STEM Careers and Technological Change

by David Deming and Kadeem Noray (2018)

James J. Heckman

THE UNIVERSITY OF CHICAGO

Econ 350, Winter 2021

Me and my work

- Economics of education, with a focus on skills, technology and inequality
  - Past topics – school choice, accountability, for-profit colleges, online learning, school segregation, and others

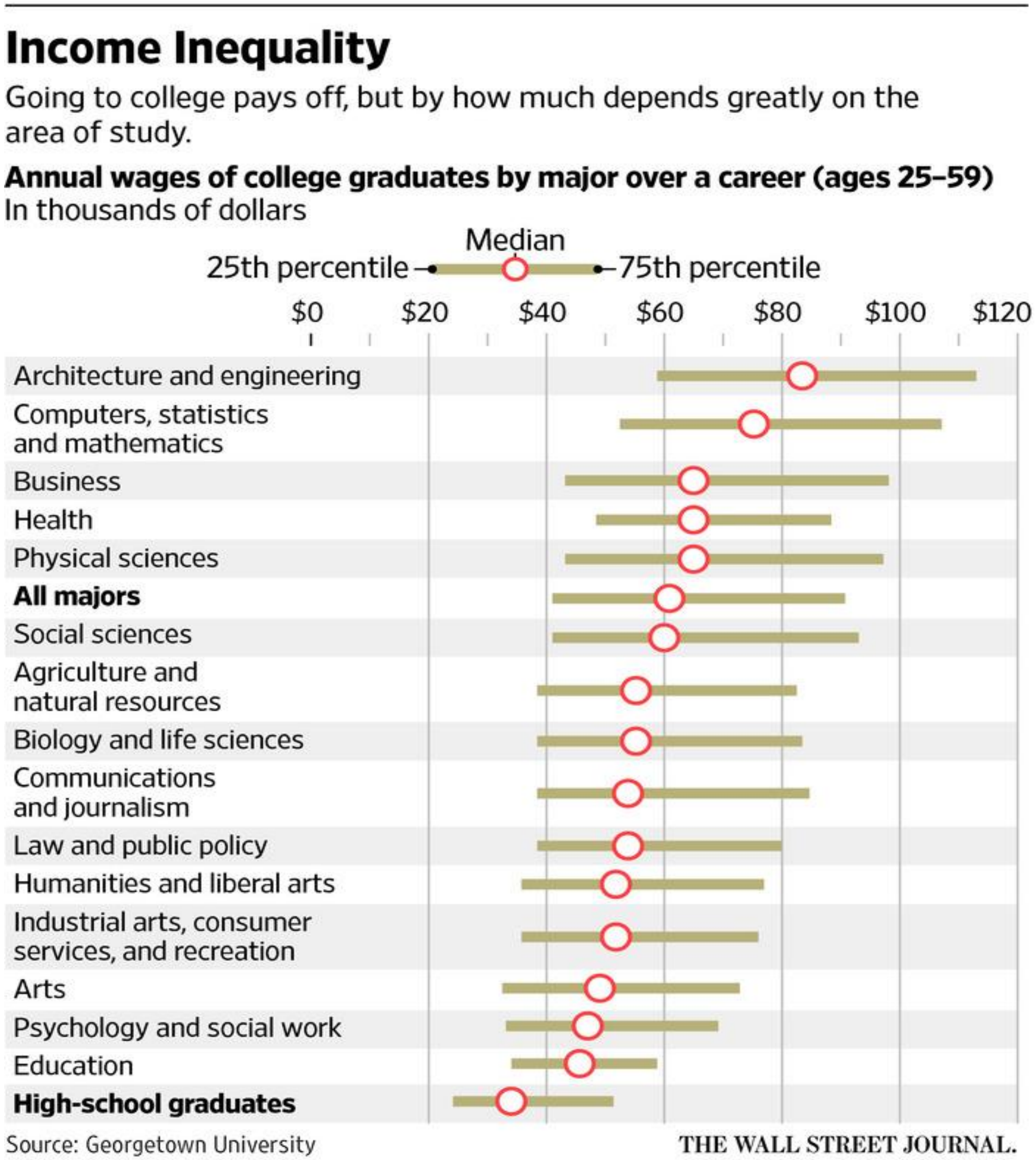
- Two agendas right now:
  - Postsecondary education and inequality
    - CLIMB initiative (with Chetty and Friedman)
    - LR perspective on resource allocation in higher education, distributional implications
    - Impact of higher ed on local economies, innovation and growth

  - Skills and "the future of work"
    - Using new microdata to understand how jobs are changing, and what that implies for returns to skills and training (BLS TAC)
    - Impacts of AI

STEM Crisis – Myth or Reality?

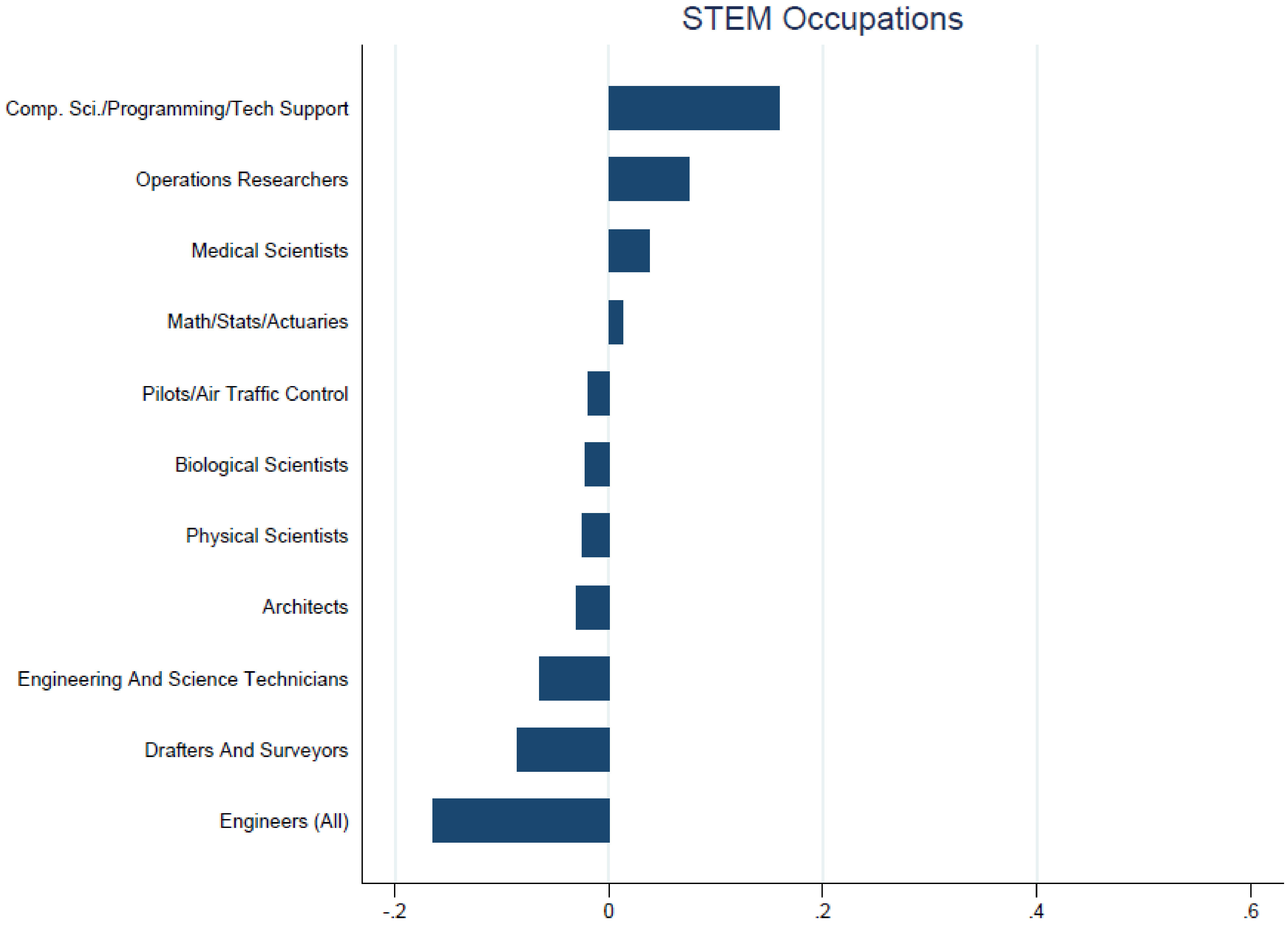
- STEM jobs are a key contributor to innovation and growth in most advanced economies
- Yet despite high payoff to STEM majors and careers, widespread perception of shortages (e.g. National Academies, Carnevale et al 2011)
- “Cobweb” growth in STEM careers, boom-bust cycles (Freeman 1976; Beaudry, Green and Sand 2016)

