Occupational Projections, Automation, and the Future of Work

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All views expressed in this paper are those of the author and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

The big question

Will artificial intelligence and advanced robotics eliminate vast numbers of jobs in 10-20 years?

Unprecedented rate of technological advance and job displacement?

I. Intellectual background

Leading theories of growing wage inequality since 1980 based on IT

Extreme automation scenarios are the latest iteration of this idea

But there are alternative, institutional explanations, as well

A. Initial explanations of inequality growth

Stagflation and crisis in U.S. manufacturing during 1970s

Bluestone & Harrison (1982, 1988): decline of working-class jobs that paid middle class wages → rising inequality

1. **Deindustrialization → fewer middle-income jobs for less educated workers**
2. **Replaced by low-wage service jobs** (e.g., fast food, discount retail)
3. **Deunionization, concession bargaining**
4. **Outsourcing, offshoring, trade**
5. **Growth of non-standard employment** (contingent workers, temp workers)
6. **Corporate restructuring favoring shareholders over stakeholders** (M&A, LBOs)
7. **Declining real value of minimum wage**
8. **Deregulation of labor, product, and financial markets**
9. **Macroeconomic austerity**

"Polarizing of America" (Harrison and Bluestone 1988)

B. Mainstream response (1988-2000)

Strong prior belief postwar inequality stable (empirical data, Kuznets theory)

Skeptical of declining middle thesis → good jobs/bad jobs debate (1980s)

Switch: inequality grew because IT increased demand for skills (HC)

Evidence 1: Rising education wage premium (race between tech. and education)

College education essential to compete in a high-skill, knowledge economy

Conclusion: Increase college attainment to decrease inequality

Evidence 2: Real wage growth a smooth linear function of pct. rank

- **Top percentile's wages grew fastest**
- **Other upper percentiles grew fast but not as fast…and so on…**
- **Bottom percentiles had negative wage growth** (declines)
- **Each narrow skill level rewarded more than the level below**
- **Consistent, pervasive upgrading, not a declining middle**

PCs did it

Classic theory of skill-biased technological change (SBTC) (1990s)

C. Challenge and reformulation (late 1990s-ca. 2013)

Institutionalists: Skill upgrading gradual, secular trend, did not accelerate in tandem with trends in inequality or tech (Mishel and Bernstein 1998)

Roaring late 1990s narrowed gap between 50th and 10th wage percentiles

High-pressure economy narrowed lower-half inequality

Stronger institutions and worker bargaining power did it (macro strength)

Switch2: New SBTC theory—IT biased against middle skills (2003-2013)

Middle-skill jobs are codifiable, programmable, computerizable, "routine"

Low-wage service jobs are not routine, nor are professional/managerial jobs

Computers polarizing jobs, tasks, wages. Declining middle thesis is back.

This aspect comes full-circle back to BH's original claims (1982-1988)

But theory of routine-biased technological anchors it in IT and HC theory

D1. The challenge from AI (2010-present)

"Routine" tasks = codifiable, replaceable by rules-based software (*if-then*)

Non-routine: Pattern recognition tasks, hard to program (visual perception, speech recognition, NLP, contextual understanding, common sense, interaction)

Driving vehicles is non-routine, non-programmable

"…it is hard to imagine discovering the set of rules that can replicate the driver's behavior" (Levy & Murnane 2004)

2005: 5 driverless cars complete 132-mile, off-road DARPA Grand Challenge

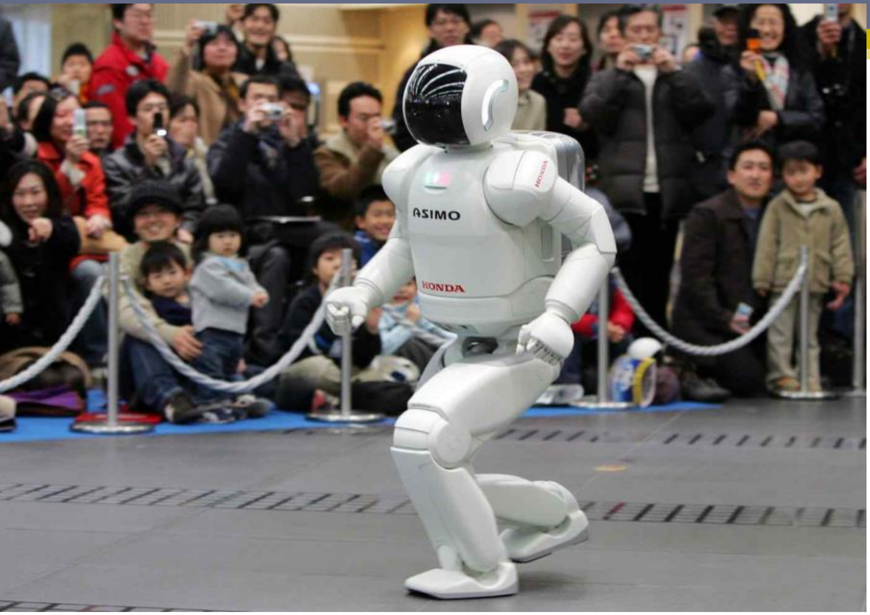
Winner's success depends on machine learning (ML), not hand-coded rules

Pattern recognition algorithms → remarkable series of AI breakthroughs

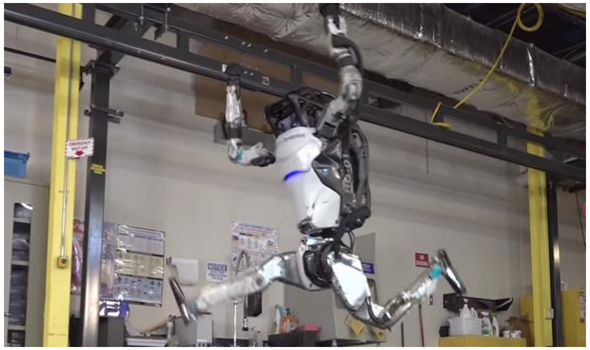
- **Image recognition**
- **Machine vision**
- **Speech recognition, natural language processing**
- **New robotics**

D2(a). Examples—robots (2000 -)

1. **Honda's humanoid robot ASIMO walks, runs, climbs stairs, serves food, responds to voice commands, navigates complex environments** (2000-on)
2. **BigDog** (2005)**, Cheetah, Atlas, Spot, highly agile field robots from Boston Dynamics**
3. **Roomba vacuum** (2002) **from iRobot**
4. **Baxter factory "co-bot" inexpensive and works safely with humans** (2011)
5. **Robots in warehouses, delivering packages, patrolling malls, checking store shelves for inventory, cleaning floors, laying bricks, sewing garments, cooking food, mowing lawns, assisting surgery**
6. **Autonomous vehicles—cars, taxis, shuttles, minibuses, freight trucks, mining trucks**



Cheetah (2015)



Atlas (2020)

BigDog (2011)

"In 2009, robots developed by Boston Dynamics were barely able to walk. In 2019, they were doing gymnastics" (BI, 2020)

D2(b). Examples—software

1. **IBM Watson beats *Jeopardy!* champion** (2011) → **healthcare field**

2. **AlphaGo beats world champion decade before expected** (2016)

3. **Image recognition error rates fall from 28% in ImageNet competition's first year (2010) to 2% (2017), some surpass humans**

4. **Machine translation**

5. **Digital assistants, call center software communicate with humans, answer verbal questions with informed responses**

6. **Legal document processing**

7. **Text generation for news stories, press releases**

Lots of truly surprising, rapid AI/robot gains after decades of meager progress

Almost all "non-routine" tasks!

Abrupt increase in 3 critical inputs: training data (internet, social media) **and hardware** (GPUs from video game industry)**, plus improved algorithms**

E1. Current SBTC theory—Disruptive automation (2011-now)

Burst of AI/robotics = a new era, Moore's Law + AI → exponential change

"stuff of science fiction" Brynjolfsson and McAfee (2011, 2014)

Mass displacement possible for jobs at all levels in near future, including non-routine jobs at low and high ends of skill spectrum

Frey and Osborne (2013,2017) **aside from some bottlenecks,**

> ***"…it is largely already technologically possible to automate almost any task provided that sufficient amounts of data are gathered for pattern recognition."***

(Use BLS Projections database, 2010-2020) **Conclude 47% of U.S. jobs in 2010**

> ***"…are potentially automatable over some unspecified number of years, perhaps a decade or two"*** **[i.e., 2020 or 2030].**

E2. Frey and Osborne methodology

Seminar held with ML researchers hand-labeled 70 occupations as automatable using current leading technology or not (0/1)

Only labeled occupations they were "most confident all tasks automatable"

Used 9 O*NET skill variables reflecting their concept of current bottlenecks to automation and ML methods to predict their own ratings of the 70 occupations with high accuracy

Applied algorithm to all 700 occupations to classify them as automatable or not based on their O*NET scores and ML-derived weights (out-of-sample)

Result: 47% of jobs in 2010 have 70% probability of belonging to the highly automatable group based on similarity of their O*NET scores to the labeled data

Original labels (criterion) **based on expert judgment, not empirical data**

E3(a). Hugely influential

Over 6,800 citations for Frey/Osborne (2013, 2017) (Google scholar, 11/2020)

Over 5,600 citations for Brynjolfsson/McAfee (2014) (11/2020)

6,000 citations for Autor, Levy, Murnane (2003) (11/2020)

Massive news media coverage

E3(b). Replications and uses

Rapid replications for EU, Canada, Australia had broadly similar conclusions

MGI, PwC, Bain issue similar reports

Brookings *AI Initiative* uses both FO and MGI scores

US Federal govt reports use FO classification and discuss results:

1. **Economic Report of the President** (2016)
2. ***White House Task Force on AI* report** (2016)
3. **GAO report on automation risks** (2019)

National Academy of Sciences report (2017)

ILO report (2015)**: 56% of ASEAN-5 jobs "at high risk of displacement due to technology over the next decade or two"**

World Bank's WDR (2016)**: 48% of highly at high risk after adjusting for wages**

European Central Bank conference (2017) **discusses possible "robocalypse"**

Calls for Universal Basic Income to address disastrous rise in mass idleness

Summary

- Real-world rapid breakthroughs
- Expert judgment on job automatability in near-future (FO)
- Widespread acceptance and replication

Congress notices. Asks BLS:

> "develop a strategy to better understand how automation, digitization, and artificial intelligence are changing the employment landscape" (2018, 2020)

But there are reasons for skepticism….

