GENDER, TECHNOLOGY, AND THE FUTURE OF WORK

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Automation and the Changing Landscape of Jobs

- Technological advancement—**AI, digitalization, machine learning**—and reductions in the cost of technology are changing the nature of work
- Repetitive, codifiable (routine) tasks are at the highest risk of automation owing to high substitutability with technology:
  - Past: assembly line jobs *[Autor, Levy, Murnane, 2003]*
  - Future: white-collar office jobs [*Frey and Osborne, 2017; Acemoglu and Restrepo, 2018; Brynjolfsson, Mitchell, and Rock 2018]*
- Helping people adapt to changing landscape of work will be the defining challenge of our time
- New technologies could provide opportunities for more flexible work *[Zervas, Proserpio, Byers, 2017; World Bank 2019]*

Key Questions

1. Which workers are most susceptible to automation?
2. Are women more vulnerable to risk of displacement by technology?
3. What policies are needed to ensure that technological change supports a narrowing of gender gaps in the labor market?

Roadmap

1

Construct index of routine-task intensity at work using the OECD's PIAAC dataset

2

Document gender differences in routineness across occupations, sectors, and countries

3

Estimate likelihood of women losing jobs due to gender disparities in task composition

What Distinguishes our Analysis

- Existing literature uses **aggregate US-based data** at occupational level *[Goos, Manning, and Salomons, 2014; Das and Hilgenstock, 2018]*

- OECD's PIAAC dataset provides **individual level data** on task composition at work across multiple *countries*

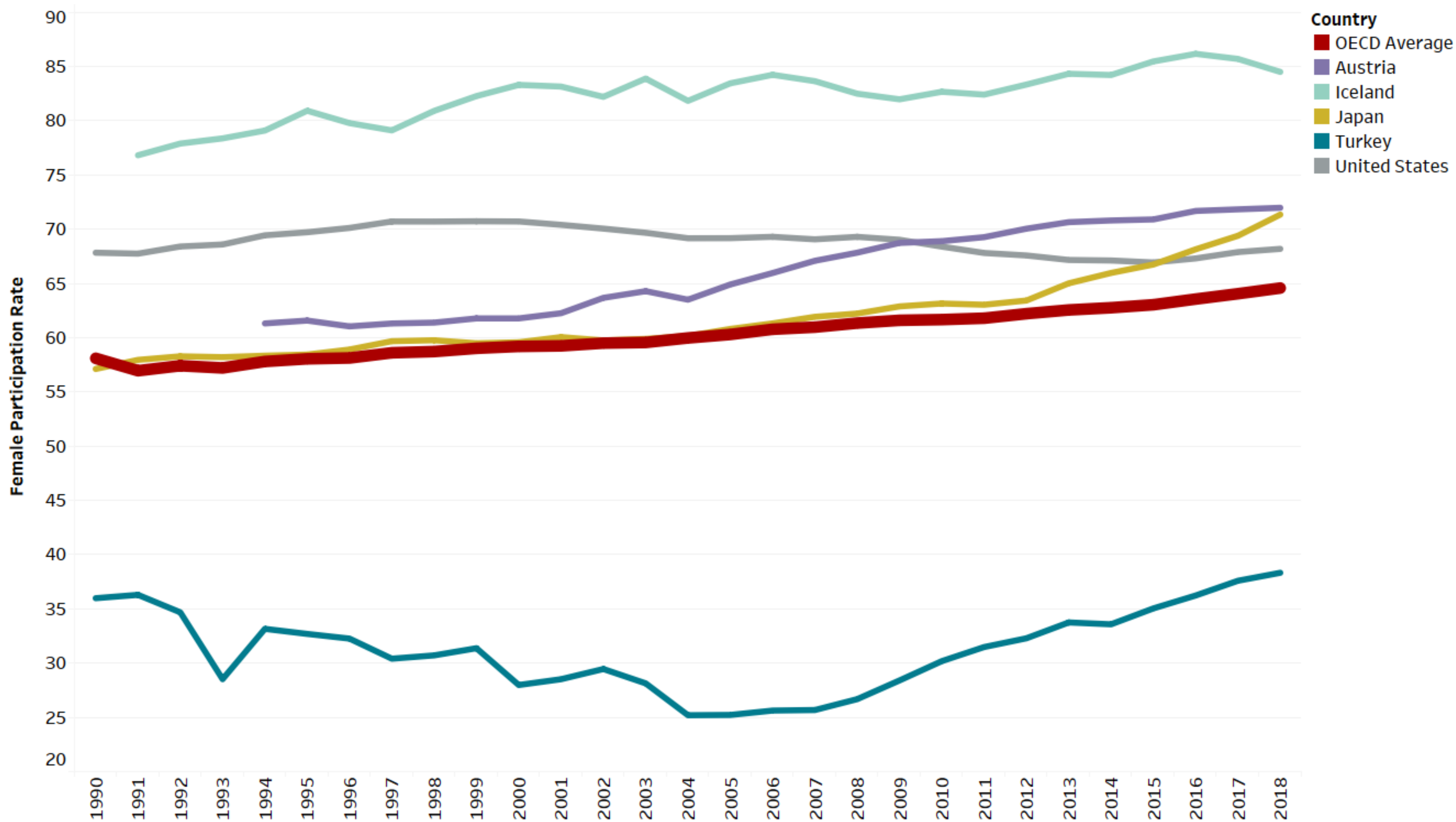
→ Relax assumption that occupations have the same task composition across countries, sectors and individuals

