and Treating Practitioners	0.86
272	Entertainers and Performers	1.12
259	Other Education, Training and Library Occupations	1.15
292	Health Technologists and Technicians	1.29
251	Postsecondary Teachers	1.36
193	Social Scientists and Related Workers	1.40
211	Counselors and Social Workers	1.51
274	Media / Communications Equipment Workers	1.76

Table 1: Life-Cycle Earnings and Employment for STEM Majors

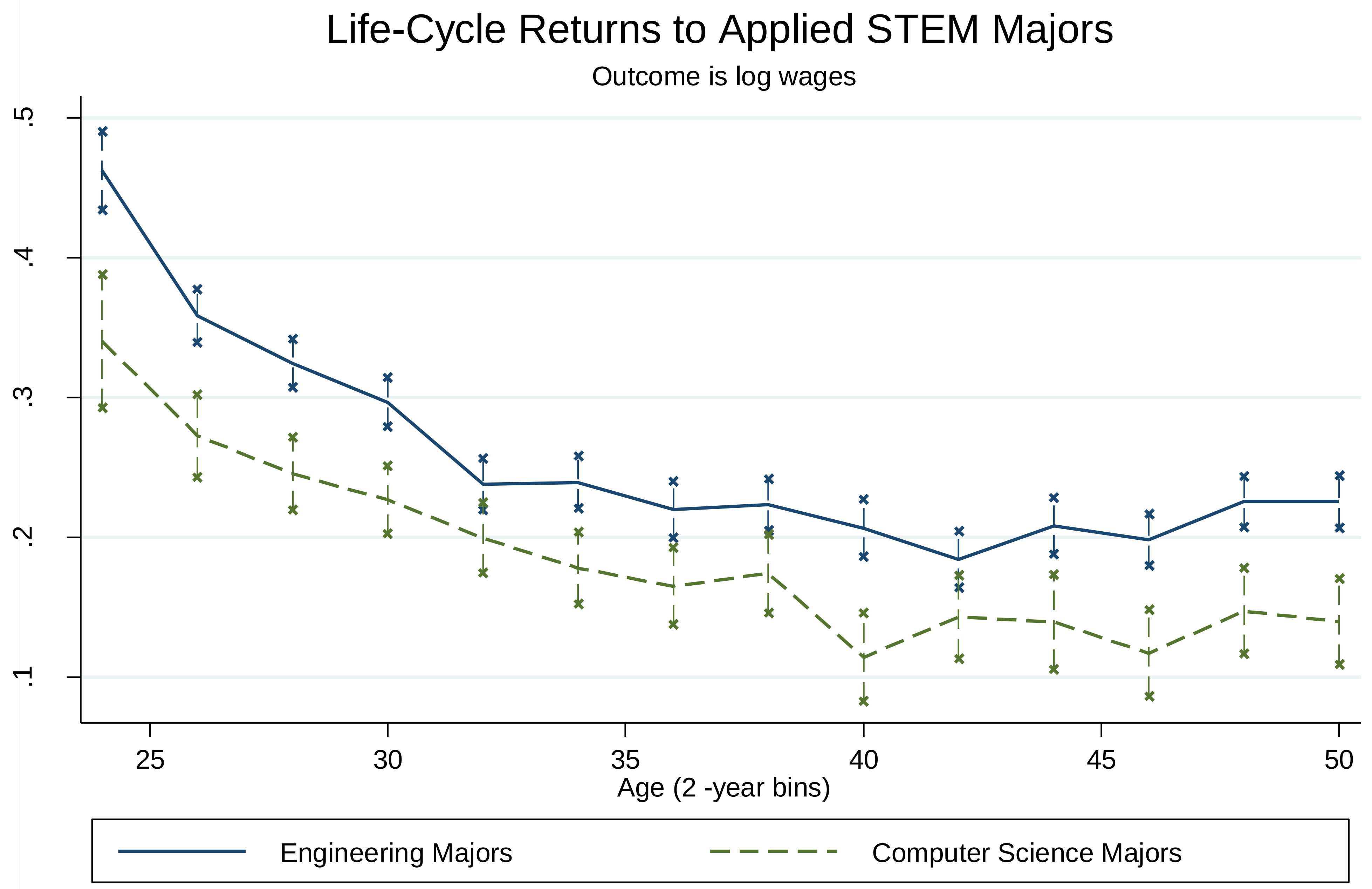
Age	Non-STEM Major		"Pure" Science		"Applied" Science	
	Wages	Share in STEM Job	Wages	Share in STEM Job	Wages	Share in STEM Job
	(1)	(2)	(3)	(4)	(5)	(6)
24	36,632	0.123	35,909	0.353	52,727	0.891
26	46,918	0.123	49,472	0.360	61,558	0.880
28	54,856	0.124	57,243	0.297	69,590	0.856
30	62,787	0.124	69,109	0.293	76,309	0.845
32	71,933	0.123	79,894	0.271	83,536	0.802
34	79,971	0.117	98,442	0.265	91,542	0.753
36	89,875	0.119	111,807	0.261	99,114	0.722
38	94,453	0.123	117,943	0.260	108,081	0.678
40	99,952	0.116	123,224	0.256	111,678	0.629