Reasons for caution

- Past fears of technological displacement and jobless futures
- AI’s history of large claims/predictions
- Practical problems and delays
- Methodological issues with Frey/Osborne study

F1. Past forecasts of mass technological displacement wrong

Era	Years	Issue	Outcome
Great Depression	1930s	Record productivity ↑ (1920s)	Record job market WWII
Mainframe computers, automation	1950-1964	Periods of recession BLS automation studies begin	Boom (1965-69)
Personal computers	1980s	"Jobless recovery" (early 1990s)	Boom (late 1990s)
		End of Work Jeremy Rifkin (1995)	
		The Jobless Future, Aronowitz and DiFazio (1994)	
Financial crisis	2010s	Slow recovery, skills mismatch, automation (Brynjolfsson/McAfee 2011)	Boom (2017-Feb. 2020)

Common mistake: cyclical downturn = secular technology trend

Solow Commission (1965) **and Cyert/Mowery** (1987): **macro forces > tech.**

F2. AI has history of overoptimism and grandiosity

	YEAR	FORECAST
AI founding conference	1956	“significant advance” in machine intelligence over summer
Herbert Simon	1958	Computer will beat #1 chess player in 10 years (actually 40)
Herbert Simon	1960	“machines will do any work” humans can do by 1980 (1985)
Marvin Minsky	1967	AI ≈ human intelligence “within a generation”
Hans Moravec	1988	“general-purpose robot usable in the home within ten years”
Hans Moravec	1988	$1,000 computer = human intelligence by 2030
Shane Legg (Deep Mind)	2009	“roughly human-level AI” around 2028
Pew expert canvas	2013-4	robots/software displace sig. BC and WC workers (48%)
Pew respondent		“AI will pass adult reading comprehension test by 2020”
Elon Musk	2019	“Sometime next year, you’ll be able to have the car be autonomous without supervision.”

Journal of Economic Perspectives—Volume 29, Number 3—Summer 2015—Pages 51–60

Is a Cambrian Explosion Coming for Robotics?

Gill A. Pratt

About half a billion years ago, life on earth experienced a short period of very rapid diversification called the "Cambrian Explosion."…Today, technological developments on several fronts are fomenting a similar explosion in the diversification and applicability of robotics.

[Leading AI expert] ***recalled tossing and turning on the night in 2015 when he signed a contract to lead Toyota's $1 billion research arm for artificial intelligence and robotics.***

"Ever since, we've tried to turn down the hype and make people understand how hard this is…None of us have any idea when full self-driving will happen."

Gil Pratt interview New York *Times* (June 20, 2019)

F3. Beyond the hype, some real setbacks and roadblocks

ASIMO discontinued	2018	Little profit after 18 years
Rethink Robotics	2018	Closed, sold assets to German automation group, relaunched
Robot vacuums	2021	Few other household robots after 20 years
Boston Dynamics	--	Robots not autonomous, no commercial products
Autonomous vehicles	~2019	Optimism cools
IBM Watson-Health	2021	Leading application, unprofitable, sale explored

"…billed as a 'bet the ranch' move by Big Blue; now the company is prepared to throw in the towel" (WSJ 2021)

"How IBM Watson Overpromised and Underdelivered on AI Health Care" *IEEE Spectrum* (2019)

"IBM pitched its Watson supercomputer as a revolution in cancer care. It's nowhere close" *Stat+* (2017)

F4(a). Problems with Frey and Osborn study

Methodological weaknesses:

- **No external validation** (ML algorithm predicts hand-labeled ratings)
- **No devil's advocate to counter optimism bias →**
  - **Confirmation bias**
  - **Overconfidence**

Questionable classification as highly automatable: roofers, models, construction equipment operators, personal care aides, animal breeders—no plausibility check

Rodney Brooks (2017)**:**

"We are surrounded by hysteria about the future of Artificial Intelligence and Robotics"

"it appears to say that we will go from 1 million grounds and maintenance workers in the US to only 50,000 in 10 to 20 years, because robots will take over those jobs. How many robots are currently operational in those jobs? Zero. How many realistic demonstrations have there been of robots working in this arena? Zero."

F4(b). Problems with Frey and Osborn study

3 other studies modify assumptions → ~10% of jobs at high risk

One finds high-risk jobs decline at rate of 1 percentage point per decade

Point of agreement with FO (and MGI)**: No polarization**

Lower end of labor market most at-risk.

Linear relationship between risk and education, income, job skill level

Most professionals/managers not at risk

What role for BLS occupational projections in this debate?

- Projections conducted since 1960s
- Frey and Osborn data are BLS projections file for 2010-2020
- No sign anyone in debate has consulted them

There are reasons for this, historical and contemporary…

G. Projections controversies

Workforce 2000 (1987) Hudson Institute

- **Rapid job skill upgrading is coming** (education, math, verbal, reasoning skills)
- **BLS projections (1984-2000) + Dictionary of Occupational Titles** (DOT) **scores**
- **By 2000: "even the least-skilled jobs will require a command of reading, computing, and thinking that was once necessary only for the professions"**
- **Structural break in 16 years (1984-2000)**
- **Lots of media attention**

Mishel and Teixeira (1991) reanalysis, constructed time series

- **Skill upgrading decelerates in BLS 2000 projections relative to 1973-1986**
- **Skill upgrading trend is slow and steady**
- **No structural break in projections**
- **Much less media attention**

G2. Projections controversies II

John Bishop (1991, 1996)

- **But BLS projections are biased downward**
- **Underestimated growth of college jobs** (skill upgrading) **in early 1980s**
- **Predicts projections for 2000 & 2005 too conservative**
- **BLS needs to say we need much more college education (SBTC theory)**
  - **But not as extravagant as Workforce 2000**
- **Influenced economists, negative view of BLS projections** (no media attention)

BLS response (1991)

- **Bishop's comparisons over time inappropriate**
- **Changes in occupational coding systems complicate evaluation**
- **Acknowledges BLS cautious in projecting dramatic change**
  - **Generally supported by historical record, shows gradual change**

Anthony Carnevale (2010) reiterates Bishop's criticisms—more college needed, SBTC is powerful trend, media covers this

G3. Why do automation studies ignore projections?

New era renders all traditional methods irrelevant (Moore's Law, AI)

"As we look further ahead—into the 2020s and beyond—we see androids…"

"…technology is steadily encroaching on human skills and abilities..."

"In the coming decade **[2014-2024]** ***we will have the good fortune to witness a wave of astonishing technologies unleashed…we are convinced that we are at an inflection point"*** **(Brynjolfsson/McAfee 2014)**

Automation studies ignore projections

Frey and Osborne use BLS projections file, but only use base year values

> ***While the 2010–2020 BLS occupational employment projections predict US net employment growth across major occupations, based on historical staffing patterns, we speculate about technology that is in only the early stages of development. This means that historical data on the impact of the technological developments we observe is unavailable…***
>
> ***BLS projections are based on what can be referred to as changes in normal technological progress, and not on any breakthrough technologies that may be seen as conjectural (2017, p.265)***

Machine learning and mobile robotics "will profoundly affect the demand for skills by 2030" (Frey and Berger 2017, p.5)

Summary: Four perspectives

	TREND	RATE	BLS PROJECTIONS
Classic SBTC	Skill upgrading	Moderate acceleration	Biased down moderately (remediable)
Routine SBTC	Skill polarization	Moderate acceleration	Biased down moderately (remediable)
AI/robotic automation SBTC	Skill upgrading	Structural break, blindingly fast	Unsalvageable, useless, need new forward-looking methods
Institutional views of rising inequality	Skill upgrading	Gradual, no acceleration	Basically sound

Who's (mostly) **right?**

Data and measures

BLS Projections files: 2019-2029, 2008-2018, various previous

Occupational Employment Statistics (OES) **: 1999-2018**

Occupational Information Network (O*NET) **: 2020** (v.25)**, 2008** (v.13)

Current Population Survey (CPS) **: various years**

Dictionary of Occupational Titles (DOT) **: 1977** (4 ed.)

Measures

1. **Changes in 1-digit occupational distribution** (college jobs, low-skill jobs)
2. **Changes in Index of Dissimilarity** (total reallocation across occupations)
3. **Changes in O*NET score means and distributions** (incl. polarization)

Major occupations = quasi-ordinal, detailed SOC codes = nominal
O*NET & DOT = quantitative skill scores for detailed occupations

Projections data methods

Labor Force
Total and by age, sex, race and ethnicity

→

Aggregate Economy
GDP, total employment, and major demand categories

↔

Industry Final Demand
Sales to consumers, businesses, government and foreigners

↕

Industry Output
Use and Make Relationships, Total Requirements Tables

↔

Industry Employment
Labor productivity, average weekly hours, wage & salary employment

↔

Occupational Employment
Job openings due to growth & separations

bls.gov/emp/documentation
/projections-methods.htm

Projections model assumes full employment (current CBO NAIRU)

Frey/Osborne ambiguous: mass unemployment or mass reallocation?