→ Examine differences within occupation and across countries

Key Findings

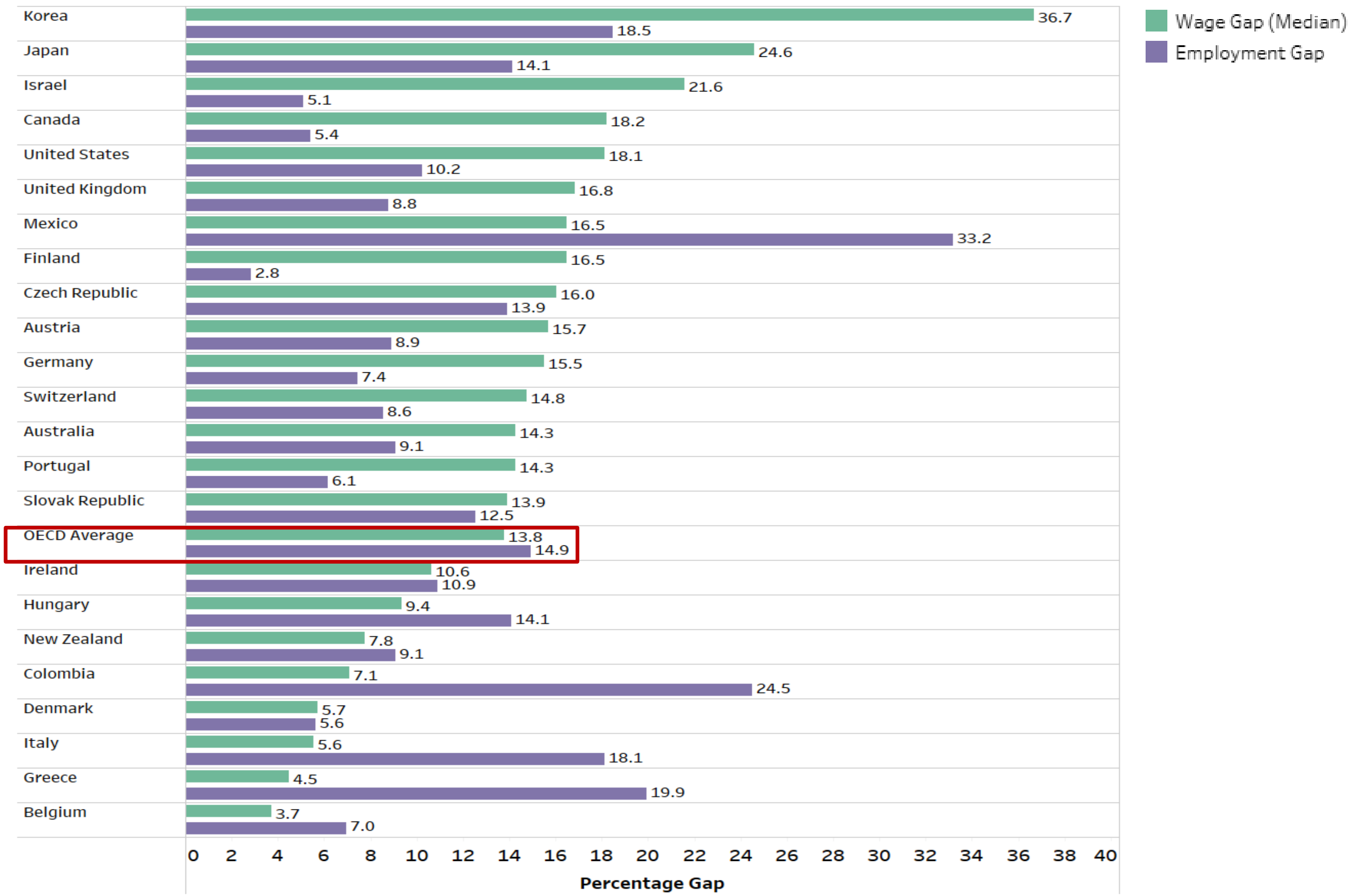
1. Women perform more routine and less analytical tasks than men across all countries, sectors and occupations
2. 26 million female jobs (in 30 countries) at high risk of being automated, females at higher risk than men in many countries
3. Less well-educated and older female workers, and those in low-skilled positions, are disproportionately exposed to automation

Modest Up-tick in Female Labor Force Participation Rates Over the Last 30 Years



Source. OECD (2018)

Wage and Employment Gaps Remain Significant in OECD Countries



Note. The employment gap is male minus female employment rates. The wage gap is the difference between median earnings of men and women relative to median earnings of men.
Source. Wage gap, OECD (2016); Employment gap, OECD (2018).