Notes: This table presents population-weighted average annual wage and salary income and employment shares in STEM occupations by age, using the 2009-2016 ACS. The sample is restricted to FT employed men with at least a college degree. Earnings are in constant 2016 dollars. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.



Sample is full-time working men with at least a college degree; 2009-2016 ACS

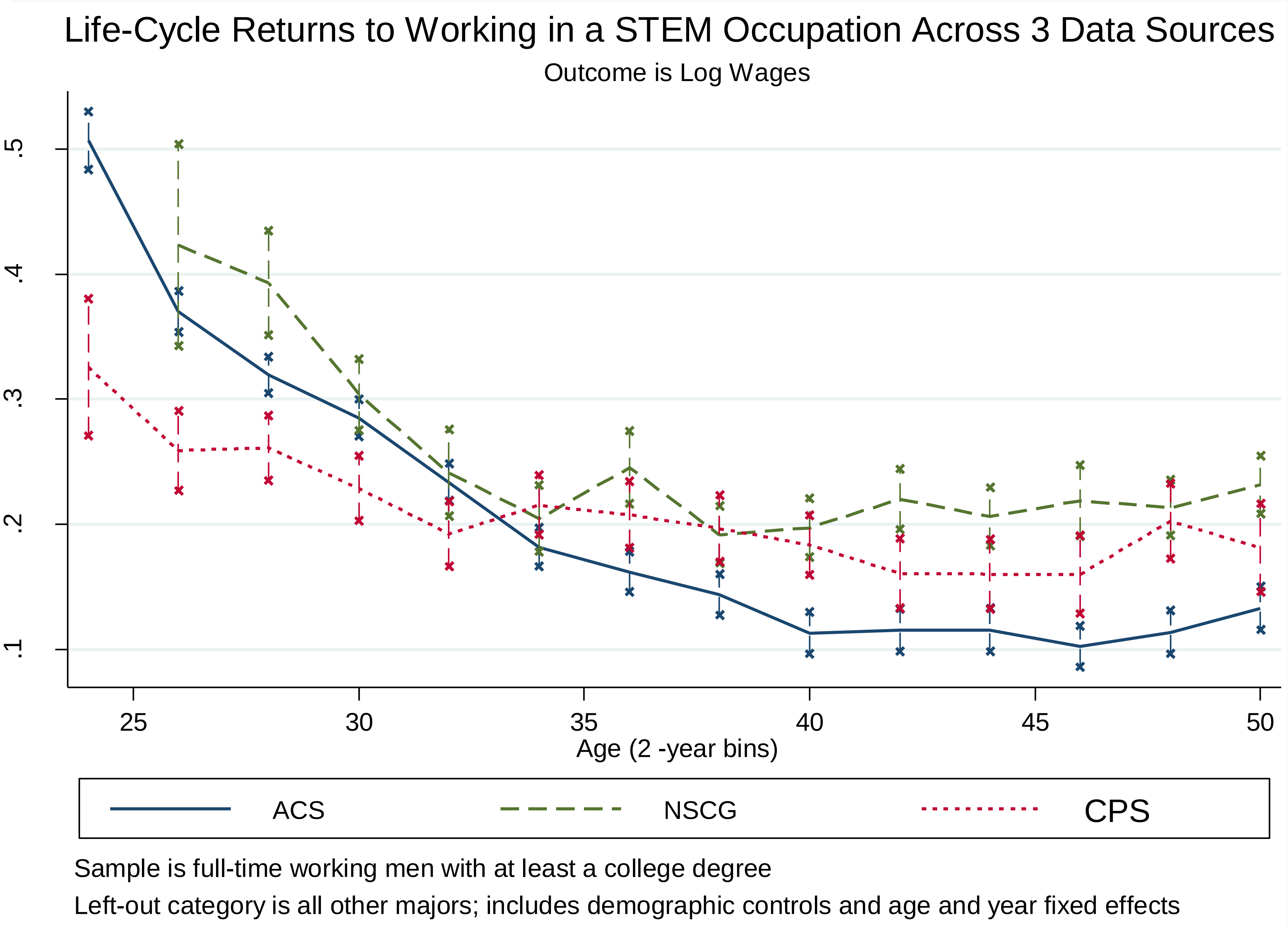
Left-out category is all other majors; includes demographic controls and age and year fixed effects