STEM graduates are in high demand, especially in “Applied” majors……

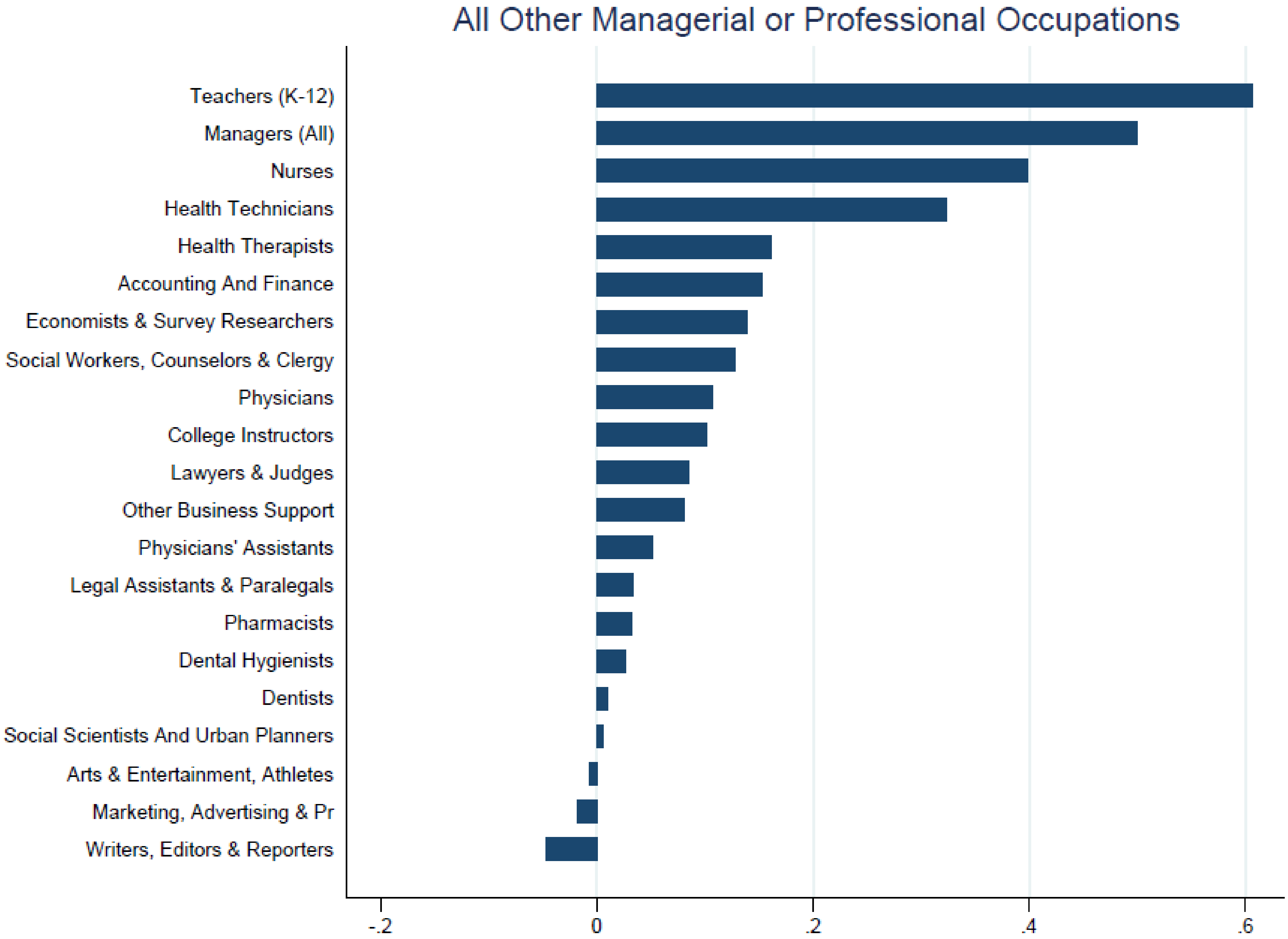


Yet slow employment growth in STEM jobs…

(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?

Monthly Labor Review
mlr BLS

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 patterns consistent with this hypothesis using ACS, NSCG, CPS, NLSY
  - Consistent under a wide variety of spec choices, samples, surveys
  - Cross-sectional and longitudinal surveys

Measuring job task change

- Data on near-universe of online job vacancy postings
  - Burning Glass Technologies, a labor market analytics firm

- Calculate a detailed measure of changing job task demands over the last decade (2007-2017)

- Look at earlier periods using classified ad data from Atalay et al (2018)

Simple, stylized model of educational and career choice

- Workers learn career-specific skills in school
  - Technical fields of study give more job-relevant skills but are costly to attain
  - Cost is decreasing in ability

- Also learn skills on-the-job – higher ability workers learn more per period

- Define (and measure) a career-specific rate of task change
  - In each year, some share Δ_j of tasks get replaced by new tasks
  - Productivity increases with learning gains and decreases with obsolescence (because you have to start over)

Model Predictions

1. Lower wage growth in careers with higher Δ_j

2. Sorting out of high Δ_j careers over time

3. Technical fields have higher starting wages, and high ability workers sort into these fields after graduating

4. High ability workers sort *out* of technical fields over time
   - Intuition – being a faster learner has a lower payoff in fields where knowledge doesn't accumulate
   - Strong support for this finding in the NLSY

Contributions

1. New evidence on life-cycle returns to STEM careers, and a framework in which to interpret it
   - STEM majors are high-skilled vocational ed – lower long-run payoff (Hanushek et al 2017)

2. Empirical foundation for macro models of vintage capital and technology diffusion (e.g. Griliches 1957, Chari and Hopenhayn 1991, Galor and Tsiddon 1997, Violante 2002)
   - Rate of technological change governs diffusion and extent of growth

3. Richer understanding of the impact of technology on labor markets
   - Classic papers (e.g. Autor, Levy and Murnane 2003) infer nature and direction of tech change by looking at broad shifts in employment/wages across occupations
   - Our approach is within-occupation - could be even more detailed

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.

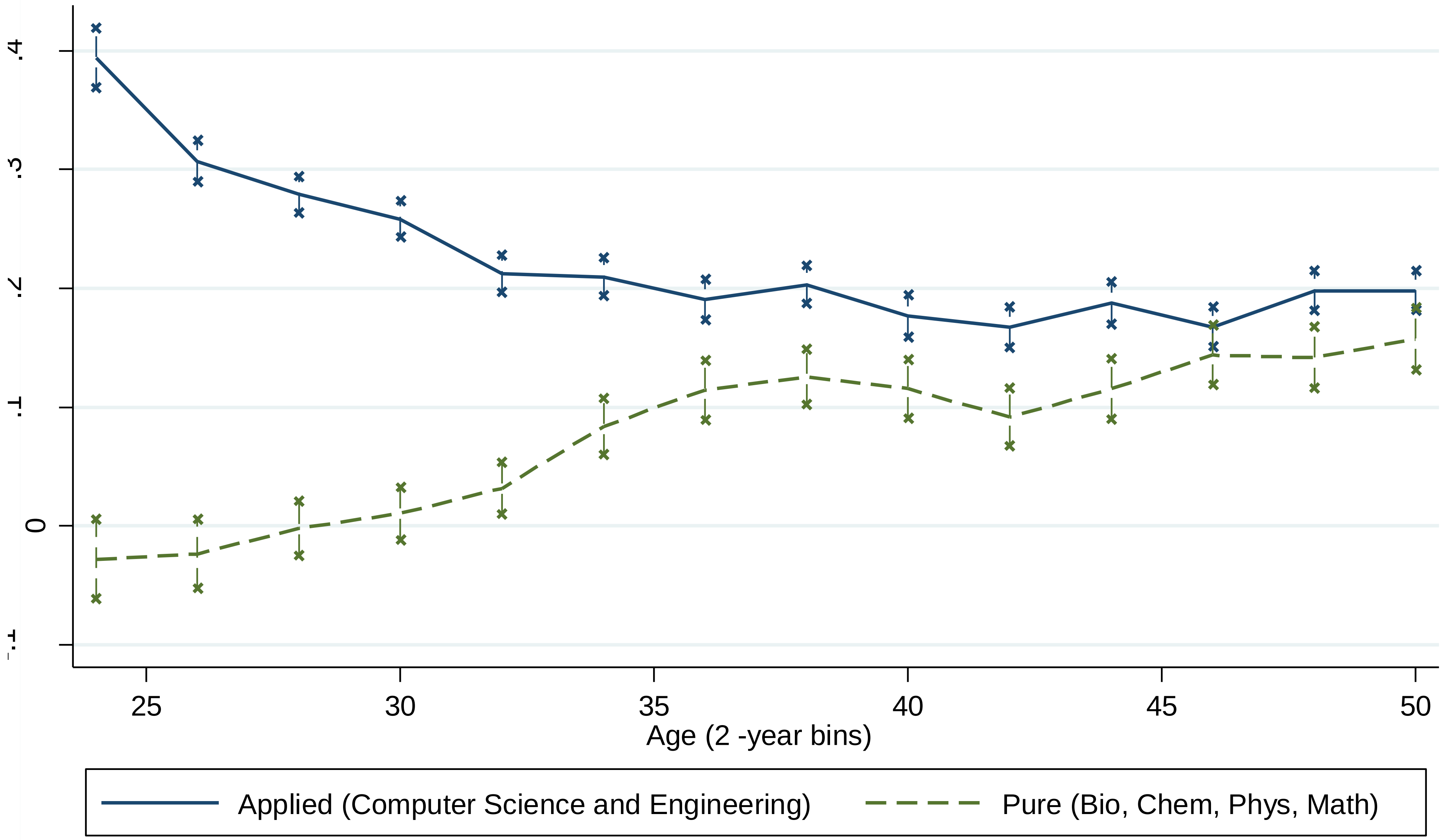
Empirical Model

$$\ln y_{it} = \alpha_{it} + \sum_{a}^{A} \beta_a A_{it} + \sum_{a}^{A} \gamma_a \left(A_{it} * AS_{it}\right) + \sum_{a}^{A} \delta_a \left(A_{it} * PS_{it}\right) + \zeta X_{it} + \theta_t + \epsilon_{it}$$