Final projections phase—producing estimates for target year

1. **Previous phase provides projected total industry employment**
2. **Current data provides occupational shares within industries**
3. **Research indicates whether current shares should be applied to** (1)
4. **If not, within-industry shares changed based on**
   - **current size of occupation**
   - **past trends**
   - **qualitative research**
   - **apparent strength of tech and other forces**
   - **general magnitudes of occupational change**
     - **e.g., ± 10% for large occs and mature trends, ± 20-30% converse**
     - **larger values** (± 50%) **possible but considered carefully**

Treatment of technology

BLS research distinguishes

1. Technical feasibility
2. Innovation introduction
3. Innovation diffusion

Technical feasibility alone insufficient to impact projections

Projections do not get ahead of innovation cycle

Likely source of difference with Frey and Osborne

Projection uncertainty dilemmas

1. How long to wait to see if a technology will be impactful?
2. When is/will a new trend emerge?
3. How long will it unfold?
4. Will ongoing trend accelerate, decelerate, or cease over next 10 years?

Key indicators used in tables

1. **Occupational** (aggregate) **composition** (e.g., % high white-collar)
2. **Index of dissimilarity—occ composition** (aggregate, detailed)
3. **O*NET skill/task ratings of job characteristics**

3 parts to Results

1. **Projections for 2019-2029 and contrast with Frey/Osborne**
2. **Performance of 2008-2018 Projections during first half of FO interval**
   A. **Plus evaluations of prior projections**
3. **Recent historical time series** (1999-2018) **for perspective on change**

O*NET (Employment and Training Administration, DoL)

Multiple worker surveys → ratings of job skill requirements, et al.

Data are occupational means at detailed SOC level

This paper uses:

1. **Education required by job**
2. **Required experience, formal training, OJT**
3. **9 standardized scales from 74 items**
   A. **Cognitive** (math, verbal, general cognitive)
   B. **Interpersonal** (general interpersonal, public contact, management)
   C. **Manual** (craft, general physical, fine motor)
4. **Repetitiveness item** (1= repetitive motions > 50% of time)

Scales have high reliability ($\alpha > 0.9$, 1st PCA component explains >70% variance)

Major SOC group explains high % of variance for most skill variables

O*NET scales and scale properties

	Scales and items	Cronbach's α and $r_{item\text{-}rest}$	Variance explained (%) and loadings PCA 1	PCA 2
C	**General cognitive demands scale**	**0.97**	**0.74**	**0.06**
1	Analytical thinking	0.80	0.29	-0.18
2	Critical thinking	0.87	0.30	-0.25
3	Complex problem-solving	0.85	0.29	-0.21
4	Active learning	0.86	0.30	-0.24
5	Analyzing data/information	0.87	0.30	-0.15
6	Processing information	0.81	0.28	-0.12
7	Thinking creatively	0.74	0.26	-0.15
8	Updating/using knowledge	0.83	0.29	-0.24
9	Deductive reasoning	0.88	0.30	0.33
10	Inductive reasoning	0.87	0.30	0.32
11	Fluency of ideas	0.80	0.28	0.34
12	Category flexibility	0.75	0.27	0.59
D	**General interpersonal demands scale**	**0.94**	**0.58**	**0.09**
1	Persuasion	0.83	0.30	0.13
2	Negotiation	0.78	0.29	0.22
3	Speaking skills	0.85	0.31	0.03
4	Instructing skills	0.74	0.27	-0.27
5	Service orientation	0.74	0.27	0.28
6	Face-to-face discussions (frequency)	0.47	0.18	0.10
7	Public speaking (frequency)	0.68	0.25	-0.26
8	Interpersonal Relationships	0.76	0.28	0.15
9	Resolving conflicts/negotiating w/others	0.72	0.27	0.22
10	Training/teaching others	0.68	0.25	-0.47
11	Interpreting information for others	0.72	0.27	-0.33
12	Education/training knowledge	0.71	0.26	-0.35
13	Social orientation	0.46	0.18	0.35
14	Social perceptiveness	0.83	0.30	0.23
G	**Craft skills scale**	**0.95**	**0.77**	**0.09**
1	Controlling machines/processes	0.78	0.36	-0.57
2	Repair/maintain mechanical equipment	0.86	0.39	-0.43
3	Repair/maintain electronic equipment	0.76	0.35	-0.02
4	Equipment maintenance	0.89	0.40	-0.04
5	Troubleshooting operating errors	0.78	0.36	0.50
6	Repairing machines	0.91	0.41	0.08
7	Installing equipment, machines, wiring	0.81	0.37	0.48

Absolute employment levels

Actual and projected job growth

	Absolute (millions)			Δ (percent growth)		
	Base year	Projected	Actual	Projected	Actual	P-A
Previous						
1978-1990	96.5	125.8	122.9	30.4%	27.4%	3.0%
1984-1995	106.7	122.8	130.0	15.0%	21.8%	-6.8%
1988-2000	118.1	136.2	143.8	15.3%	21.7%	-6.4%
2008-2018	150.9	166.2	161.0	10.1%	6.7%	3.4%
Current						
2019-2029	162.8	168.8	--	3.7%	--	--

Note: P-A = Projected value minus Actual value

Top-line results, projections 2019-2029

No structural breaks

Actual and projected occupational distribution, 2019-2029

	Employment		Δ shares
	2019 actual	**2029** projected	**2019-2029** projected
Managers	12.1%	12.3%	0.2%
Professional, technical	21.5%	22.2%	0.7%
All upper white-collar	***33.6%***	***34.5%***	***0.9%***
Sales	9.5%	9.0%	-0.5%
Admin. support, clerical	12.7%	11.7%	-1.0%
Service	21.4%	22.6%	1.2%
Agriculture	0.7%	0.7%	0.0%
Craft	8.3%	8.3%	0.0%
Production, transport	13.9%	13.4%	-0.5%

Index of dissimilarity (D)	**2019-2029**
1-digit occupation (n=8)	0.0207
Major group (n=22)	0.0214
Detailed occupation (n=790)	0.0299

Mean job requirements, actual (2019) and projected (2029) (2020 O*NET)

Projected O*NET skills trends 2019-2029

		2019	2029	Δ
1.	Education (mean)	13.58	13.61	0.03
2.	≥ BA (%)	28.3	28.9	0.6
3.	Postgrad (%)	9.2	9.6	0.4
4.	Prior experience (yrs)	2.0	2.0	0.0
5.	Training (years)	0.52	0.52	0.00
6.	OJT (years)	0.58	0.57	-0.01
7.	Job zone 1 (%)	6.7	6.8	0.1
8.	Job zone 2 (%)	42.5	41.7	-0.8
9.	Job zone 3 (%)	22.4	22.4	0.0
10.	Job zone 4 (%)	22.1	22.4	0.3
11.	Job zone 5 (%)	6.3	6.7	0.4
12.	Math	0.000	0.001	0.001
13.	Verbal	0.000	0.005	0.005
14.	Cognitive	0.000	0.013	0.013
15.	Interpersonal	0.000	0.015	0.015
16.	Public	0.000	0.002	0.002
17.	Management	0.000	0.009	0.009
18.	Craft	0.000	0.005	0.005
19.	Physical (general)	0.000	0.007	0.007
20.	Fine motor	0.000	-0.004	-0.004
21.	Highly repetitive (%)	45.3	45.1	-0.2

Note: Values for scales in lines 12-20 are standardized to have mean=0 and SD=1 with respect to occupational employment in 2019

Projections and progress report on high-risk jobs

Change in employment shares by automation risk group, 2010-2029 (%)

	Projections 2010-2020 and 2018-2028					Projections 2019-2029		
	A.	B.	C.	D.	E.	F.	G.	H.
	2010	2018 p	2018	Δ P	Δ	2019	2029 p	Δ
All occs								
Low risk	33.3	33.6	33.1	0.3	-0.2	33.4	34.1	0.7
Medium risk	19.4	19.5	19.9	0.1	0.5	21.8	22.4	0.6
High risk	47.4	46.8	47.0	-0.6	-0.4	44.8	43.5	-1.3
Total (%)	**100.0**	**100.0**	**100.0**			**100.0**	**100.0**	
Hand-labeled cases								
Low-Med risk	9.3	9.5	9.5	0.2	0.2	9.3	9.4	0.1
High risk	8.0	7.7	7.9	-0.3	-0.1	8.3	8.0	-0.3

2018 p = projected for 2018 (col. B)
2029 p = projected for 2029 (col. G)

D = B-A projected change, 2010-2018
E = C-A actual change, 2010-2018
H = G-F projected change, 2019-2029

Does the projections account for AI and robotics?