How Routine are Women's Jobs?

Defining the Routinization of Work (Routine Task Intensity)

RTI = Routine − Manual − Abstract

Routine

Lack of job flexibility
- Change sequence of tasks, how to do work, speed, hours

Little learning on the job
- Learn by doing, keep up with new products/services

Repetitive tasks
- Hand/finger accuracy

Manual

Long hours of physical work

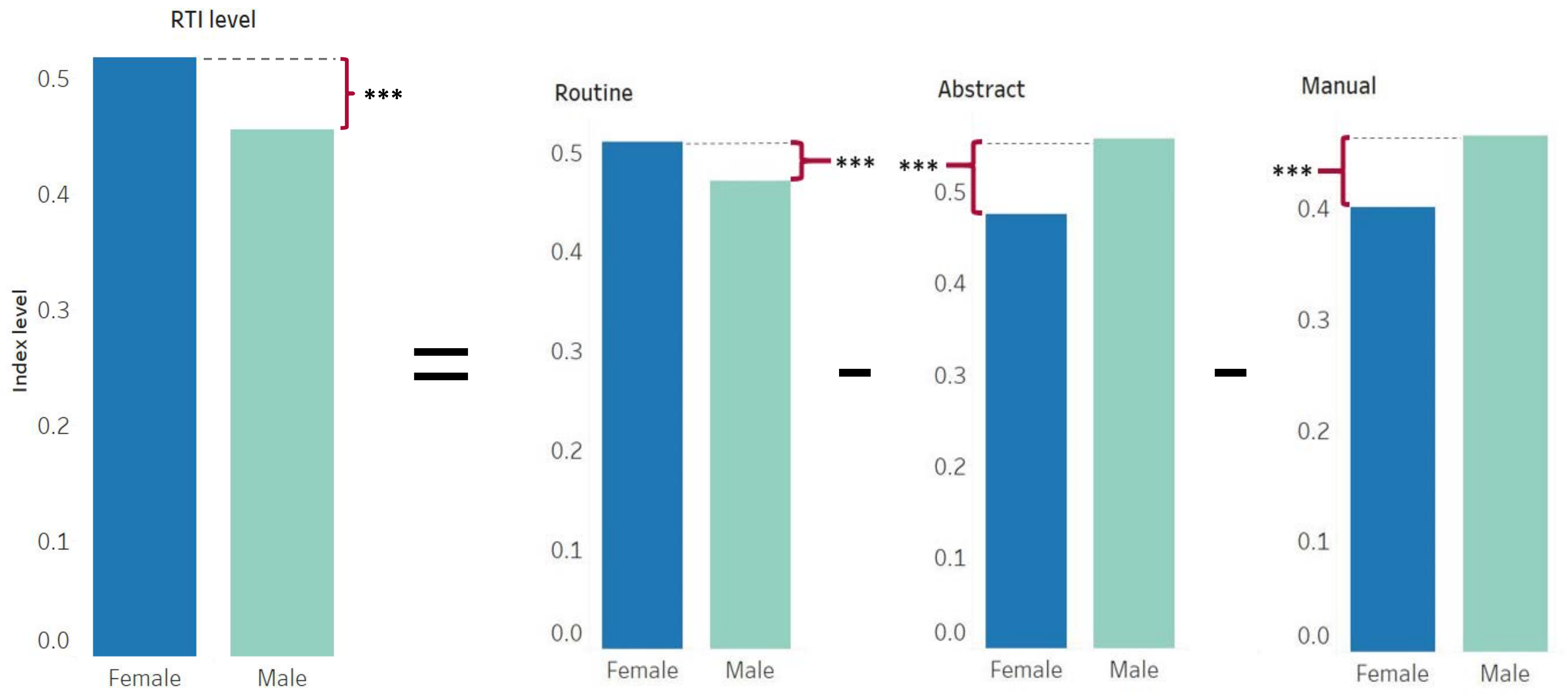
Abstract

Analytical
- Face complex problems, read diagrams, write reports

Interpersonal
- Persuade people, negotiate