Sample is full-time working men with at least a college degree; 2009-2016 ACS
Left-out category is all other majors; includes demographic controls and age and year fixed effects

What about STEM *occupations*?

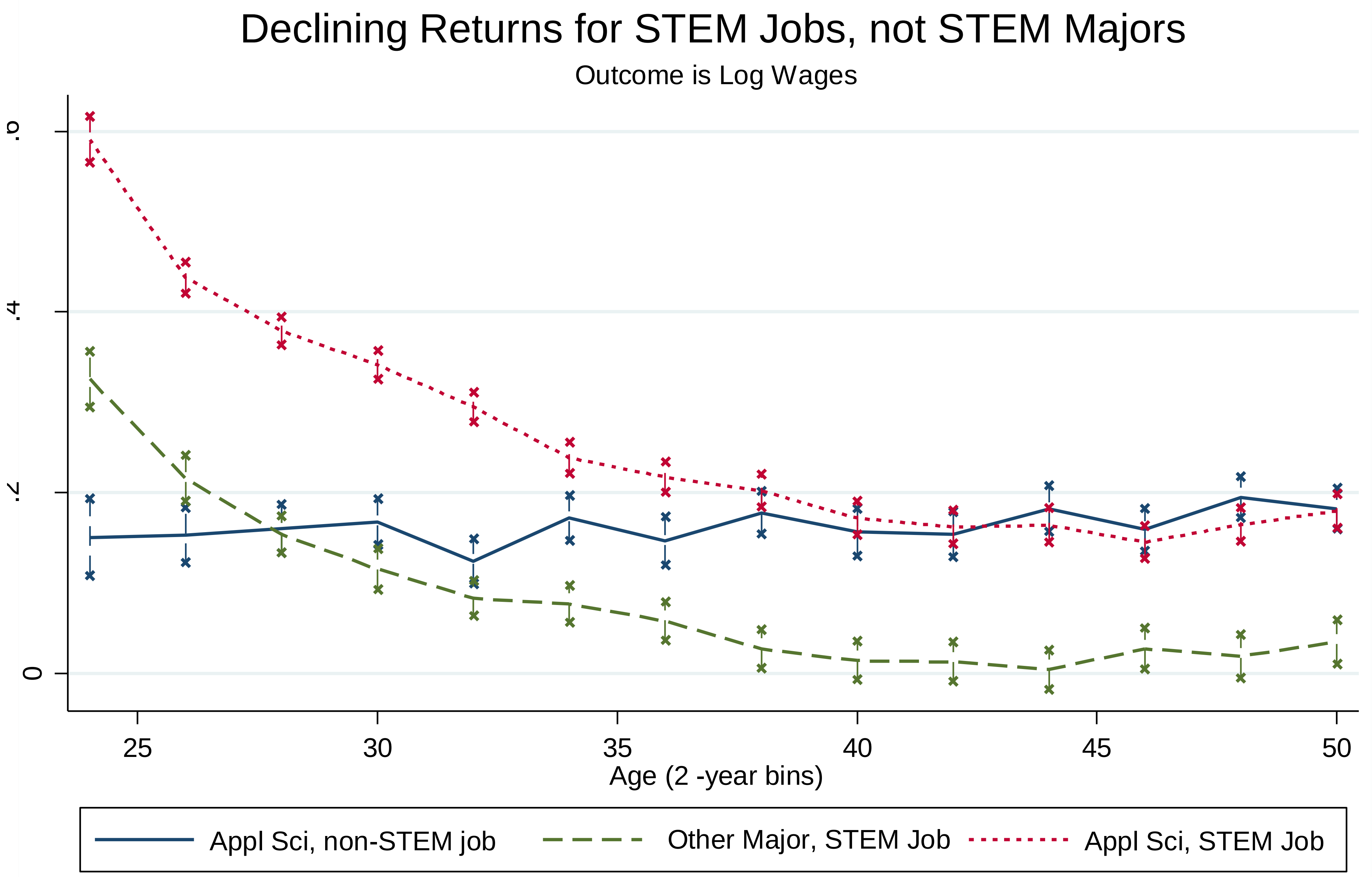
- Use 2010 Census Bureau occupation classifications
  - Does not include health jobs
- Can use multiple data sources
  - 1993-2013 National Survey of College Graduates (NSCG)
  - 1971-present Current Population Survey (CPS)