Technology-related drivers of changing occupational staffing patterns, 2019-2029

Category	% of jobs	N
Jobs researched	**59.5**	**298**
General	n.a.	
Capital/labor substitution	13.0	35
Productivity change	20.3	85
Technology	13.1	41
Electronic	2.1	5
Digital	1.2	6
Software	7.0	18
Automation, automatic	16.2	72
Production job automation	**4.3**	**36**
Robots	3.1	18
Programmable	0.6	20
Computer numerical controlled machine tools	0.6	17
Machining software	>0.0	1
Automated guided vehicle	0.7	3
Autonomous vehicle	>0.0	1
Artificial intelligence	**9.7**	**19**
Artificial intelligence	4.9	7
Machine learning	1.3	3
Smart	0.6	5
Chatbots	1.7	3
Language processing	5.2	3
Facial, handwriting, or optical character recognition	4.1	4
Robo-advisors	0.2	1

Yes, staff research uncovers many new and older high-tech drivers

Category	% of jobs	N
Tags and sensors	**2.0**	**4**
RFID	1.8	3
Barcodes	1.7	2
Sensors	1.9	3
Internet	**7.8**	**15**
E-commerce	0.6	1
Electronic shopping industry	2.8	4
Online	4.8	11
Electronic data processing, document management	**11.7**	**16**
Data processing	0.6	2
Electronic filing	1.9	2
Optical character recognition	3.3	2
Robotic process automation	3.3	2
Computer processing	0.1	1
Payment	6.5	4
E-signatures, e-delivery	0.1	1
Mobile apps	3.3	6
Any high technology from above	**31.3**	**118**
Self-service	**4.8**	**3**
Self-service	2.6	2
Self-checkout	2.2	1
Mechanical technology	**0.6**	**6**
Machines	1.1	23
Mechanize	0.6	5
Restructuring	n.a.	
Outsourcing	2.9	8
Offshoring	0.2	3

Note: Categories are not mutually exclusive, and occupations may be represented by several indicators. The category "Any above high technology" excludes the generic keywords "Capital/labor substitution," "Productivity change," and "technology."

…they just affect fewer occupations than one might think

Projected to decline to 29.9% by 2029 (-1.4 pp)

Part 1 of 3 parts to Results

1. **Projections for 2019-2029 and contrast with Frey/Osborne**
2. **Performance of 2008-2018 Projections during first half of FO interval**
   A. **Plus evaluations of prior projections**
3. **Recent historical time series** (1999-2018) **for perspective on change**

Part 1 summary: Projections for 2019-2029 + contrast with Frey/Osborne

1. **BLS research doesn't suggest structural break for total number of jobs, their occupational composition, or skill and task content for 2019-2029**
   A. **Change gradual even by standards of moderate SBTC theories**
2. **Not because emerging technologies** (AI, robotics) **ignored, but because research suggests small impacts on number of jobs and occupational composition in next decade**
3. **The projections are not naïve—they did a better job than FO of predicting 8-year changes in sizes of FO's three risk groups**
   A. **High-risk jobs likely to decline 2-4 percentage points 2010-2030**
   B. **Hand-labeled ratings greatly overestimated automation risk**
   C. **Validity of FO scores widely taken for granted, but questionable**

What about record of the 2008-2018 projections more generally?

Part 2 Projections for 2008-2018 and earlier

Value of 2008-2018 projections

1. First half of Frey/Osborne projection interval
2. Most recent period for which projections can be evaluated
3. Labor market in 2018 closely matches full employment assumption

How well were occupational composition and skill/task content projected?

Trends in occupational distribution, actual (2008, 2018) and projected (2018)

	1 Actual 2008	2 Projected 2018	3 Actual 2018	4 Δ (proj.)	5 Δ	6 A-P (5-4)
1. Mgt, prof, tech	**31.0**	**32.3**	**33.0**	**1.3**	**2.0**	**0.7**
2. Service	**19.6**	**20.2**	**21.4**	**0.6**	**1.8**	**1.1**
3. Sales, clerical	**26.5**	**25.8**	**24.0**	**-0.7**	**-2.5**	**-1.7**
Sales 41	10.5	10.2	9.8	-0.4	-0.8	-0.4
Office support 43	16.0	15.6	14.3	-0.4	-1.7	-1.3
4. Farm	**0.7**	**0.6**	**0.7**	**-0.1**	**0.0**	**0.1**
5. Craft	**9.0**	**9.1**	**8.3**	**0.1**	**-0.7**	**-0.8**
6. Production	**13.2**	**12.0**	**12.6**	**-1.2**	**-0.6**	**0.6**

Index of Dissimilarity (occupation level)	**Projected 2008-18**	**Actual 2008-18**	**Difference (A-P)**
1-digit (n=6)	0.0199	0.0381	0.0182
Major (n=22)	0.0251	0.0470	0.0219
Detailed (n=770)	0.0349	0.0887	0.0538

Actual and projected average job requirements, 2008-2018 and 2019-2029 (2008 O*NET)

		1.	2.	3.	4.	5.	6.	7.	8.
		2008-2018 projected and actual					2019-2029 projected		
		2008	2018 P	2018	Δ P	Δ	2019	2029 P	ΔP
1.	Education (mean)	13.30	13.35	13.34	0.05	0.04	13.36	13.38	0.03
2.	≥ BA (%)	23.8	24.5	24.6	0.8	0.8	24.9	25.4	0.5
3.	Postgrad (%)	7.0	7.3	7.4	0.3	0.4	7.5	7.8	0.3
4.	Prior exp. (years)	1.9	1.9	1.9	0.0	0.0	1.9	1.9	0.0
5.	Training (years)	0.48	0.49	0.47	0.00	-0.01	0.48	0.47	0.00
6.	OJT (years)	0.57	0.58	0.56	0.00	-0.01	0.57	0.57	0.00
7.	Job zone 1 (%)	17.2	16.7	17.3	-0.5	0.0	16.8	16.6	-0.2
8.	Job zone 2 (%)	32.9	32.3	32.8	-0.6	-0.1	33.1	32.7	-0.4
9.	Job zone 3 (%)	28.2	28.4	27.4	0.2	-0.8	27.3	27.2	-0.1
10.	Job zone 4 (%)	16.0	16.7	16.7	0.7	0.7	16.9	17.2	0.3
11.	Job zone 5 (%)	5.7	5.9	5.9	0.3	0.2	6.0	6.3	0.4
12.	Math	0.017	0.026	0.013	0.009	-0.004	0.020	0.015	-0.005
13.	Verbal	0.050	0.081	0.072	0.031	0.022	0.082	0.093	0.011
14.	Cognitive	0.054	0.082	0.079	0.028	0.025	0.092	0.106	0.014
15.	Interpersonal	0.043	0.065	0.061	0.022	0.018	0.073	0.093	0.020
16.	Public	0.038	0.062	0.070	0.024	0.032	0.074	0.078	0.004
17.	Management	0.070	0.087	0.084	0.017	0.014	0.100	0.108	0.008
18.	Craft	-0.003	-0.016	-0.018	-0.013	-0.014	-0.016	-0.016	-0.001
19.	Physical (general)	-0.020	-0.035	-0.028	-0.015	-0.007	-0.032	-0.028	0.004
20.	Fine motor	-0.035	-0.054	-0.052	-0.019	-0.017	-0.053	-0.058	-0.004
21.	Repetitive (%)	44.5	44.0	43.8	-0.5	-0.7	43.7	43.1	-0.6

Note: Values for scales in lines 12-20 are standardized to have mean=0 and sd=1 with respect to occupational employment in 2004.

2008-2018 Projections:

- performed reasonably well,
- did not underestimate actual skill upgrading,
- which was gradual,
- like projections for 2029

Was 2008-2018 lucky? What about earlier projections cycles?

Distribution of actual and projected employment by 1-digit occupation

	Employment shares			Change in shares	
	1988 actual	2000 projected	2000 actual	1988-2000 projected	1988-2000 actual
Managers	10.4%	11.0%	10.4%	0.6%	0.0%
Professional	12.3%	13.3%	14.2%	0.9%	1.8%
Technicians	3.3%	3.8%	3.6%	0.5%	0.3%
All upper white-collar	***26.1%***	***28.1%***	***28.2%***	***2.0%***	***2.1%***
Marketing and sales	10.3%	10.7%	10.8%	0.4%	0.5%
Admin. support, clerical	18.7%	18.1%	17.8%	-0.6%	-0.9%
Service	15.6%	16.6%	16.1%	1.0%	0.5%
Agriculture	3.0%	2.4%	2.8%	-0.5%	-0.2%
Craft	12.2%	11.6%	11.1%	-0.6%	-1.1%
Operators, laborers	14.2%	12.4%	13.2%	-1.7%	-0.9%
	1984 actual	1995 projected	1995 actual	1984-1995 projected	1984-1995 actual
Managers	9.3	9.7	10.2	0.4	0.9
Professional	12.2	12.8	13.6	0.6	1.4
Technicians	3.3	3.7	3.5	0.4	0.2
All upper white-collar	***24.8***	***26.2***	***27.3***	***1.4***	***2.5***
Marketing and sales	10.3	10.9	11.1	0.6	0.8
Admin. support, clerical	18.4	17.7	18.2	-0.7	-0.2
Service	15.2	15.9	16.1	0.7	0.9
Agriculture	3.6	3.0	2.9	-0.6	-0.7
Craft	12.6	12.3	10.9	-0.3	-1.7
Operators, laborers	15.1	14.0	13.5	-1.1	-1.6

1988-2000

Workforce 2000: Projections imply major upgrading
Mishel/Teixeira: Projections imply gradual upgrading
Bishop: Projections biased down, expect major upgrading

No underestimate

No underestimate (overestimate of 0.3 pp)

BLS projections performed poorly during a period of rapid change—Bishop's critique overgeneralized episodic issue to all periods

1984-1995 (Bishop follow-up critique)
Underestimated decline by 1.9pp

1978-1990 (Bishop critique)