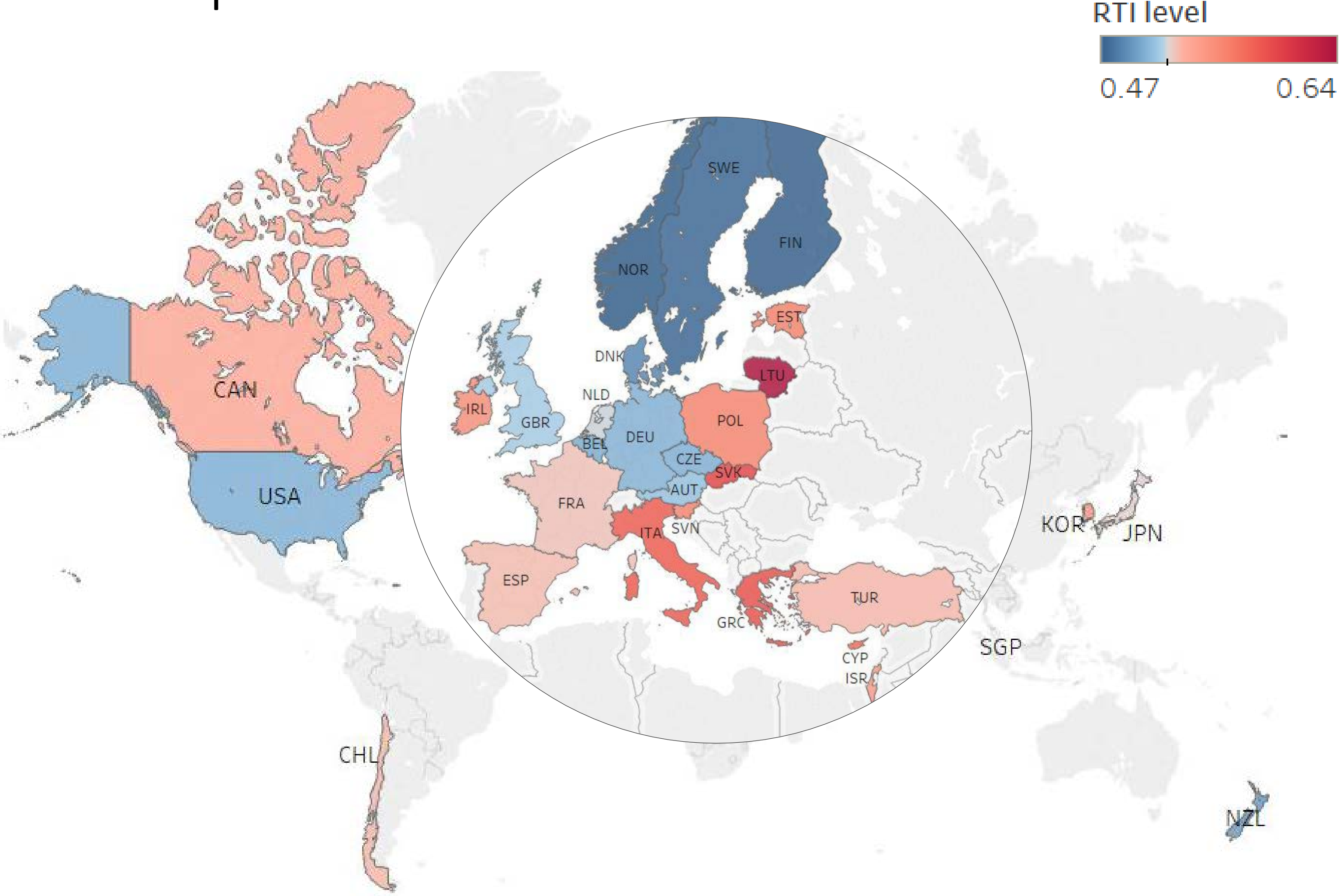
Note: Index is constructed using individual level data from the OECD's Program for the International Assessment of Adult Competencies surveys. Principal component analysis was used to derive an index for each RTI component. Index is normalized to lie between 0 and 1.

On Average, Women Perform More Routine and Less Analytical Tasks than Men



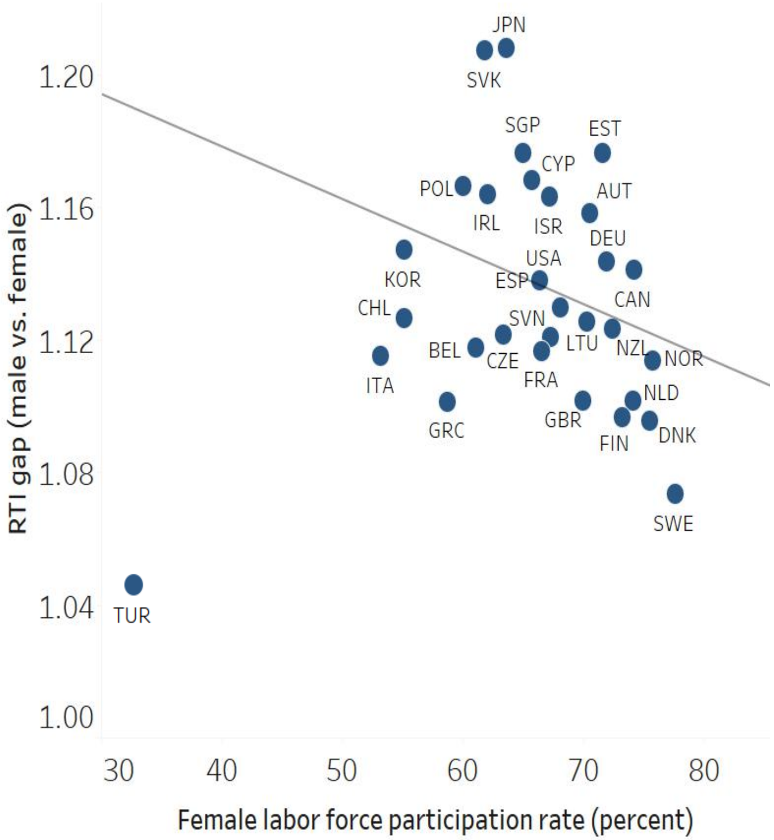
Note. Indices are normalized to lie between 0 and 1. Differences in RTI index across gender are statistically significant at 1% level.