Life-Cycle Returns to Working in a STEM Occupation Across 3 Data Sources
Outcome is Log Wages
.1
.2
.3
.4
.5
25
30
35
40
45
50
Age (2 -year bins)
ACS
NSCG
CPS
Sample is full-time working men with at least a college degree
Left-out category is all other majors; includes demographic controls and age and year fixed effects

Is it STEM jobs, or STEM majors?

- Estimate main model in 2009-2016 ACS, but with major-by-occupation interactions
  - CS/Engineering major in a non-STEM job
  - Non-STEM major in a STEM job
  - CS/Engineering major in a STEM job

- Do the same in the NLSY79 and 97, where we can control for ability and other determinants of earnings



Left-out category is other major, non-STEM job; includes demographic controls and age and year fixed effects
Sample is full-time working men with at least a college degree; 2009-2016 ACS

Summing up empirical patterns

- Initial return to STEM degree of 40% - declines by more than 50 percent in the first decade of working life
  - Holds for CS/engineering, but not “pure” science
- Most of the return to majoring in STEM is mediated by occupational choice (e.g. Kinsler and Pavan 2015)
- Declining life-cycle returns for STEM jobs, not majors

Figure 9: Jobs with Higher Rates of Skill Change Pay More to Younger Workers

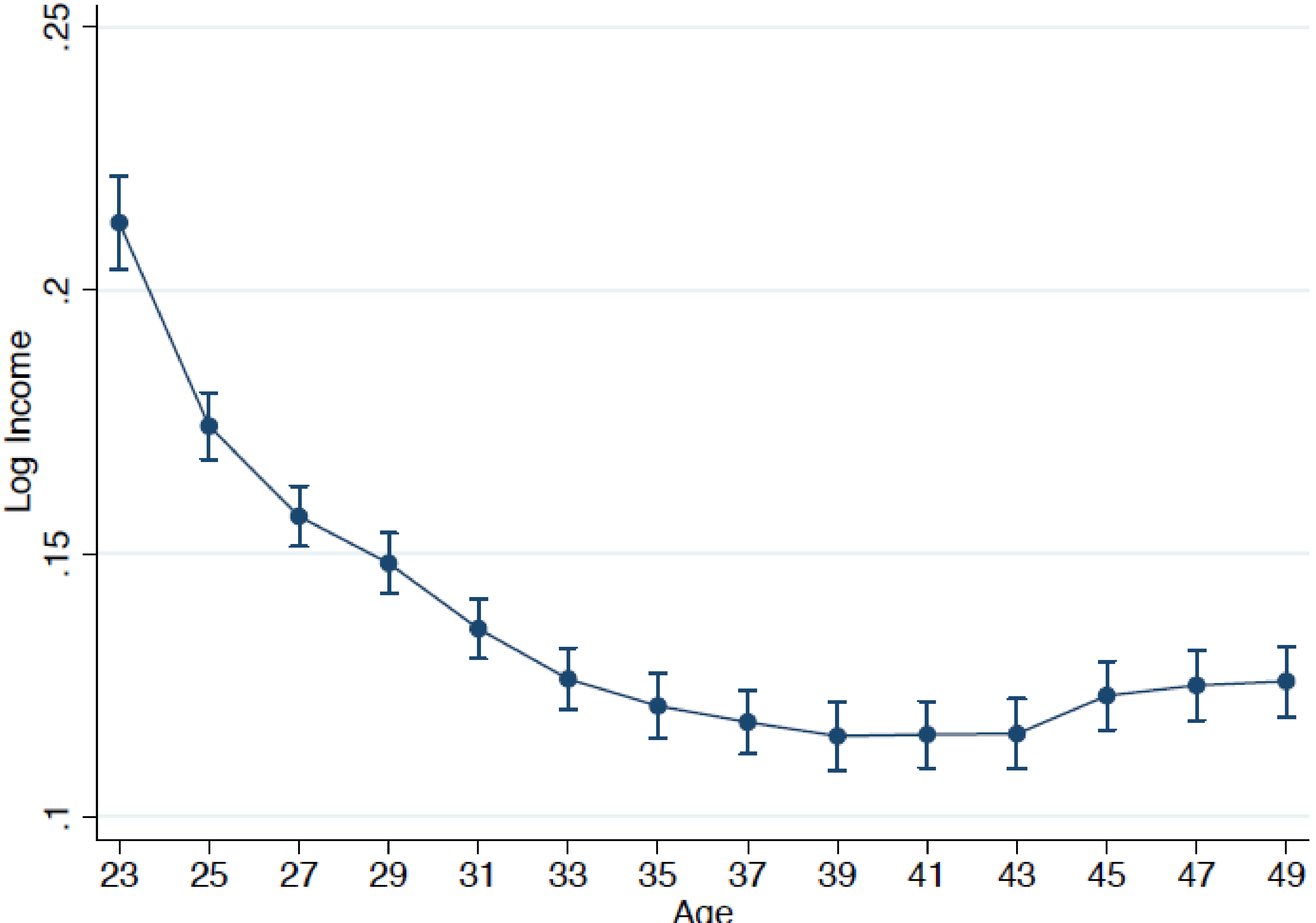
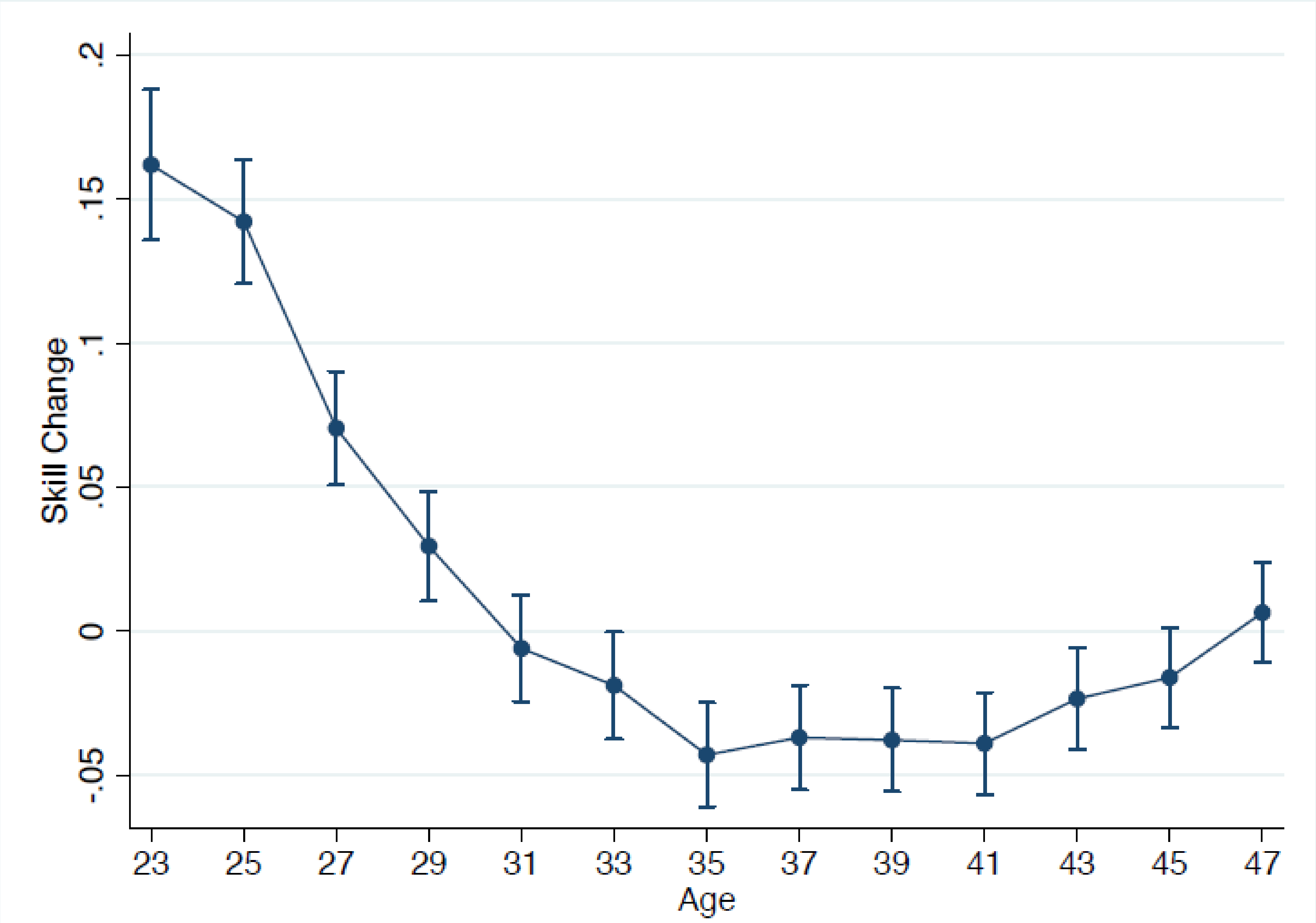