	Employment shares			Change in shares	
	1978 actual	1990 projected	1990 actual	1978-1990 projected	1978-1990 actual
Managers	10.8%	10.8%	10.2%	-0.1%	-0.7%
Professional	11.7%	11.8%	12.9%	0.1%	1.2%
Technicians	1.4%	1.7%	3.5%	0.3%	2.1%
All upper white-collar	***23.9%***	***24.3%***	***26.5%***	***0.3%***	***2.7%***
Marketing and sales	8.9%	9.3%	11.5%	0.4%	2.6%
Admin. support, clerical	17.3%	17.1%	17.9%	-0.2%	0.6%
Service	14.9%	15.9%	15.6%	1.1%	0.8%
Agriculture	3.7%	2.7%	2.9%	-1.0%	-0.8%
Craft	11.9%	12.2%	11.5%	0.3%	-0.4%
Operators, laborers	19.4%	18.6%	14.0%	-0.8%	-5.4%

Large underestimates of occupational change, 4.6 pp
(but not 45 or 23 pp)

Index of Dissimilarity for projected and actual occupational distributions (ten-year rates)

	A. base vs. proj.	B. base vs. actual	C. error (B-A)	D. actual vs. proj.	E. % of jobs
Aggregate level					
1978-1990 (n=9)	0.0175	0.0606	0.0431	0.0507	~100
1980-1990 (n=8)	0.0139	0.0614	0.0475	0.0528	~100
1984-1995 (n=9)	0.0242	0.0378	0.0136	0.0200	~100
1988-2000 (n=9)	0.0283	0.0260	-0.0023	0.0178	~100
2008-2018 (n=22)	0.0251	0.0470	0.0219	0.0407	100
2019-2029 (n=22)	0.0214	--	--	--	
Detailed occupations					
1980-1990 (n=131)	0.0397	0.0957	0.0560	0.0865	47.4
1984-1995 (n=348)	0.0421	0.0762	0.0341	0.0625	63.1
1988-2000 (n=338)	0.0357	0.0703	0.0347	0.0638	77.8
1996-2006 (n=243)	0.0450	0.0923	0.0473	0.0864	47.9
2008-2018 (n=770)	0.0349	0.0887	0.0538	0.0801	100.0
2019-2029 (n=790)	0.0299	--	--	--	

Part 1 of 3 parts to Results

1. Projections for 2019-2029 and contrast with Frey/Osborne
2. **Performance of 2008-2018 Projections during first half of FO interval**
   A. **Plus evaluations of prior projections**
3. Recent historical time series (1999-2018) for perspective on change

Part 2 summary: Performance of 2008-2018 projections & previous

1. **2008-18 projections did not foresee large changes in the first half of Frey/Osborne projection interval**

2. **2018 data close to projections values for 1-digit occupation shares** (and D values) **and O*NET means—occ and skill change was very gradual**

3. **Larger divergence in Index of Dissimilarity for detailed occupations not meaningful in terms of skill scores in this case**

4. **Earlier performance: very good (1988-2000), good (1984-95), not as good (1978-1990). Criticisms mistook contingent problems for basic flaw.**

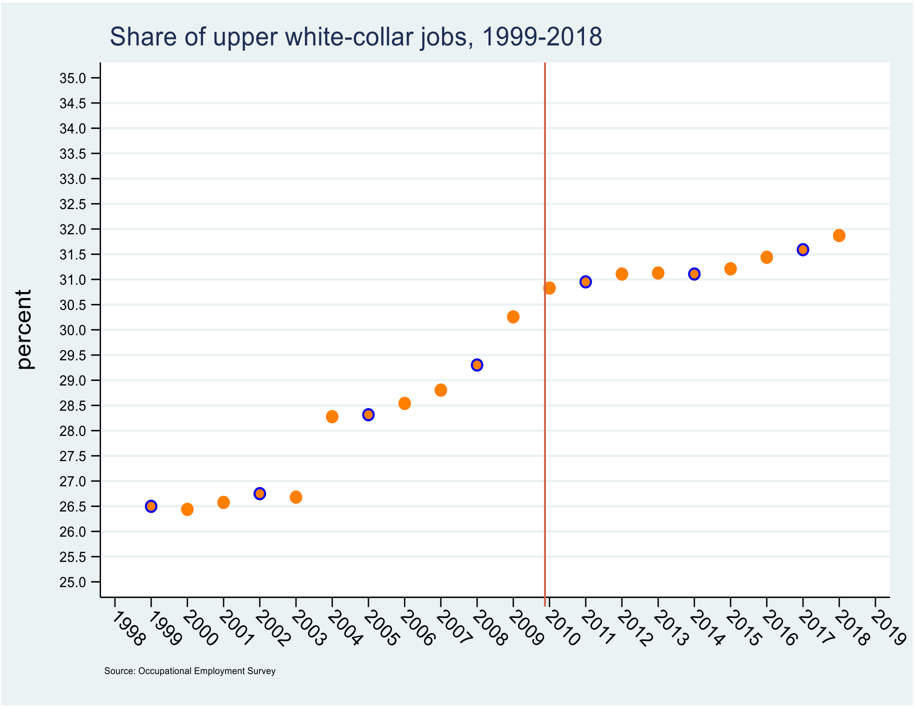
What does fuller time series show?

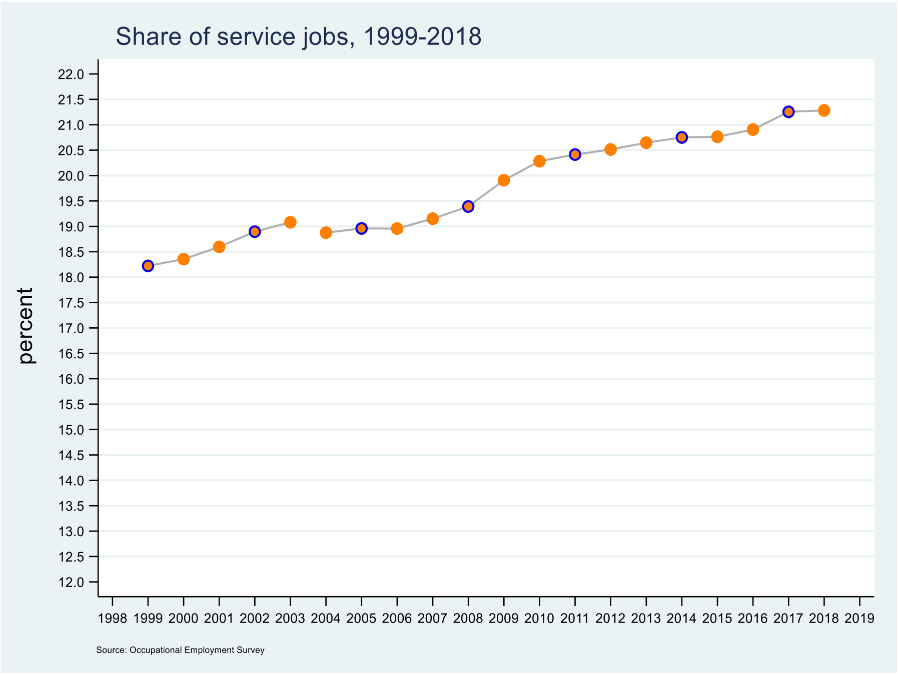
Part 3 Time series 1999-2018

What are expected patterns of occupational change?

Recent historical trends (OES) in

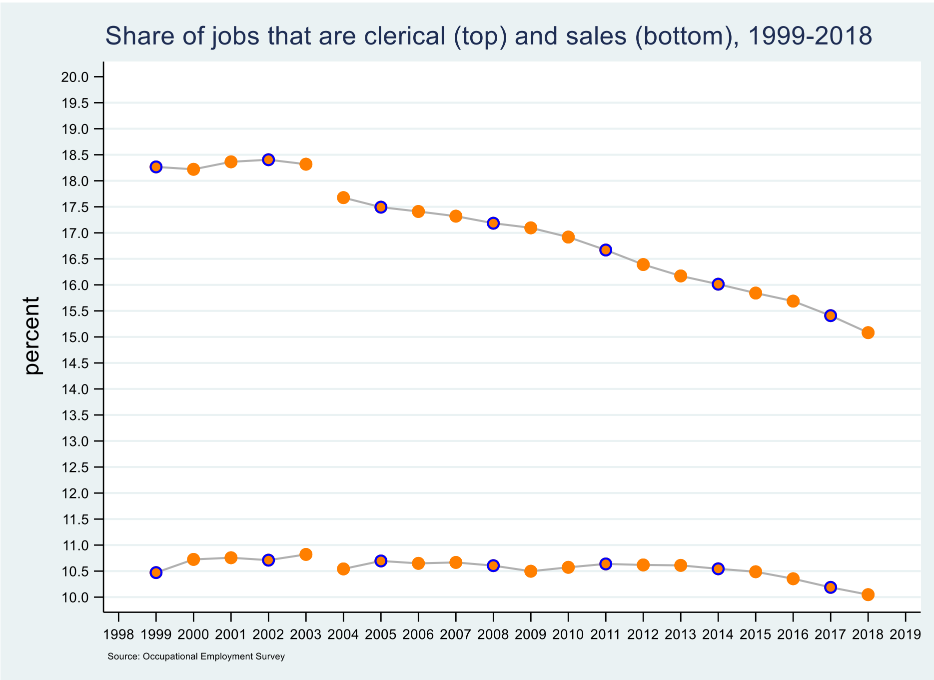
1. **Occupation shares**
2. **Index of dissimilarity**
3. **O*NET skill/task measures**
4. **OES has coverage shift between 2003 and 2004**