- Regress log earnings on 2-year age bins, age*major interactions, covariates, year fixed effects
  - Return to STEM major in each period, relative to non-STEM majors
  - Population-weighted, sample is FT working men age 23-50 with at least a college degree
  - Appendix: women, all men, BA, add industry fixed effects
  - Employment and STEM occupation as outcomes

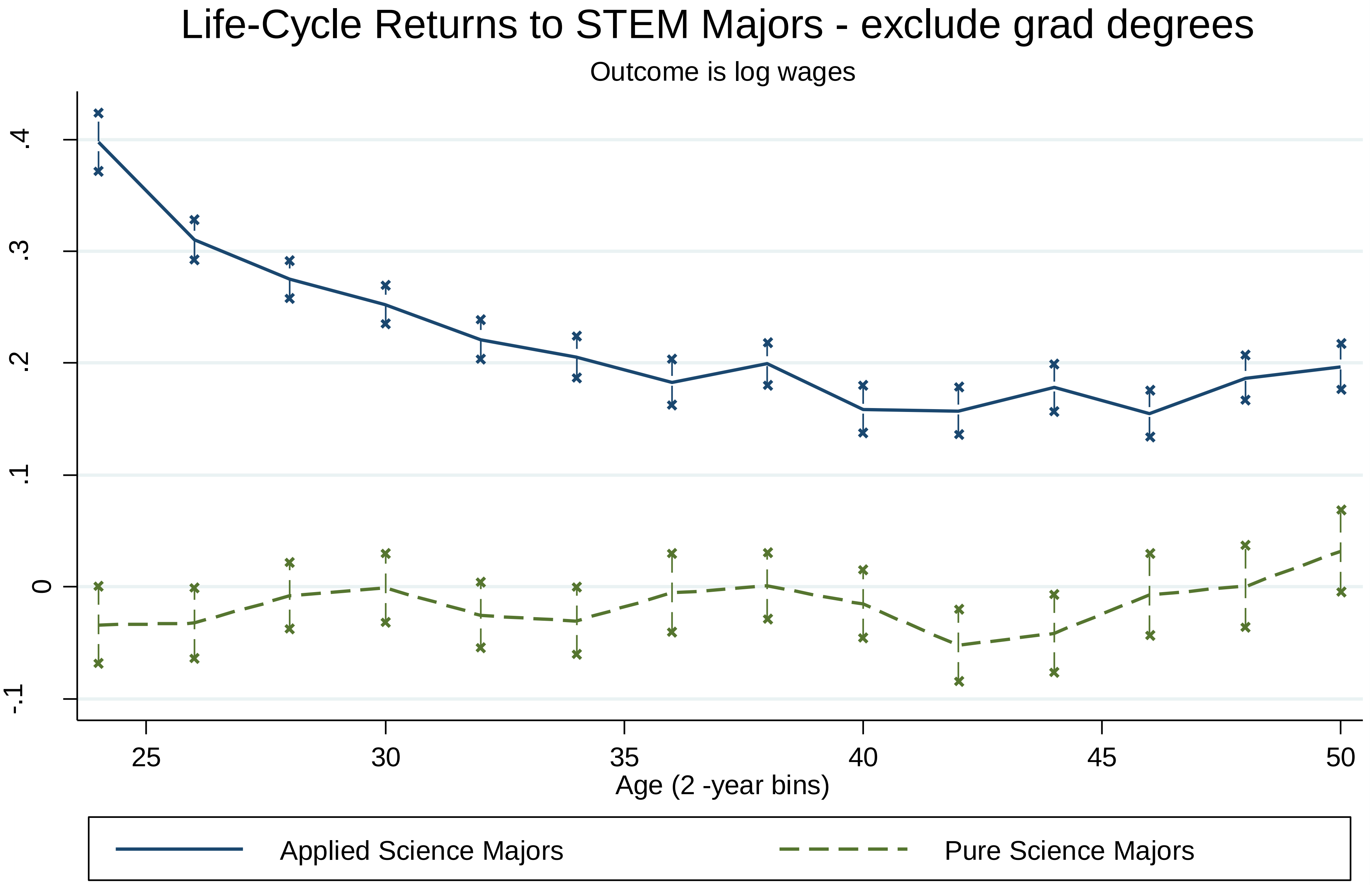
Declining Life-Cycle Returns to Majoring in STEM