Figure 10: Jobs with Changing Skill Demands Employ Younger Workers

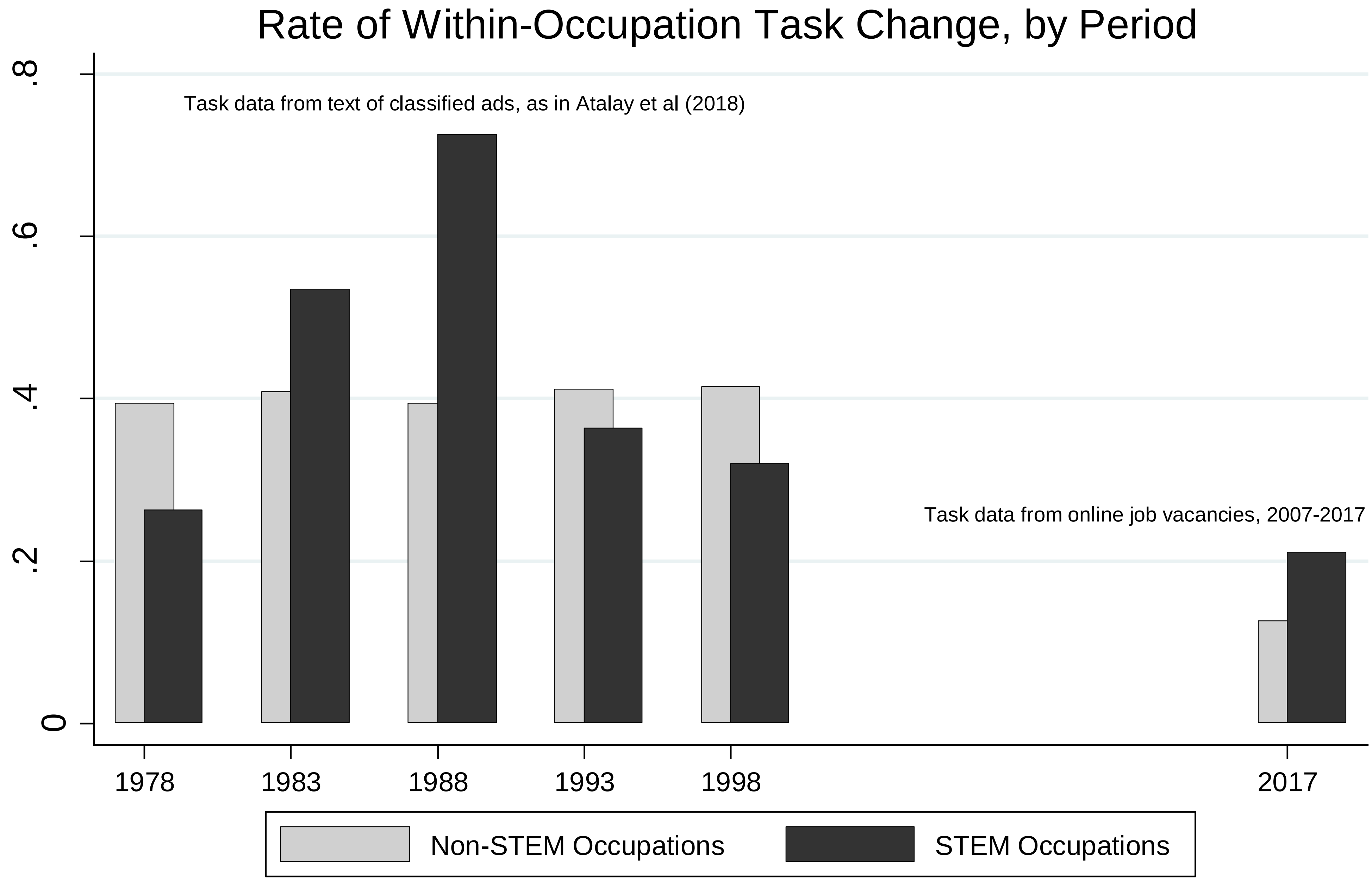


What about earlier periods of job change?