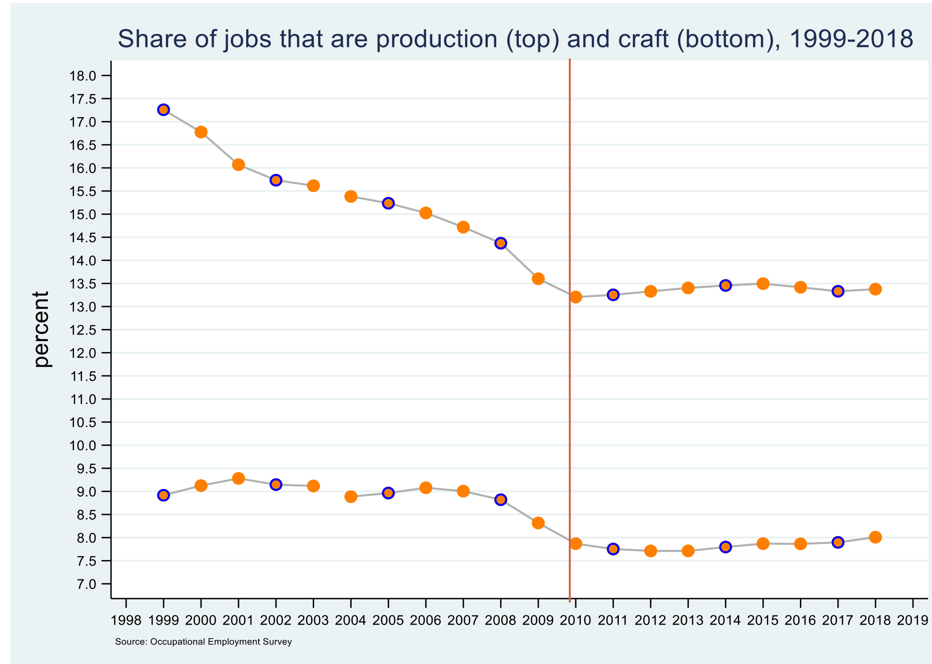




Smooth, gradual change

No structural breaks, no consistent acceleration



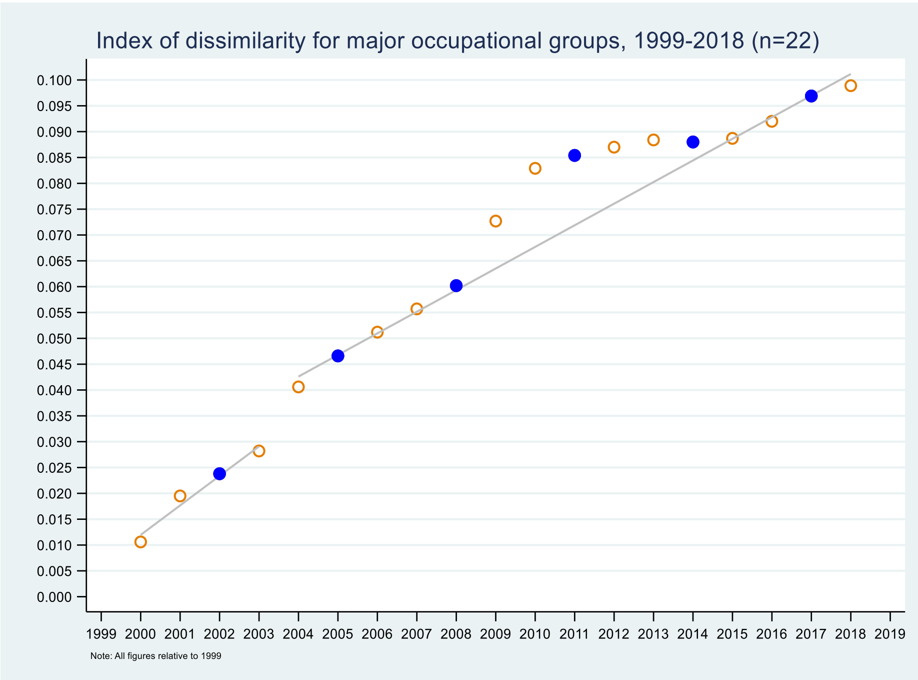


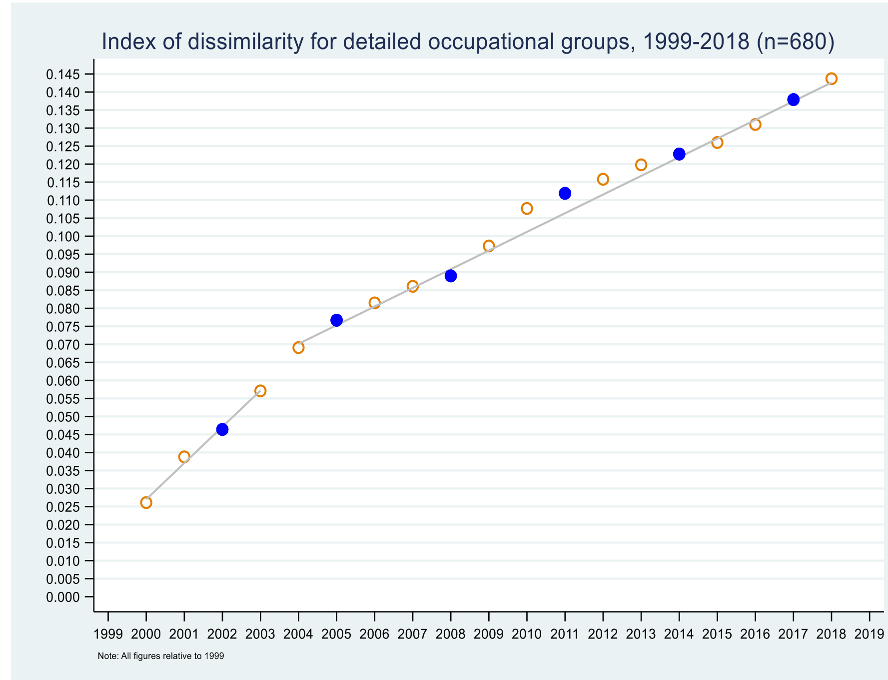
Smooth, gradual change

No structural breaks, deceleration of trends for production and craft

Steady clerical decline begins after 2003 in this series (-1.8pp per decade)