2009-2016 ACS



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



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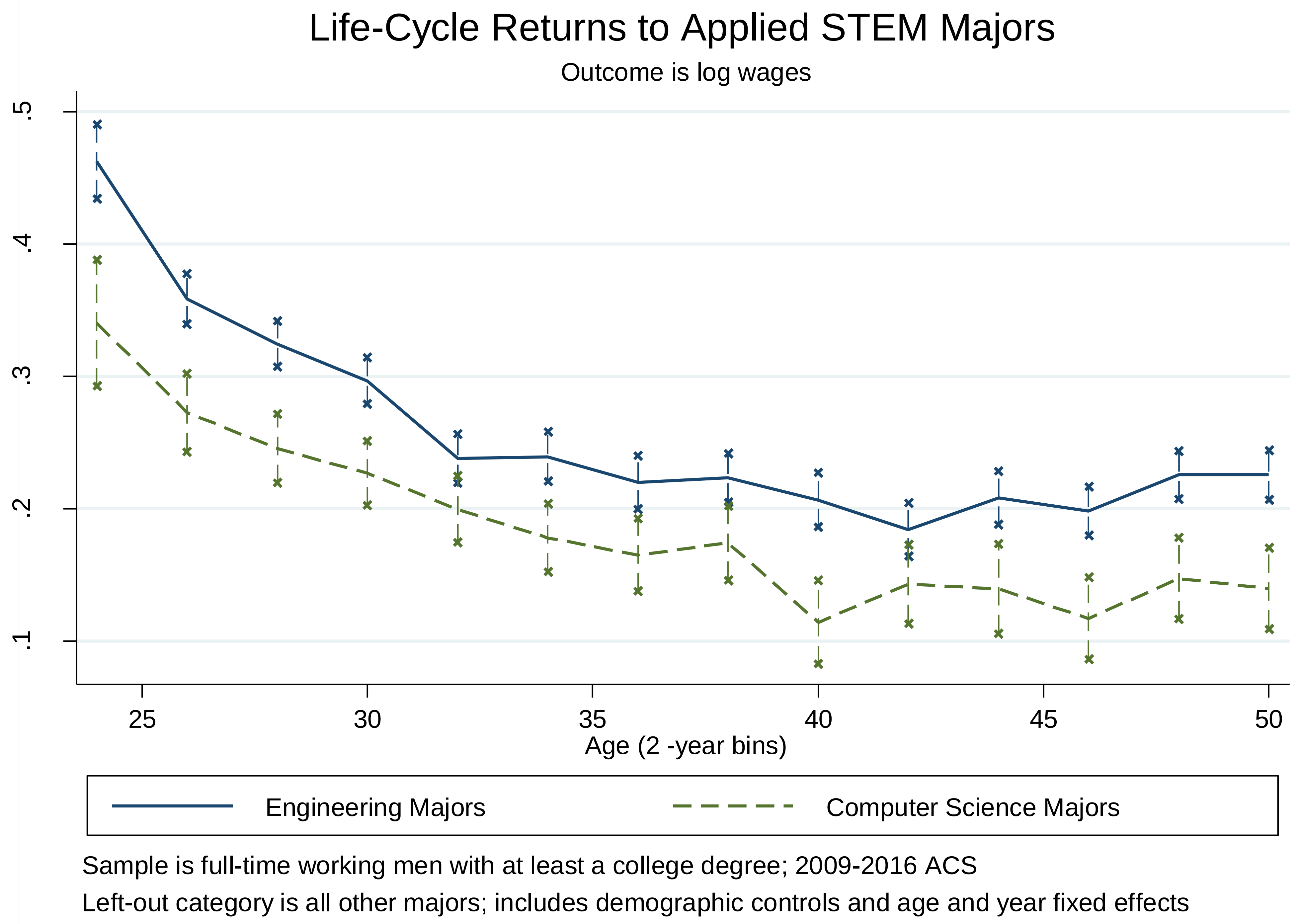
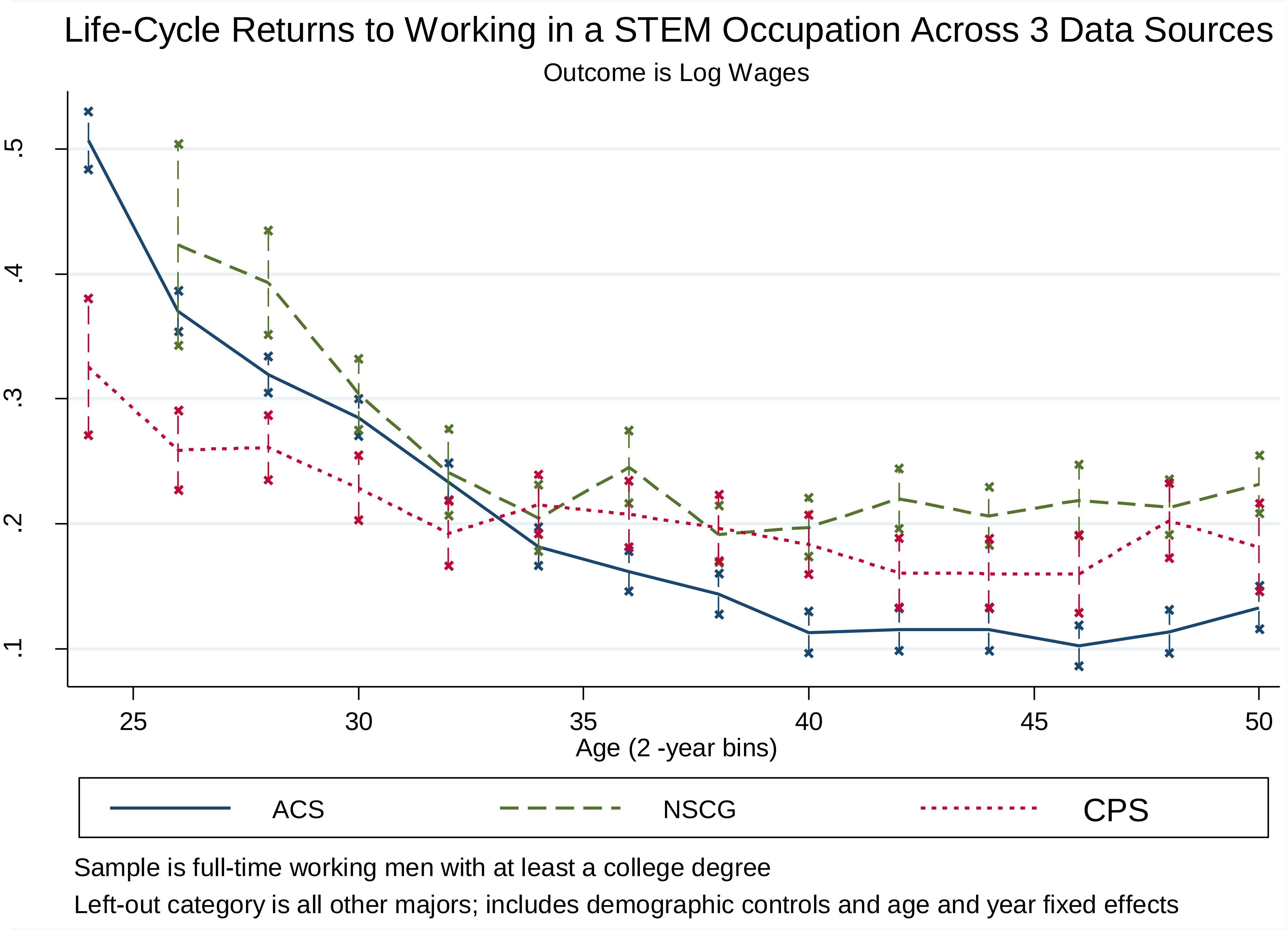

Life-Cycle Returns to Applied STEM Majors
Outcome is log wages
.5
.4
.3
.2
.1
25
30
35
40
45
50
Age (2 -year bins)
Engineering Majors
Computer Science Majors
Sample is full-time working men with at least a college degree; 2009-2016 ACS
Left-out category is all other majors; includes demographic controls and age and year fixed effects

What about life-cycle returns in 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

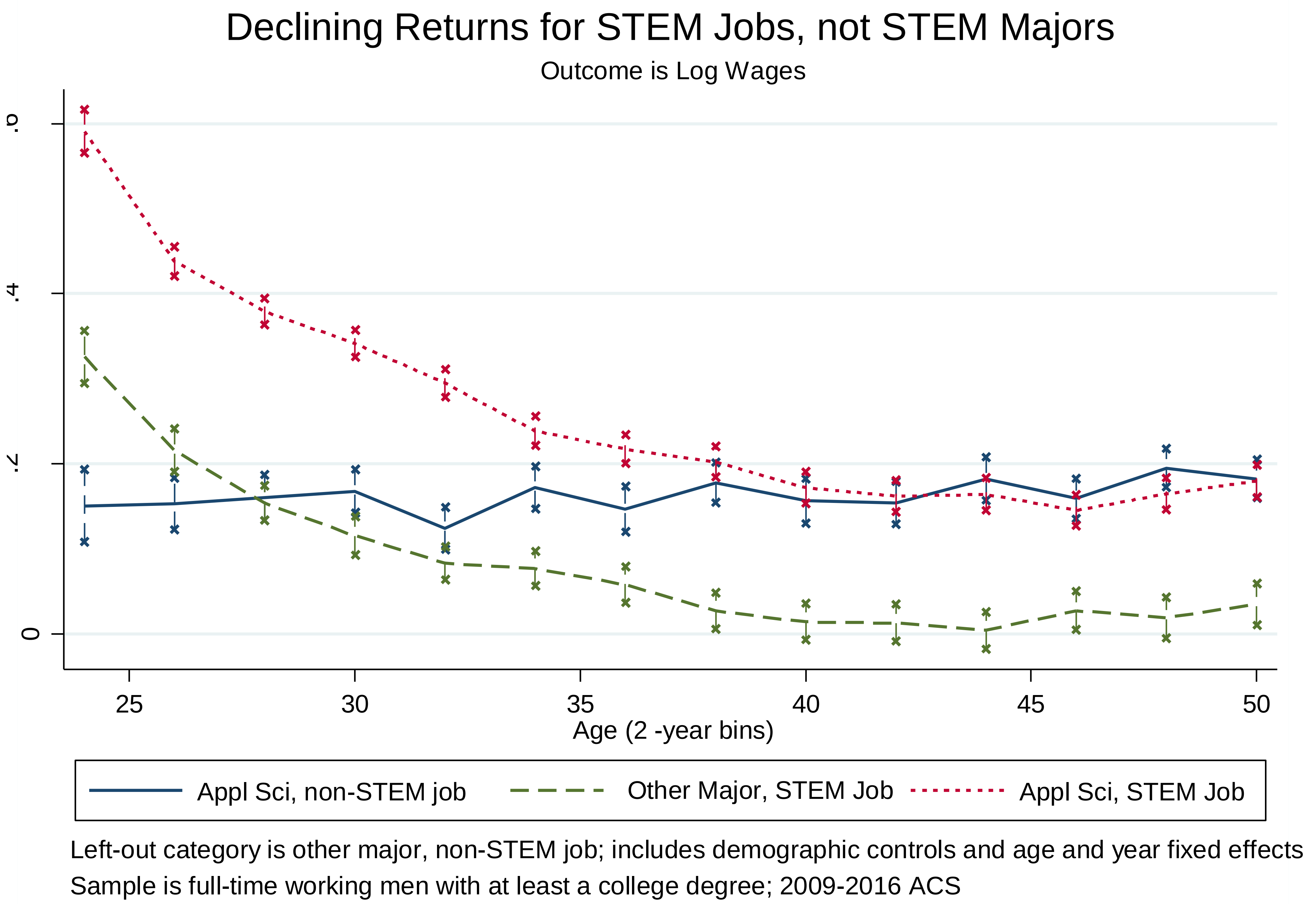
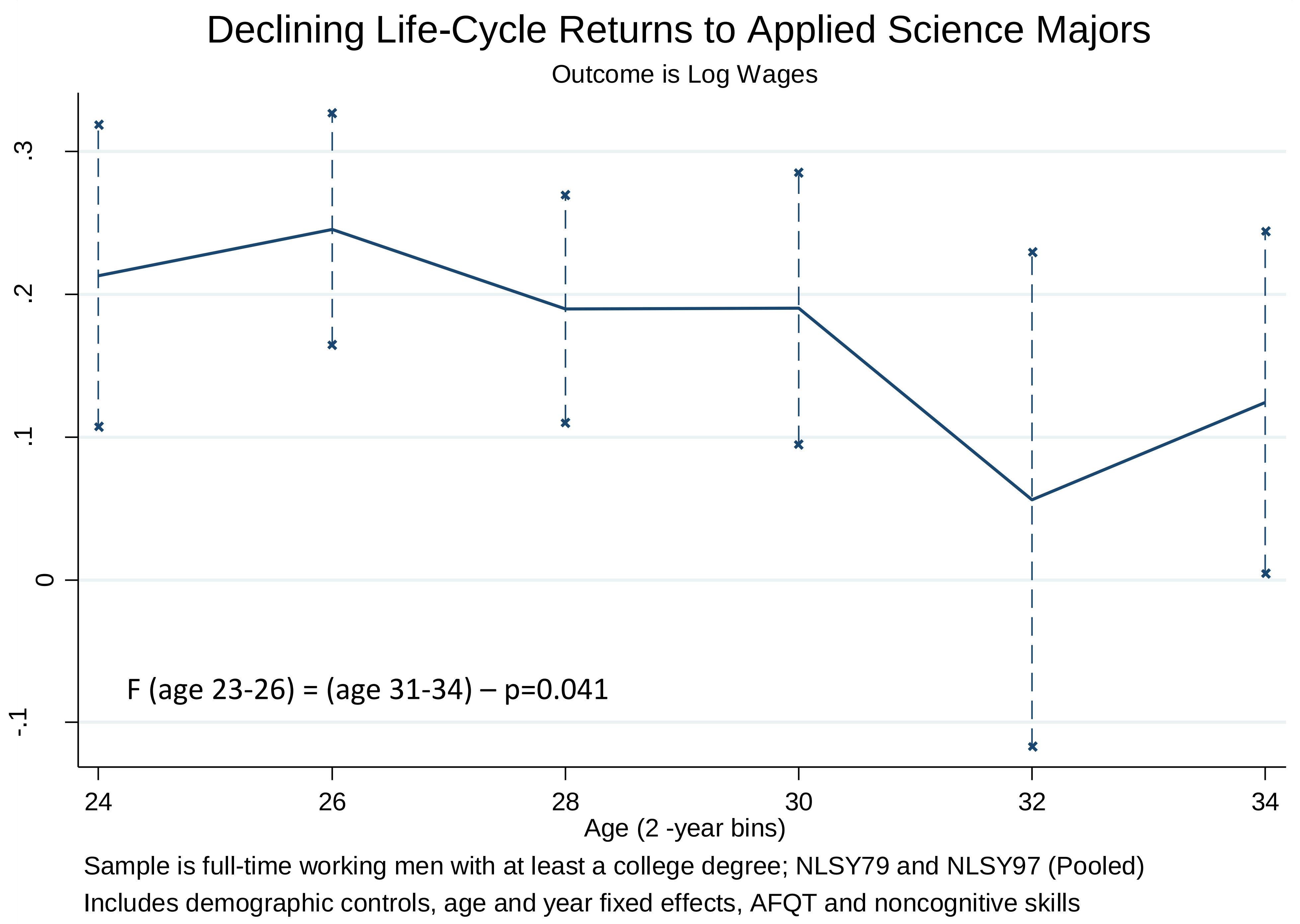