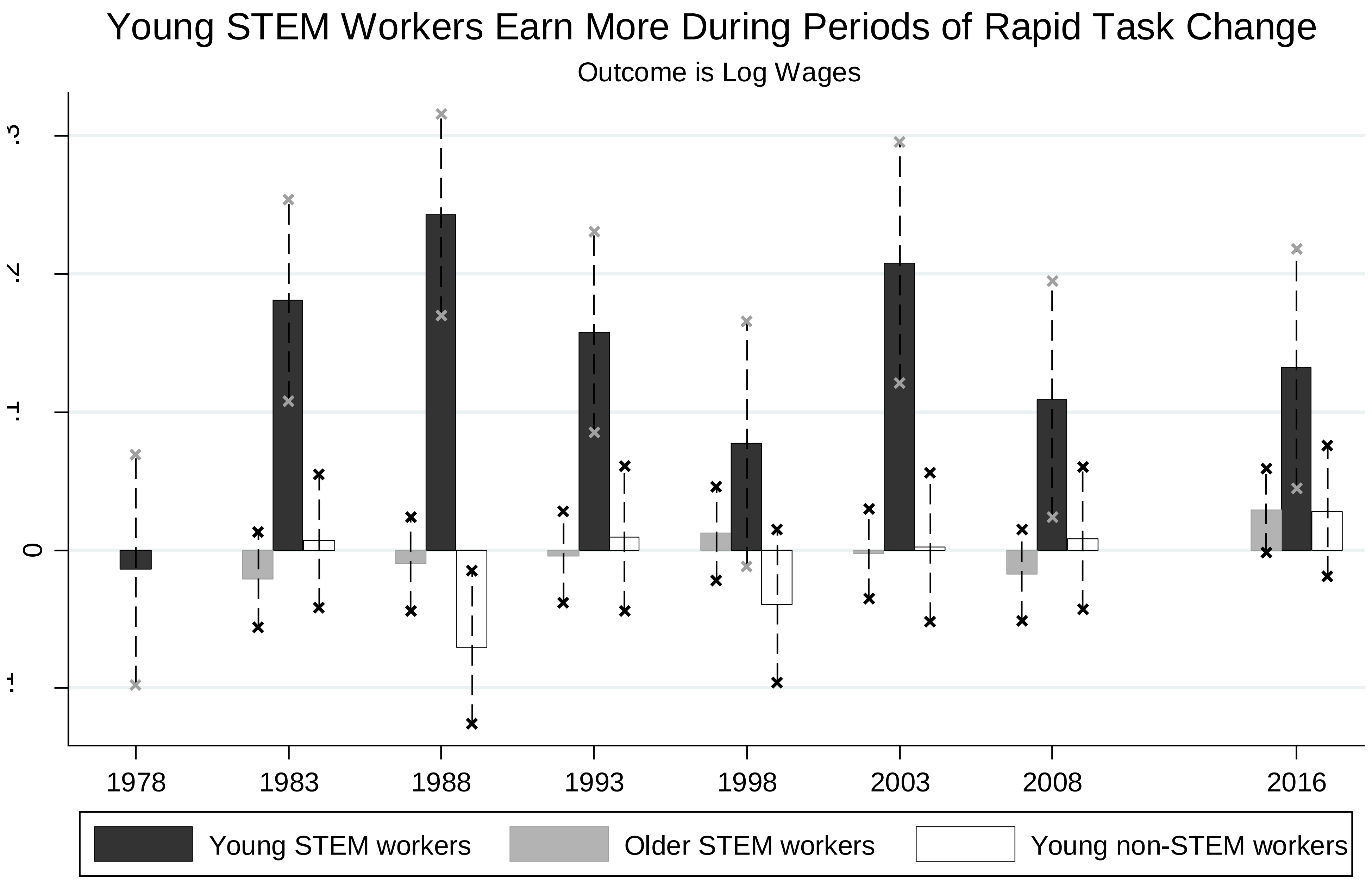
- BGT data only go back to 2007

- Use classified ad data from Atalay et al (2018) to calculate similar measures of job task change back to 1978
  - Hard to compare in levels

- Do we see higher relative wages for young STEM workers during periods of rapid job task change?
  - Regress log wages on STEM occ * age * year interactions, using CPS data back to 1973



Calculated over five year periods beginning with 1973-1978; see text for details
1973-1998 data taken from Atalay et al (2018); 2007-2017 data from Burning Glass



Sample is full-time men with at least a college degree; 1973-2016 CPS

Includes controls for demographics and age and year fixed effects; "young" is age 23-26

Summing up

- New evidence on declining life-cycle returns to applied STEM careers
  - Key mechanism is *job task change*
  - Jobs with higher rates of task change – both STEM and non-STEM – have flatter age-earnings profiles and employ younger workforces

- Short vs. long-run tradeoff between general and specific skills (Hanushek et al 2017)

- Rapid technological progress makes skill shortages more acute, training more necessary
  - Complementarity between faster job skill change and investments in training (both in school and on the job)

Thanks!

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