Routinization Levels for Women are Highest in Eastern and Southern Europe and Lowest in Scandinavia and Central Europe



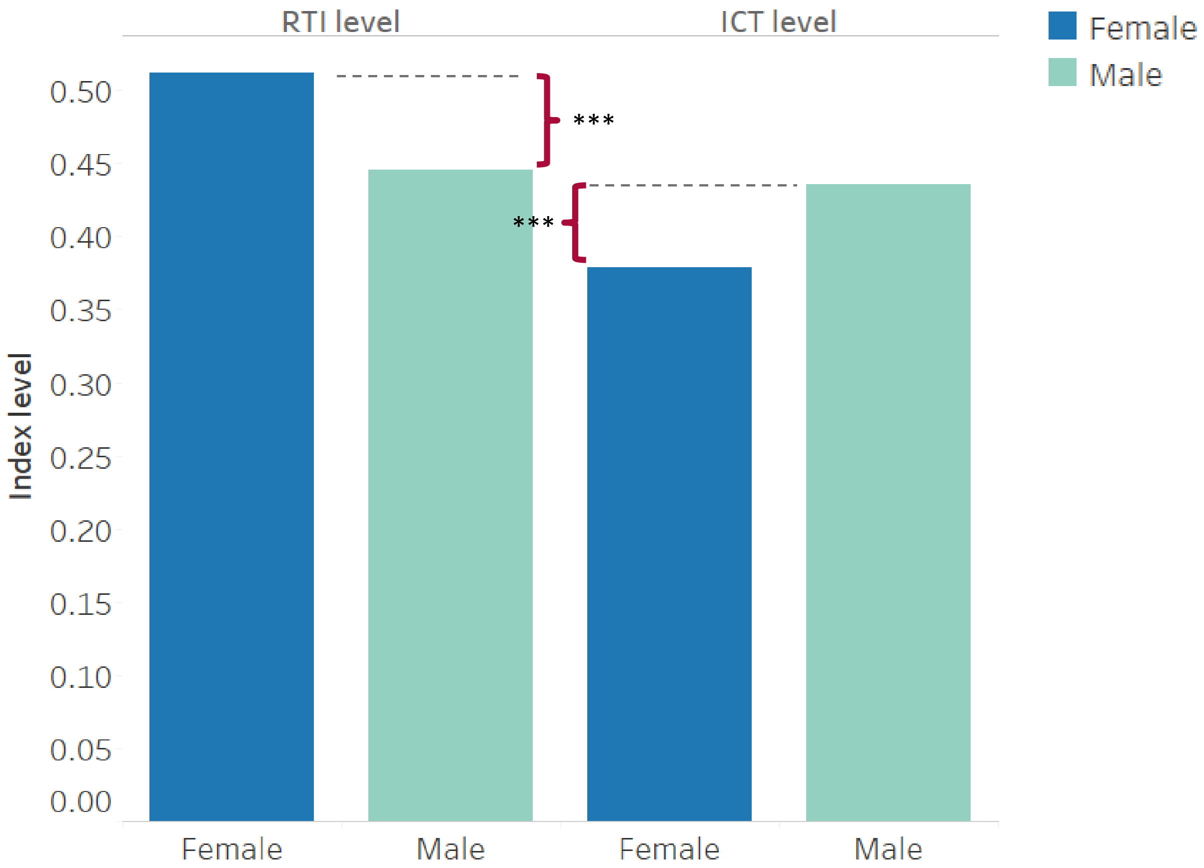
Note. RTI index is calculated at the female level using information on routine, abstract, and manual tasks performed.