Index of dissimilarity 1999-2018



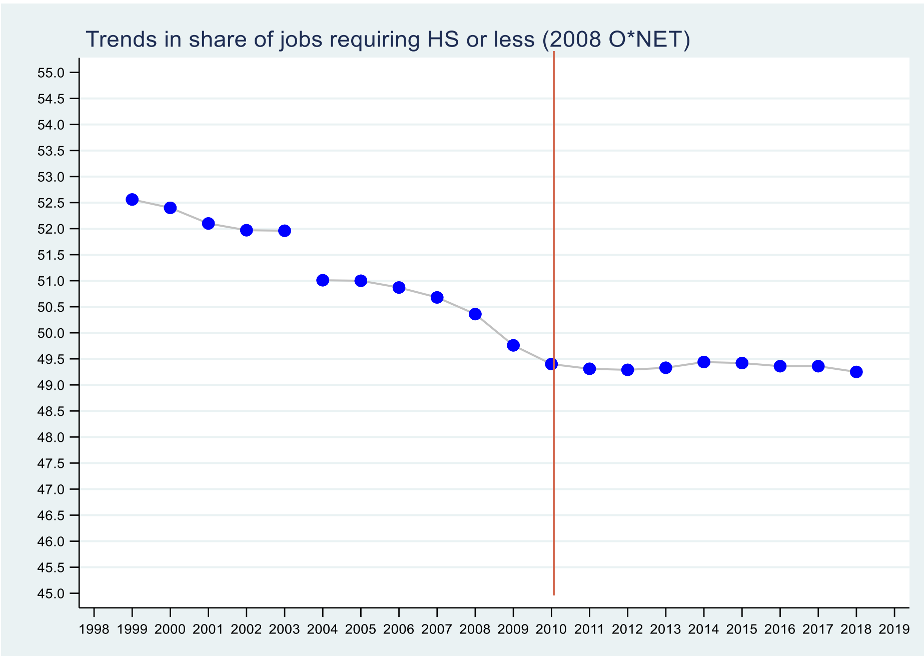


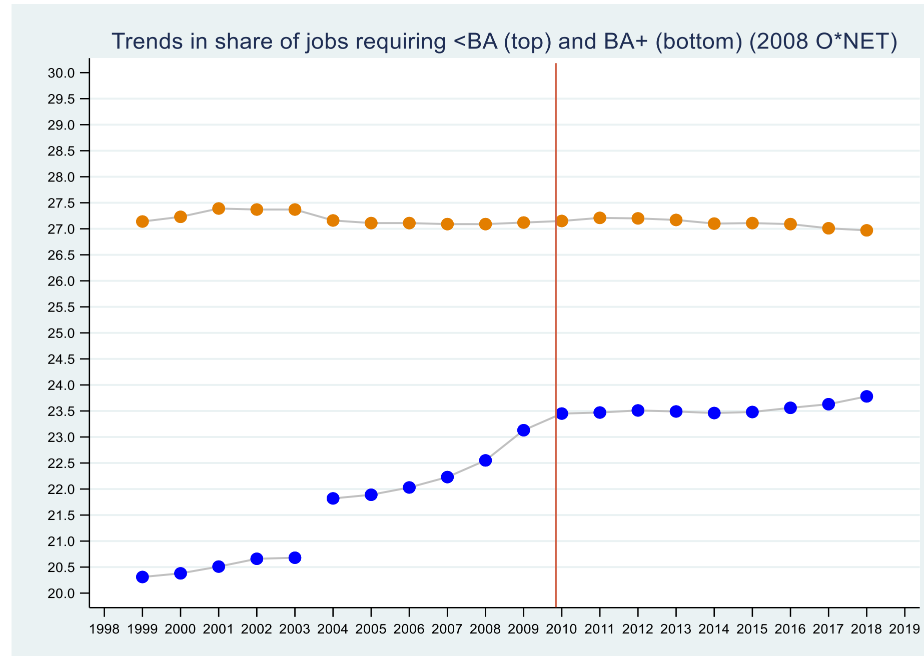
Smooth, gradual change

No structural breaks, no consistent acceleration

Evolutionary change in occupational structure, not revolutionary change

Trends in O*NET scores are slow and steady, 1999-2018





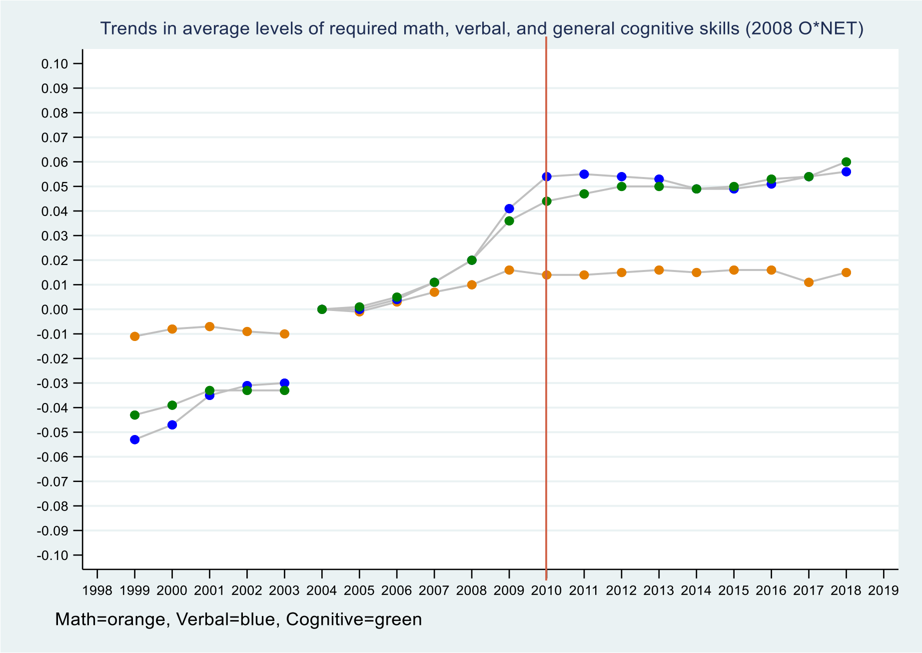
Education required by job:

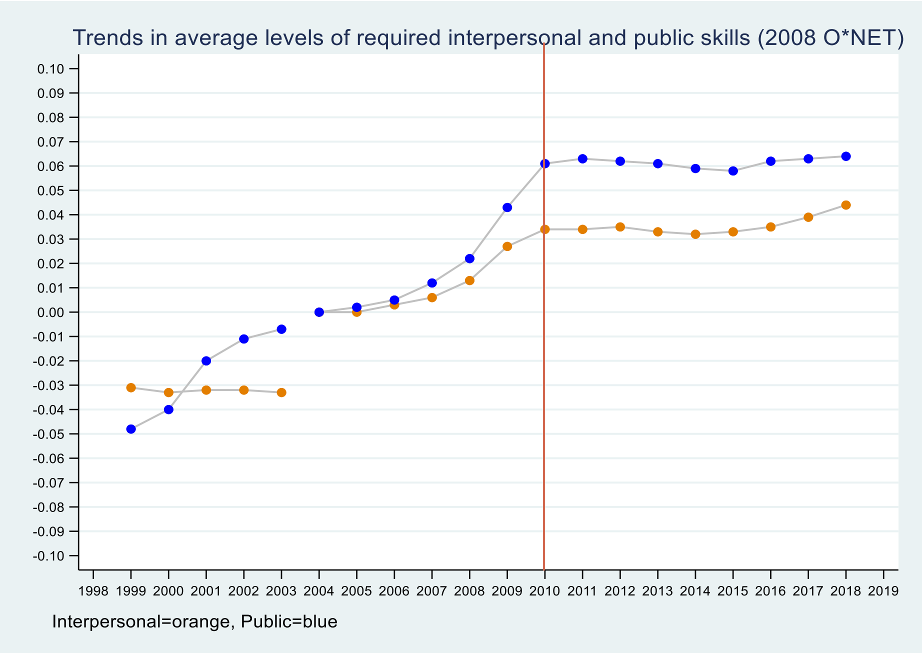
Trends flatten in recent period.

Beginning of AI era = decelerating change

Upgrading, no decline in middle-education jobs

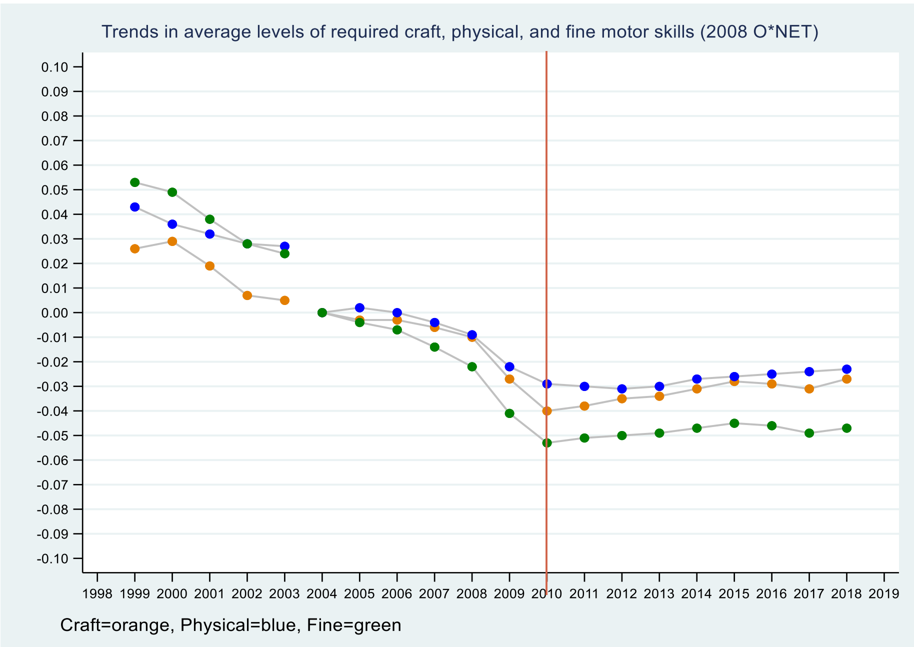
O*NET cognitive and interpersonal scores, 1999-2018

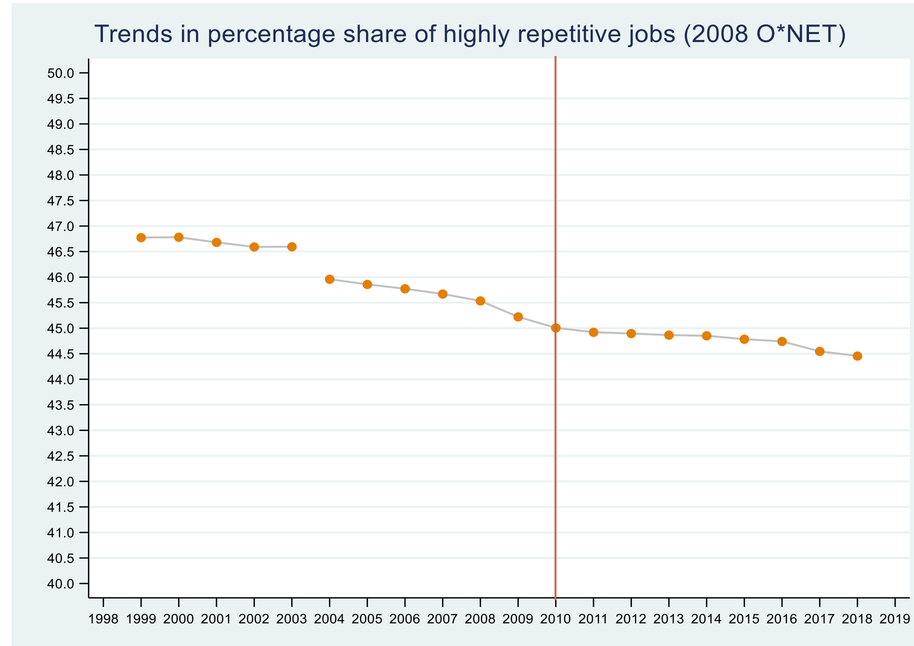




These trends also flatten in recent period

O*NET manual and repetitiveness scores, 1999-2018





Manual score trends (left) **flatten in recent period**

Very gradual decline in job repetitiveness—not disappearing anytime soon

Main conclusions to Part 3

BLS projections have a somewhat conservative tendency

But so do the data!

Time series generally show very gradual, steady change

No inflection points, no exponential change, no trend breaks, acceleration

More consistent with institutional accounts, rather than pre-AI SBTC views. Not surprising that extreme automation not supported.