Declining Returns for STEM Jobs, not STEM Majors
Outcome is Log Wages
0
.2
.4
.6
25
30
35
40
45
50
Age (2 -year bins)
Appl Sci, non-STEM job
Other Major, STEM Job
Appl Sci, STEM Job
Left-out category is other major, non-STEM job; includes demographic controls and age and year fixed effects
Sample is full-time working men with at least a college degree; 2009-2016 ACS

Table 3: Labor Market Returns to STEM Majors in the NLSY

Outcome is Log Hourly Wage (in 2016 dollars)	(1)	(2)	(3)	(4)	(5)	(6)
Applied Science Major	0.179***	0.180***	0.072*	0.034	0.013	0.046
	[0.035]	[0.036]	[0.037]	[0.034]	[0.041]	[0.044]
STEM Occupation			0.241***	0.143***	0.119***	
			[0.028]	[0.027]	[0.029]	
Applied Science Major * STEM Occupation					0.057	
					[0.051]	
Cognitive Skills (AFQT, standardized)		0.129***	0.113***	0.076***	0.076***	0.063
		[0.025]	[0.024]	[0.021]	[0.021]	[0.031]
Demographics and Age/Year FE	X	X	X	X	X	X
Industry Fixed Effects				X	X	
Occupation-by-Industry Fixed Effects						X
R-squared	0.225	0.244	0.259	0.397	0.397	0.649
Number of Observations	8,634	8,634	8,634	8,634	8,634	8,634

Notes: Each column reports results from a regression of real log hourly wages on indicators for college major, occupation and/or industry (in columns 3 through 5), individual skills, indicator variables for race and years of completed education, age and year fixed effects, and additional controls as indicated. The data source is the National Longitudinal Survey of Youth (NLSY) 1979 and 1997, and the sample is restricted to men with at least a college degree. Person-year is the unit of observation, and all standard errors are clustered at the person level. The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** p<0.01, ** p<0.05, * p<0.10.



Declining Life-Cycle Returns to Applied Science Majors
Outcome is Log Wages
-.1
0
.1
.2
.3
F (age 23-26) = (age 31-34) – p=0.041
24
26
28
30
32
34
Age (2 -year bins)
Sample is full-time working men with at least a college degree; NLSY79 and NLSY97 (Pooled)
Includes demographic controls, age and year fixed effects, AFQT and noncognitive skills

Summing up

- 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

Measuring Job Task Change

- Each vacancy contains a number of job skills/tasks, based on a text parsing algorithm developed by BGT

- Calculate shares for each unique skill/task, 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, sum over all tasks and then divide by the total
  - “Replacement rate” of tasks in an occupation - ranges between 0 and 1

$$TaskChange_o = \frac{\sum_{t=1}^{T} \left\{ Abs \left[\left(\frac{Task_o^t}{JobAds_o} \right)_{2017} - \left(\frac{Task_o^t}{JobAds_o} \right)_{2007} \right] \right\}}{\sum_{t=1}^{T} \left[\left(\frac{Task_o^t}{JobAds_o} \right)_{2017} + \left(\frac{Task_o^t}{JobAds_o} \right)_{2007} \right]}$$

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

SOC code	Occupation Title	Rate of Task Change
231	Lawyers, Judges and Related Workers	0.239
171	Architects and Surveyors	0.217
192	Physical Scientists	0.207
191	Life Scientists	0.203
172	Engineers	0.197
173	Drafters and Engineering Technicians	0.197
152	Mathematical Scientists	0.184
113	Operations Specialties Managers	0.173
254	Librarians, Curators and Archivists	0.172
232	Legal Support Workers	0.165

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

SOC code	Occupation Title	Rate of Task Change
173013	Mechanical Drafters	0.404
151131	Computer Programmers	0.355
173011	Architectural and Civil Drafters	0.344
151133	Software Developers, Systems Software	0.301
112011	Advertising and Promotions Managers	0.282
172081	Environmental Engineers	0.281
132053	Insurance Underwriters	0.281
291051	Pharmacists	0.281
173012	Electrical and Electronics Drafters	0.274
152011	Actuaries	0.244

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

SOC code	Occupation Title	Rate of Task Change
193	Social Scientists and Related Workers	0.099
291	Health Diagnosing and Treating Practitioners	0.101
252	Pre-K, Primary and Secondary School Teachers	0.104
259	Other Education, Training and Library Occupations	0.105
253	Other Teachers and Instructors	0.109
292	Health Technologists and Technicians	0.117
111	Managers and Executives	0.122
194	Life, Physical and Social Science Technicians	0.126
299	Other Healthcare Practitioners	0.128
211	Counselors and Social Workers	0.131

Measuring Job Task Change

- What is the nature of task change within occupations?
  - Increase in demand for teamwork, communication, “social skills”)
    - This increase is larger for STEM jobs
  - Rise and fall of specific software and business processes (Python, AutoCAD, Revit, Root Cause Analysis)
    - Declines include UNIX, SAP, Adobe Flash

- Software responsible for about 10-15% of all job task change
  - Main results robust to using software only

- Occupational licensing and task change – may understate for some (health) jobs

- Comparison is *within*-occupation (could be within firm, labor market, industry…)

Model Sketch

- Perfectly competitive labor market
- Firms produce a unique final good by linearly summing the total production of tasks i over “career” (occupation-industry) j and year t
  - Labor is the only factor of production
- Individuals have ability a and taste parameter u, and choose a field of study $s \in [0,1]$ where $s = 1$ is the most technical major

Individual's problem

$$\underset{s,jt}{Max}\left\{\left[\sum_{t=0}^{T} PDV\left(W_{jt}(a,s,\alpha_{jt})\right)\right] - C(a,u,s)\right\}$$