Gender Routinization Gaps Vary with Female LFP and Size of Manufacturing Sector



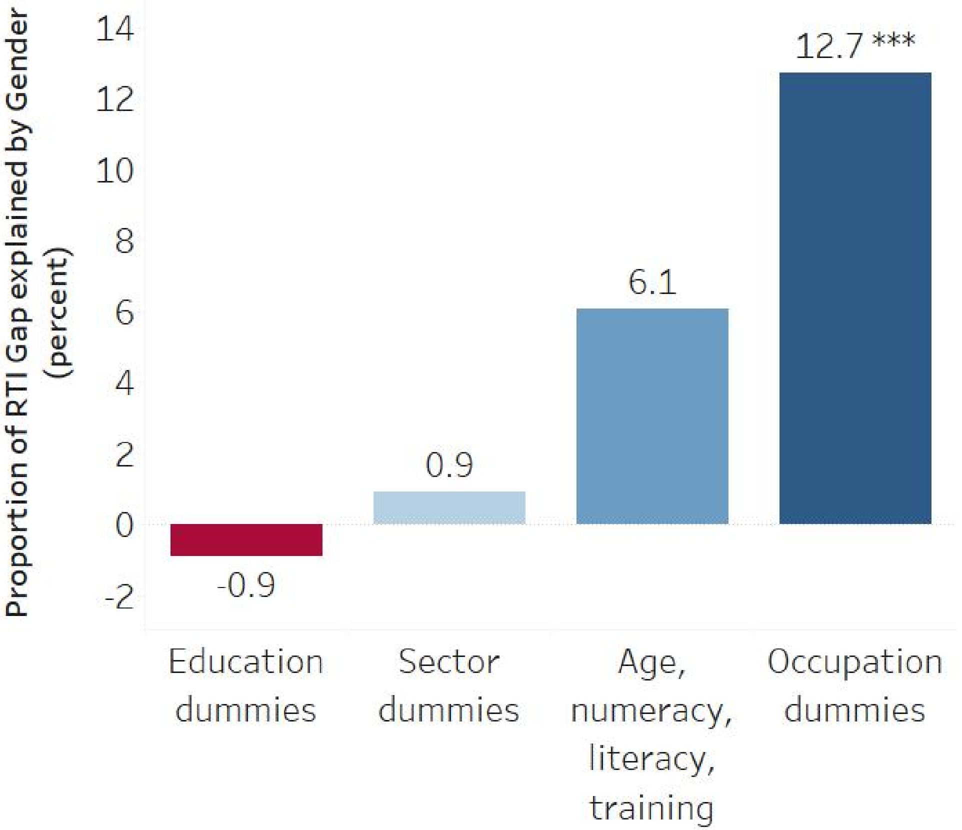
Note. RTI gap= Female RTI level/ Male RTI level. The trend line is calculated excluding the outlier of Turkey.

On Average, Women Use Less Information and Communication Technology (ICT)



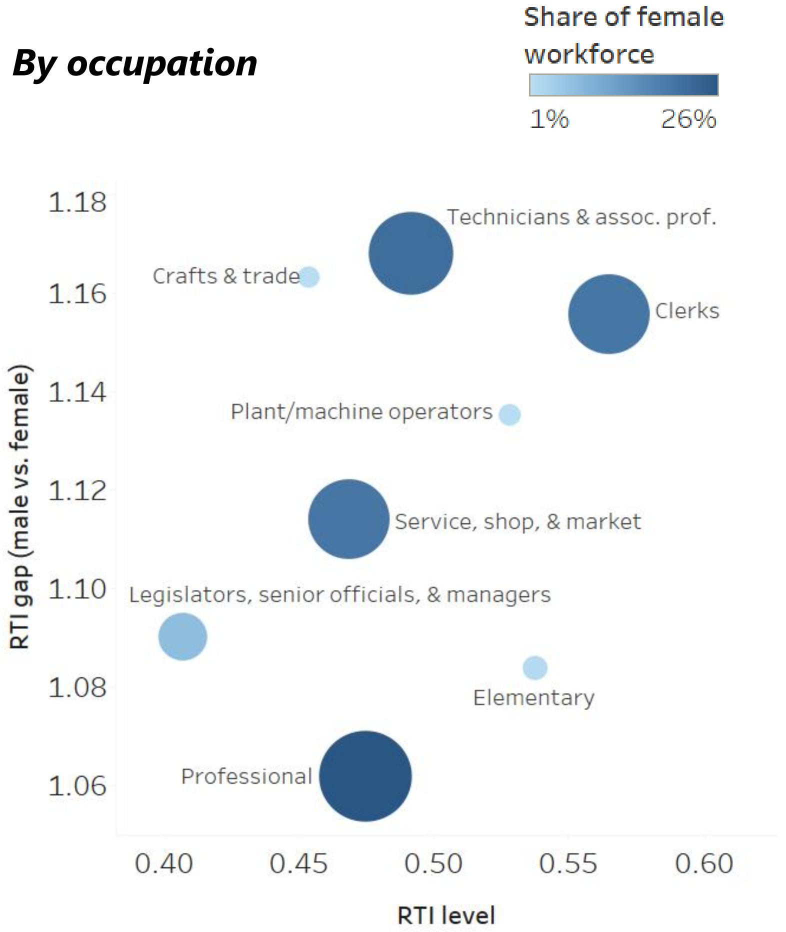
Note. Differences in RTI and ICT use indices across gender are statistically significant at 1% level.