Projections generally perform reasonably well

Surprises difficult to anticipate

Criticism of projections overgeneralize from their performance during a surprising period (early 1980s) (also 2000s & WTO)

Trends in means don't mask polarizing distributions

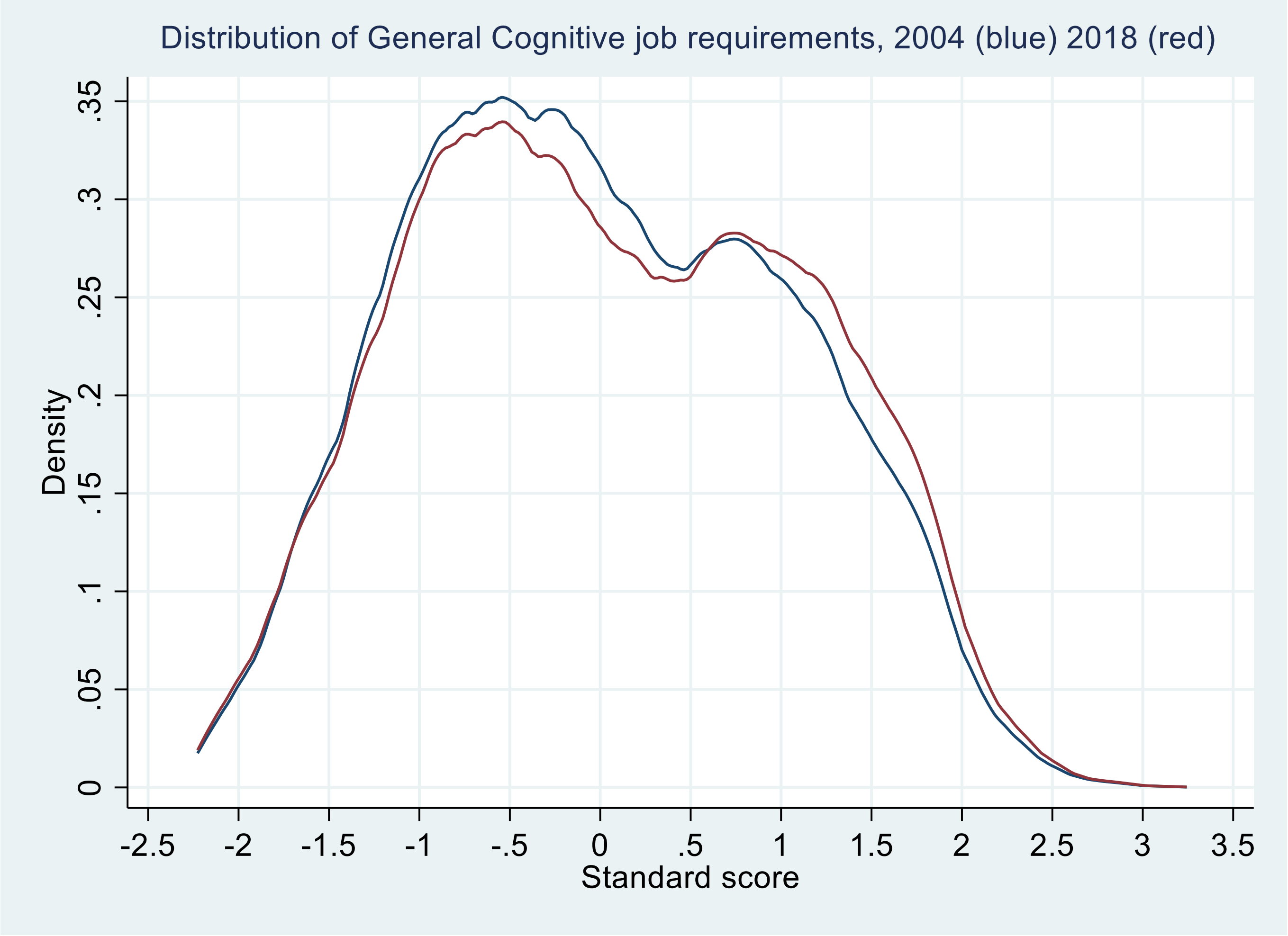
Trends in the percentage distributions of O*NET scores, 2004 and 2018

	Math			Verbal			Cognitive		
Skill level	2004	2018	Change	2004	2018	Change	2004	2018	Change
Low (< -1 sd)	13.9	13.9	0.0	18.4	17.6	-0.8	16.9	16.1	-0.9
Mid (-1 to 1 sd)	70.1	69.2	-0.9	62.7	61.3	-1.3	64.7	62.3	-2.4
High (>1 sd)	16.0	16.9	0.9	19.0	21.1	2.1	18.3	21.6	3.2
Total	100.0	100.0		100.0	100.0		100.0	100.0	
	Interpersonal			**Public**			**Management**		
	2004	2018	Change	2004	2018	Change	2004	2018	Change
Low (< -1 sd)	19.0	18.8	-0.2	18.9	17.9	-1.0	13.9	14.3	0.5
Mid (-1 to 1 sd)	65.3	64.5	-0.8	64.4	63.5	-0.9	68.5	66.0	-2.5
High (>1 sd)	15.7	16.7	1.0	16.8	18.6	1.9	17.6	19.6	2.0
Total	100.0	100.0		100.0	100.0		100.0	100.0	
	Physical			**Craft**			**Fine motor**		
	2004	2018	Change	2004	2018	Change	2004	2018	Change
Low (< -1 sd)	27.6	28.1	0.5	11.4	10.3	-1.0	19.8	20.1	0.3
Mid (-1 to 1 sd)	56.1	57.1	1.0	69.8	71.7	1.9	57.9	59.7	1.8
High (>1 sd)	16.3	14.8	-1.5	18.9	18.0	-0.9	22.3	20.2	-2.1
Total	100.0	100.0		100.0	100.0		100.0	100.0	

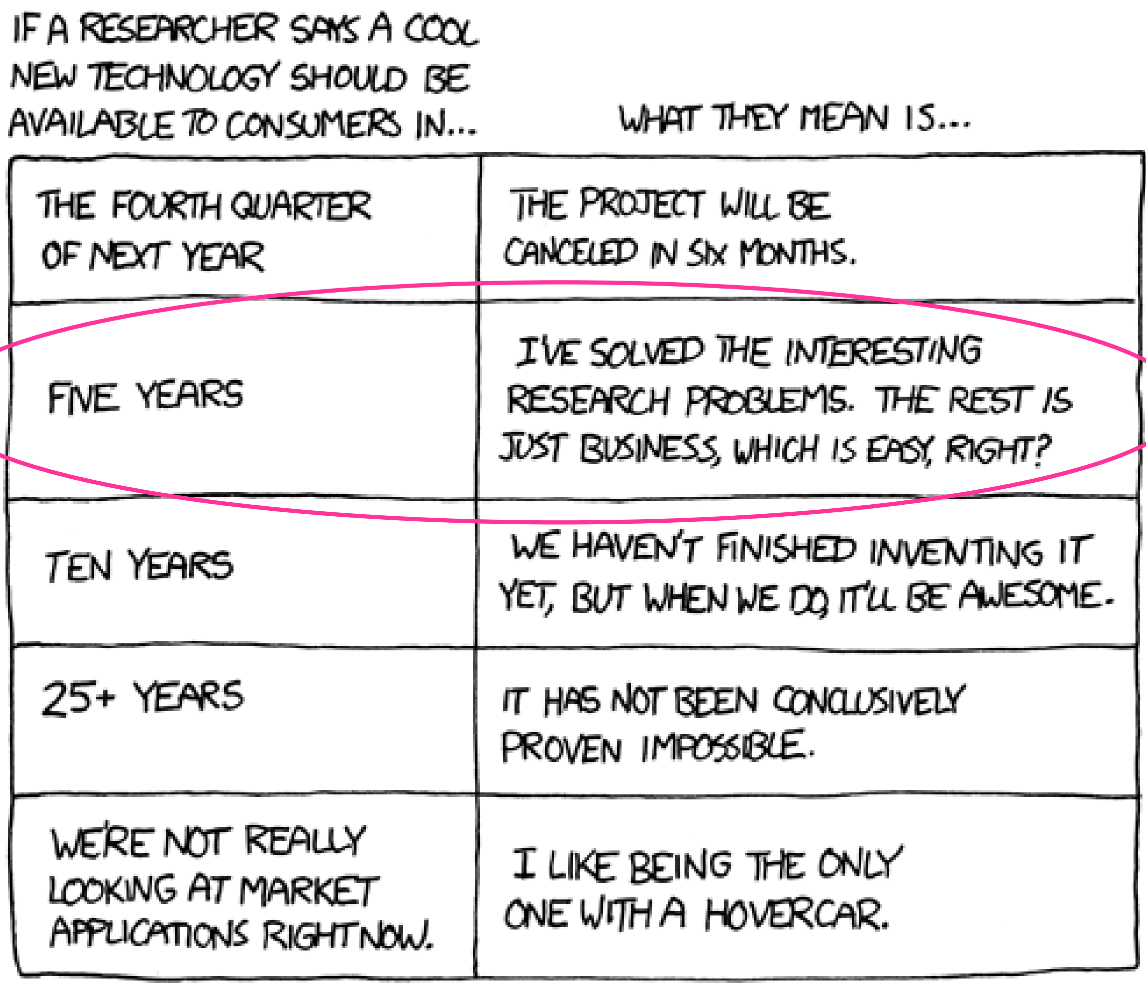
Note: In bottom panel, high scores for gross physical demands and fine motor skills indicate high demands for these kinds of tasks, so shifts in those distributions toward lower categories may be interpreted as skill upgrading. By contrast, higher levels of craft skills fit more clearly within conventional understandings of skill, so they should not be considered reverse-coded.

Very gradual upgrading trend (blue)

More upgrading than polarization 2004 2018



Researcher Translation



http://xkcd2.com/comic/678/

A technology that is '20 years away' will be 20 years away indefinitely.