- Maximize lifetime earnings given ability, schooling choice and (endogenous) productivity schedule minus the cost of schooling
  - Perfect information, so one choice of career profile
  - Spence (1978) assumption that the cost of schooling is decreasing in ability
  - Technical fields are relatively more costly to study for lower a workers

Task Production Function

$$\alpha_{jt}(i) = f\left(a, s, F_j, \Delta_j\right)$$

- Productivity in task i, career j and year t is determined by ability, schooling choice, and two career-specific parameters
  - F_j is the amount of career-specific learning that happens in school (assume increasing in s)
    - Define careers along the s space of technical complexity, and let worker productivity be $F_j S^*$, where S^* is a loss function that penalizes learning that is more "distant" from the chosen career
- Workers also learn on the job – productivity in tasks existing at time t increases by a (worker ability)
- Δ_j is a career-specific rate of task change
  - At the start of each year, a fraction Δ_j of tasks are replaced by new tasks
- This yields a productivity schedule over tasks of different vintages

Task Production Function

$$\alpha_{jt}(i) = f\left(a, s, F_j, \Delta_j\right)$$

This yields a productivity schedule over tasks of different vintages:

$$\alpha_{jt}\left(i\right) = \begin{cases} (F_j S^*) + [a(t+1)] = \alpha_{jt}^{PRE} & \text{if } v = 0 \\ a(t-v+1) = \alpha_{jt}^{POST(v)} & \text{if } v > 0. \end{cases}$$

Equilibrium Wages

$$W_{jt} = \int_0^1 p_{ijt} di = \int_0^1 \alpha_{ijt}(a,s) di$$
$$= \left\{ (1-\Delta_j)^t \alpha_{jt}^{PRE} \right\} + \left\{ \sum_{v=1}^{t;t>0} \Delta_j (1-\Delta_j)^{t-v} \alpha_{jt}^{POST(v)} \right\}$$

- Integrate over productivity schedule for tasks learned in school and on-the-job

- Productivity in initial task vintages increases through learning
  - But these gains are counterbalanced by obsolescence, new tasks

Model Predictions

1. Lower wage growth in careers with higher job task change (Δ_j)
    - As Δ_j increases, more tasks become obsolete, slowing down learning gains and flattening the age-earnings profile
    - Interact task change measure Δ_j with age categories; should hold for all occupations

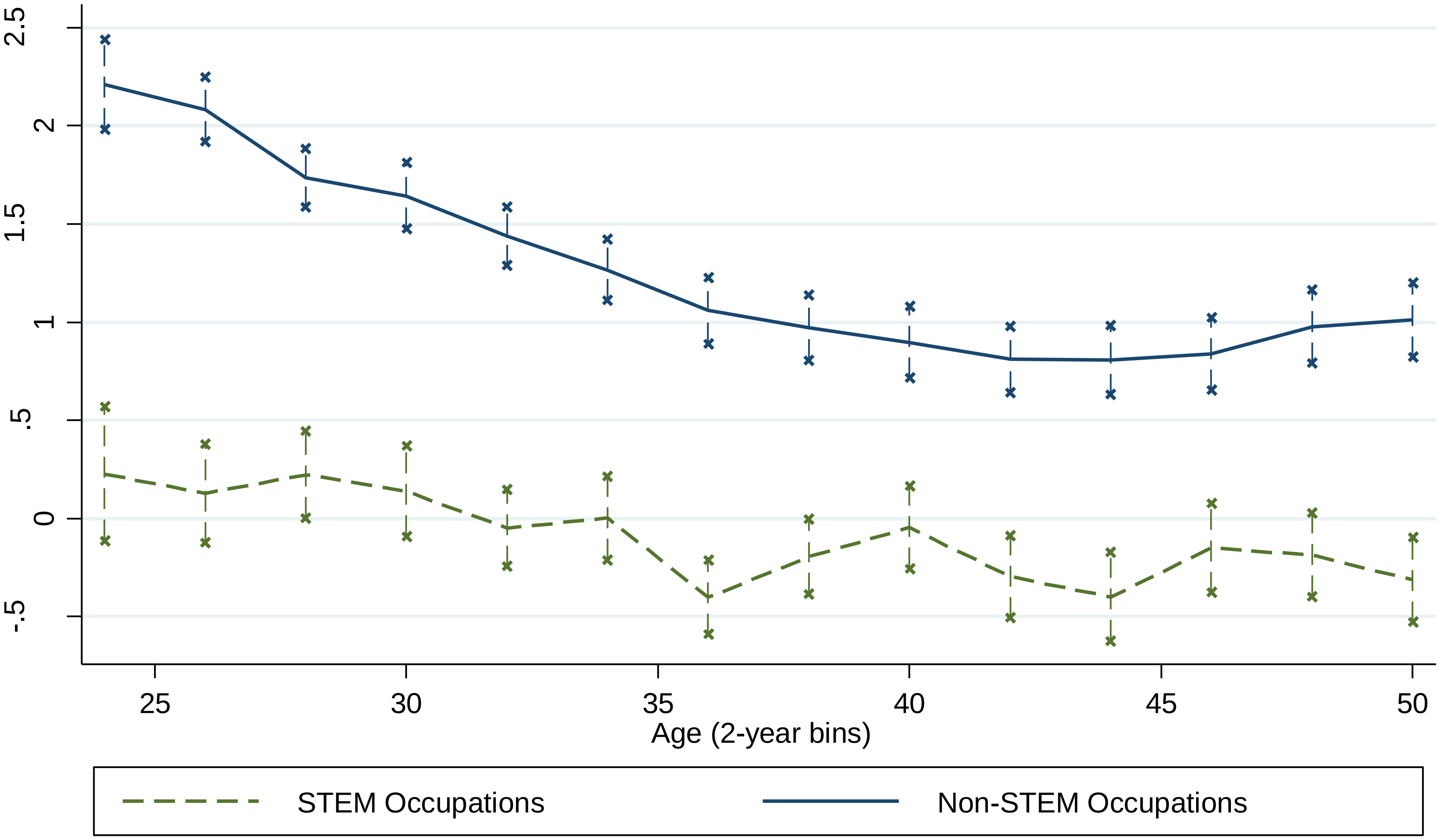
2. Sorting out of high Δ_j careers over time
    - Regress Δ_j on age indicators directly – do high task change jobs have younger workforces?

3. Technical fields have higher starting wages, and high ability workers sort into these fields after graduating

4. High ability workers sort *out* of technical fields over time
    - Intuition – being a faster learner has a lower payoff in fields where knowledge doesn't accumulate
    - Strong support for this finding in the NLSY