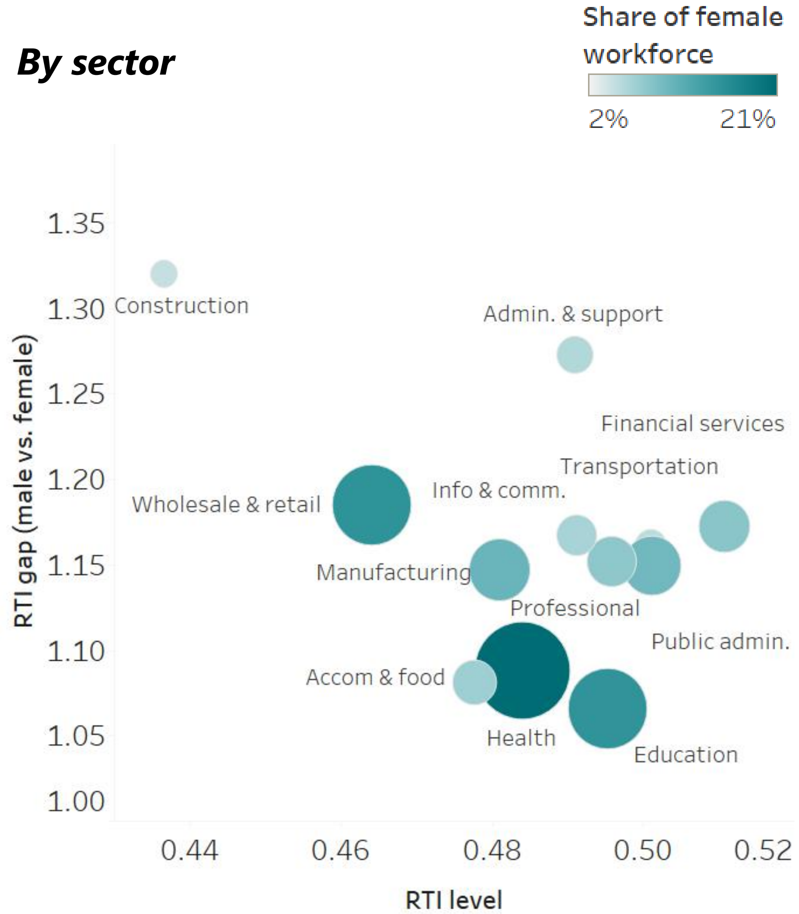
Selection into Occupations Explains Most of Unconditional Gender Gap in Routinization



Note. This decomposition is based on the individual-level regression: $RTI_i = \beta_0 + \beta_1 Female_{ic} + \sum_k \beta_k^{ind} X_{ick}^{ind} + \sum_m \beta_m^{ability} X_{icm}^{ability} + \sum_n \beta_n^{job} X_{icn}^{job} + \alpha_{ic} + \sigma_{ic} + \tau_c + \epsilon_{ic}$. Bars indicate the share of unconditional RTI gap explained by a given set of variables. Statistical significance levels: *** p<0.01; ** p<0.05; * p<0.1.

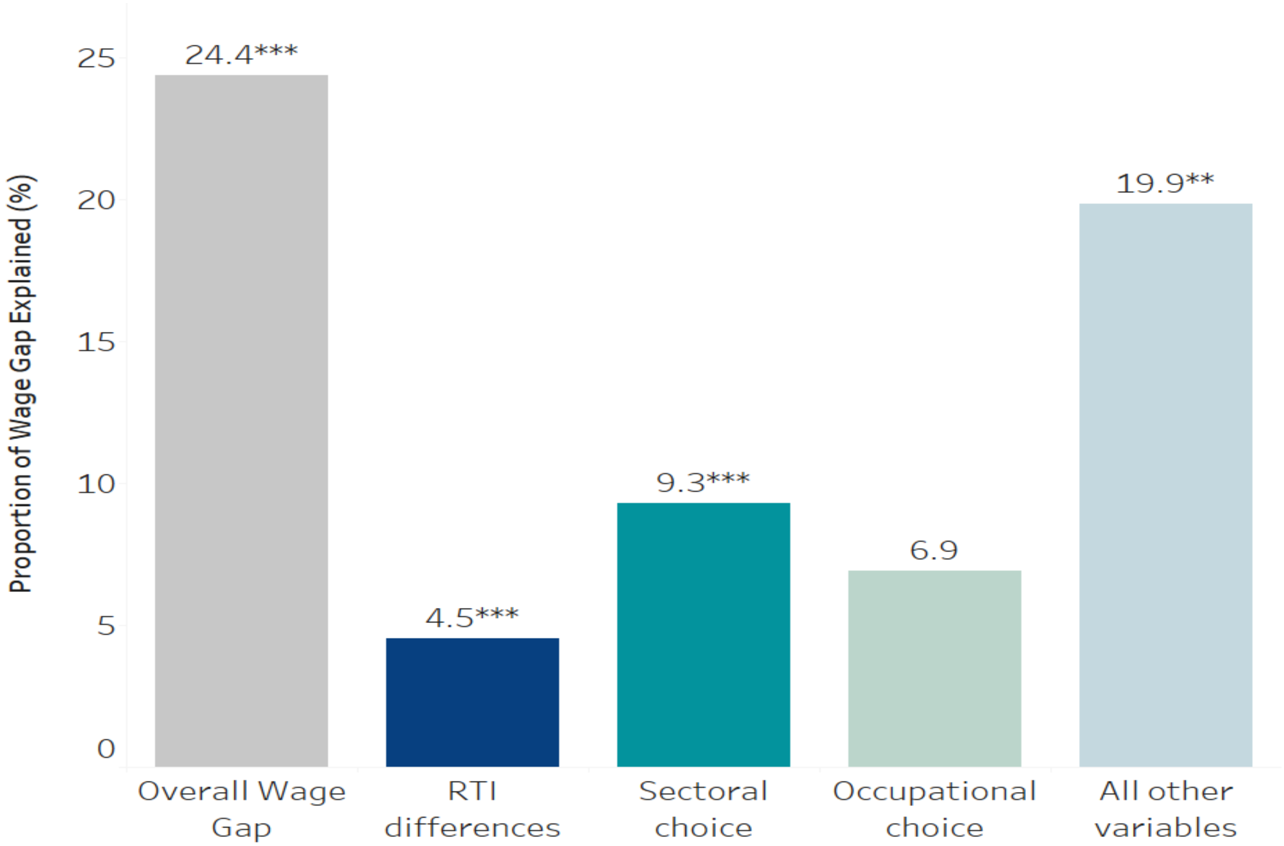
Gender RTI Gaps Exist Across All Occupations and Sectors