Jobs with Higher Rates of Task Change Pay More to Younger Workers

Wage Returns to Changing Task Demands in an Occupation

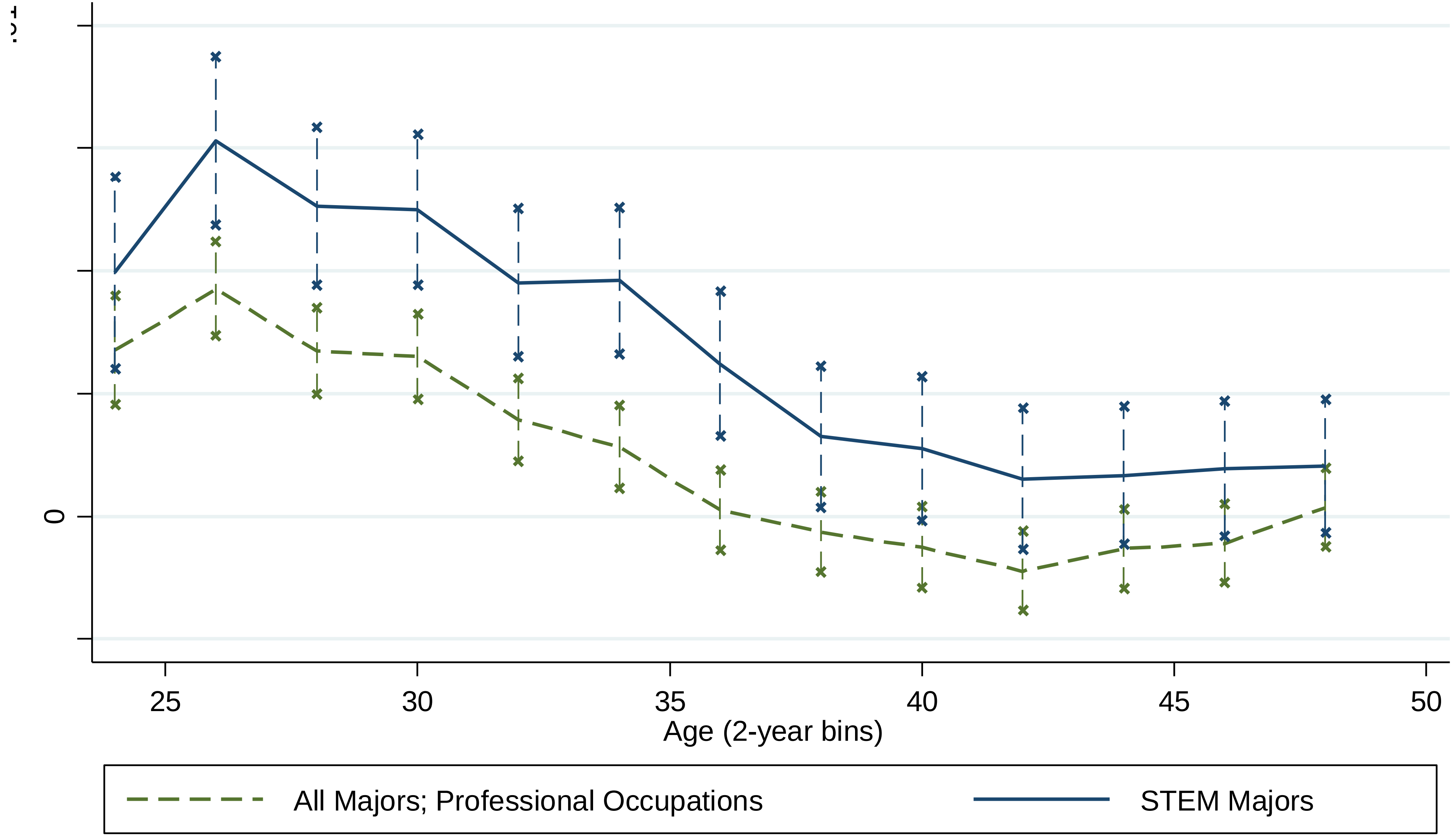


Sample: Full-time working men with at least a college degree; 2009-2016 ACS

Iincludes demographic controls and age and year fixed effects; SD(task change) = 0.056

Jobs with Changing Task Demands Employ Younger Workers

Outcome is the Task Change Measure



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Left-out category is age 49-50; includes demographic controls and age and year fixed effects

Model Predictions

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3. Technical fields have higher starting wages, and high ability workers sort into these fields after graduating

4. High ability workers sort *out* of technical fields over time
    - Intuition – being a faster learner has a lower payoff in fields where knowledge doesn't accumulate
    - Regress occupation choice and wages on STEM major * AFQT * age interactions

Table 4: STEM Majors, Relative Wages and Ability Sorting in the NLSY

	In a STEM Job		Ln (Wages)	
	(1)	(2)	(3)	(4)
STEM Major	0.352***	0.170***	0.116***	0.005
	[0.035]	[0.055]	[0.034]	[0.120]
AFQT (Standardized)	0.084***	0.066***	0.063*	0.017
	[0.016]	[0.014]	[0.033]	[0.032]
Age (Linear)	0.002	-0.001	0.013	0.007
	[0.005]	[0.004]	[0.008]	[0.009]
Age * AFQT	-0.005**	-0.006***	0.013***	0.024***
	[0.002]	[0.002]	[0.005]	[0.005]
Age * STEM Major		0.015*		0.027*
		[0.008]		[0.014]
STEM Major * AFQT		0.095**		0.187*
		[0.048]		[0.097]
STEM Major * AFQT * Age		0.000		-0.041***
		[0.007]		[0.013]
R-squared	0.183	0.190	0.237	0.242
Number of Observations	11,214	11,214	8,685	8,685

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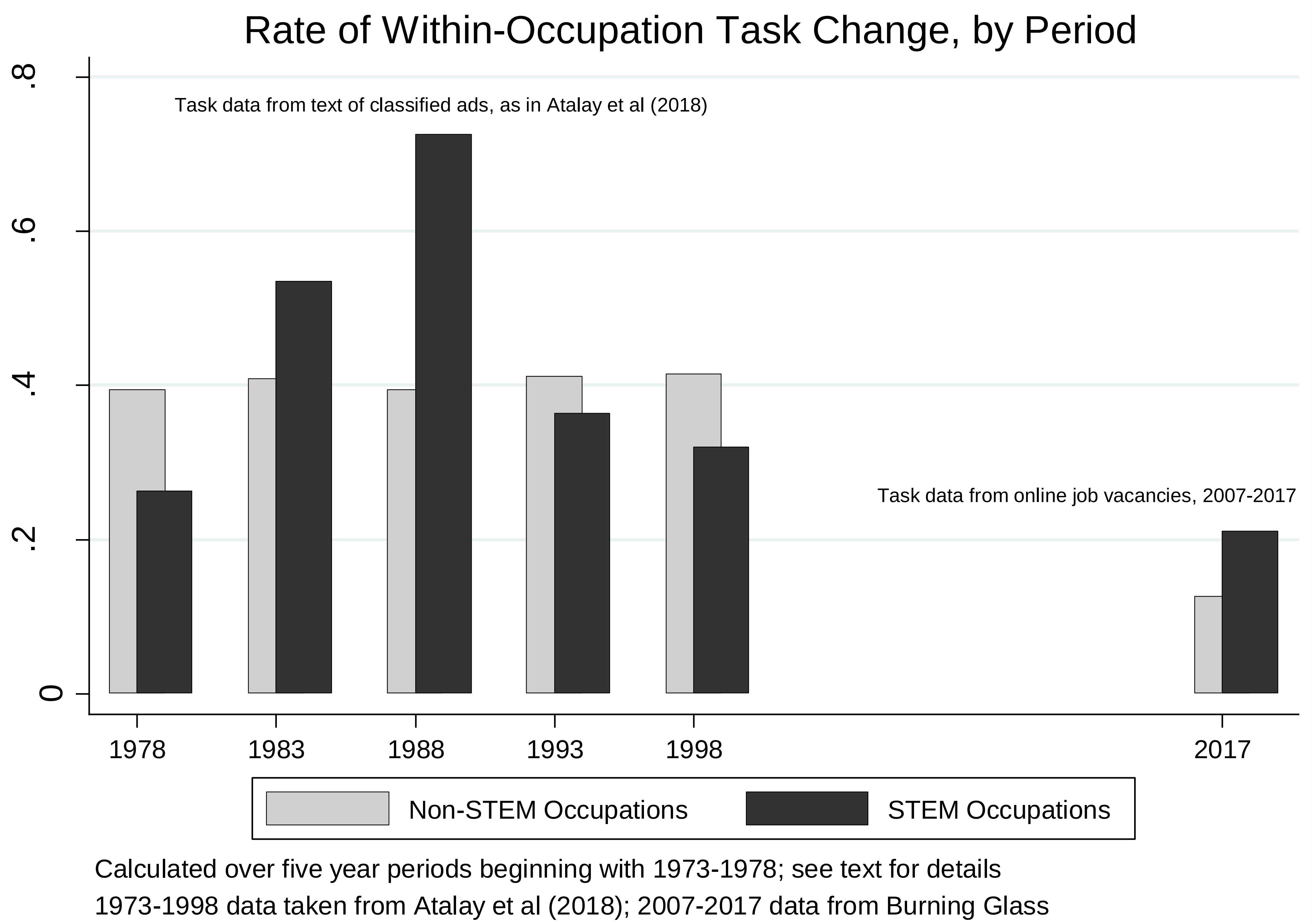
Ability Sorting

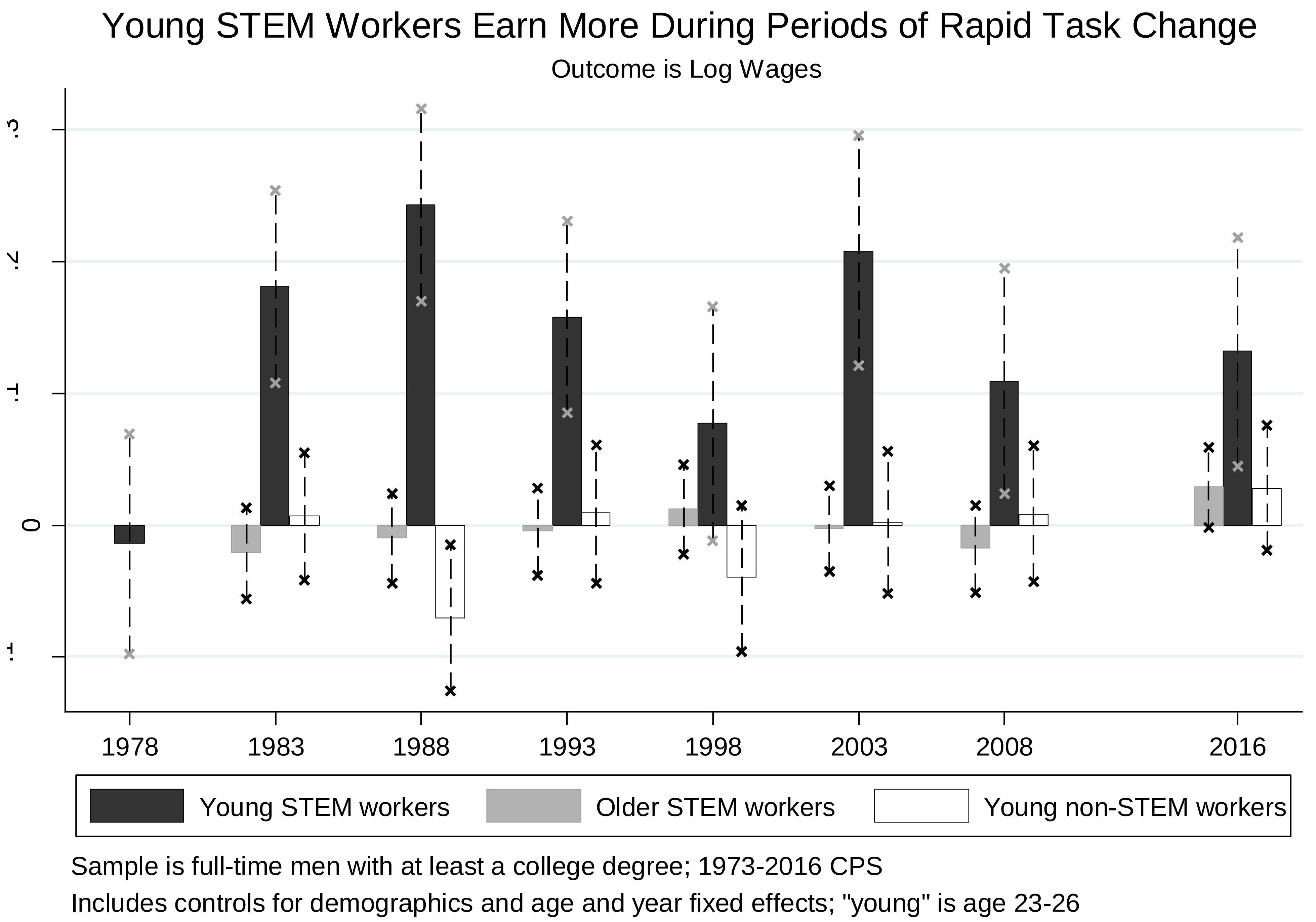
- At age 23, 1 higher SD AFQT score = 8.4 pp more likely to work in a STEM occupation
  - 3 pp by age 34, zero by age 40
- Coefficients imply that for individual with AFQT 1 SD above average:
  - STEM majors earn 21 percent premium at age 23, 40 percent at age 35
  - Non-STEM majors - 2 percent at age 23, 39 percent at age 35
  - Earlier crossing point for higher ability
- STEM earnings gap disappears within a decade for higher-ability 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



Rate of Within-Occupation Task Change, by Period
Task data from text of classified ads, as in Atalay et al (2018)
Task data from online job vacancies, 2007-2017
0
.2
.4
.6
.8
1978
1983
1988
1993
1998
2017
Non-STEM Occupations
STEM Occupations
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


Young STEM Workers Earn More During Periods of Rapid Task Change
Outcome is Log Wages
-.1
0
.1
.2
.3
1978
1983
1988
1993
1998
2003
2008
2016
Young STEM workers
Older STEM workers
Young non-STEM workers
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
  - Link between task change and returns to youth in STEM from past periods

- Simple model of educational and career choice – predicts ability sorting into STEM initially, out of STEM over time

- Policy Implications
  - 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
  - Technological change and learning (both in school and on the job) are strong complements

Thanks!

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Fastest-Changing Professional Occupations (3-digit) - Software Only

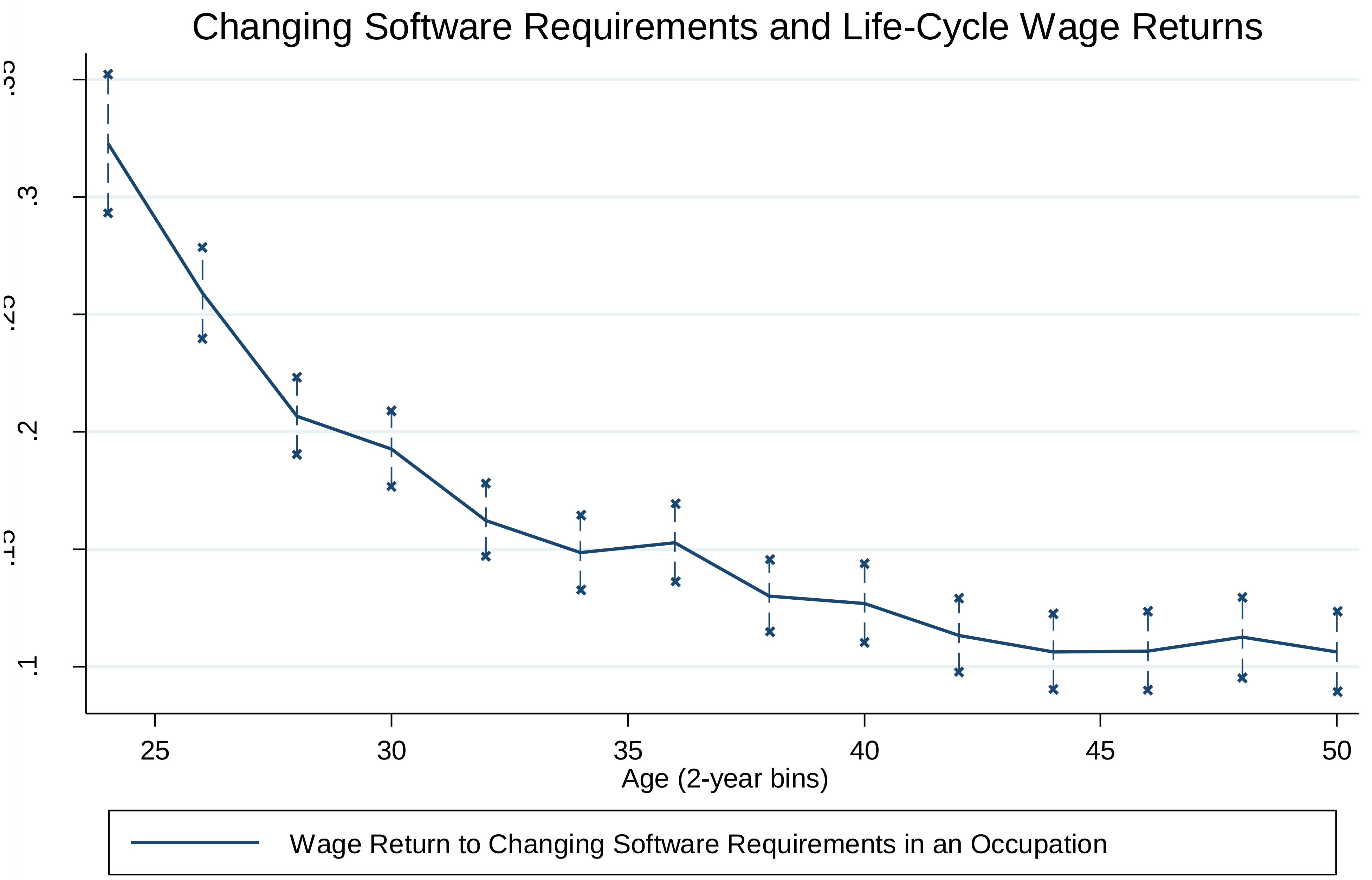
SOC code	Occupation Title	Software Task Change
171	Architects and Surveyors	0.062
151	Computer Occupations	0.058
173	Drafters and Engineering Technicians	0.030
172	Engineers	0.030
152	Mathematical Scientists	0.029
271	Art and Design Workers	0.028
273	Media and Communications Workers	0.025
274	Media and Communications Equipment Workers	0.024
131	Business Operations Specialists	0.022
132	Financial Specialists	0.019

Fastest-Changing Professional Occupations (6-digit) - Software Only

SOC code	Occupation Title	Software Task Change
151131	Computer Programmers	0.140
151133	Software Developers, Systems Software	0.133
151134	Web Developers	0.098
173011	Architectural and Civil Drafters	0.094
173013	Mechanical Drafters	0.094
271014	Multimedia Artists and Animators	0.076
151142	Network and Computer Systems Administra	0.069
271024	Graphic Designers	0.067
151141	Database Administrators	0.065
151141	Software Developers, Applications	0.065

Slowest-Changing Professional Occupations (3-digit) - Software Only

SOC code	Occupation Title	Software Task Change
291	Health Diagnosing and Treating Practitioners	0.002
252	Pre-K, Primary and Secondary School Teachers	0.004
253	Other Teachers and Instructors	0.004
292	Health Technologists and Technicians	0.004
211	Counselors and Social Workers	0.008
251	Postsecondary Teachers	0.009
259	Other Education, Training and Library Occupations	0.010
299	Other Healthcare Practitioners	0.010
191	Life Scientists	0.010
193	Social Scientists	0.010



Sample: Full-time working men with at least a college degree; 2009-2016 ACS

Includes demographic controls and age and year fixed effects; SD(software change) = 0.016