Note: The size of the circle indicates the share of women in that occupation (sector) as a fraction of the female workforce. RTI index is calculated at the individual level using information on routine, abstract, and manual tasks. Gender differences in RTI are statistically significant at 1 percent level for all occupations (sectors). Size of bubble indicates share of female workforce.

Gender Differences in RTI Explain Significant Portion of Wage Gap



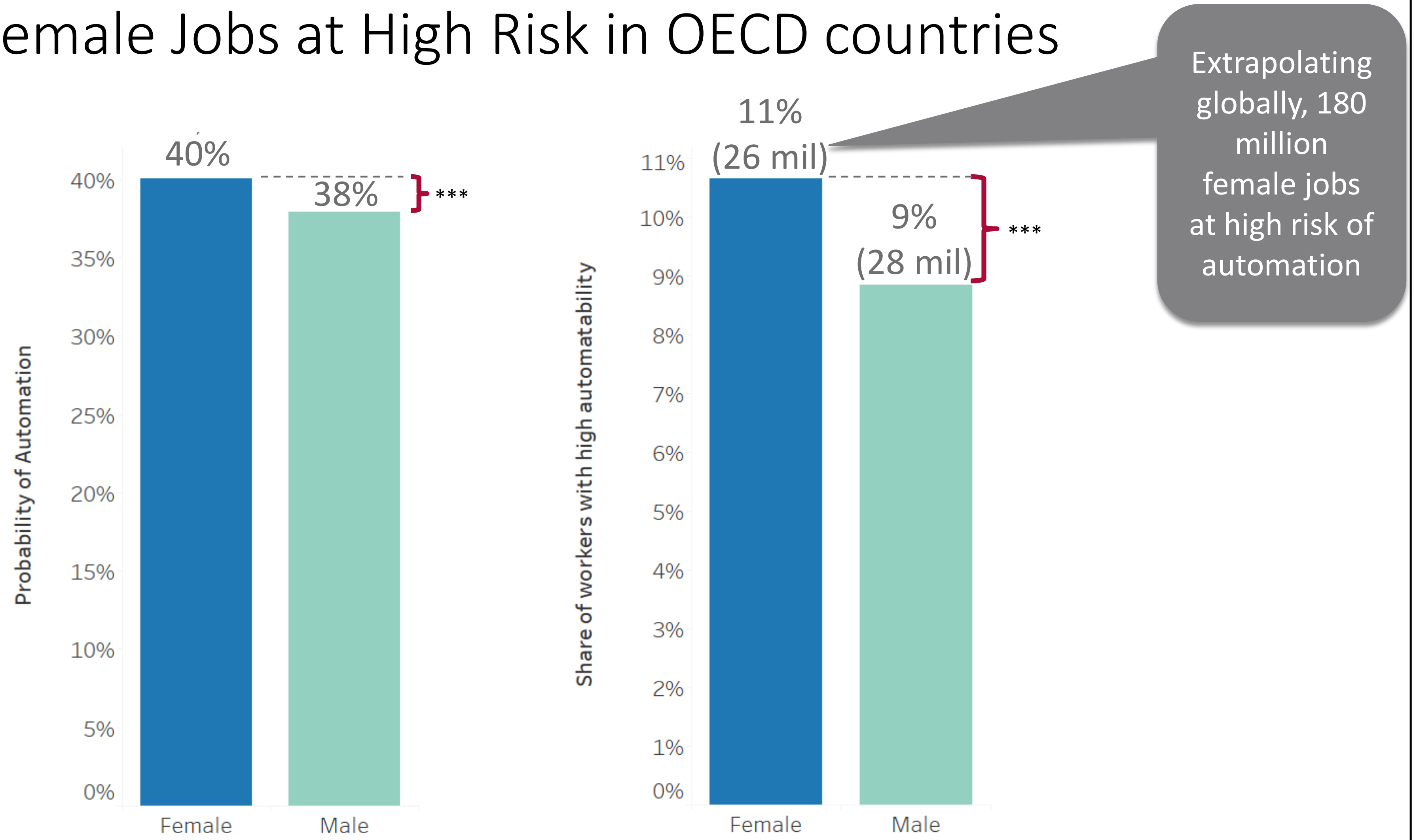
Note. This decomposition evaluates the degree to which differences in RTI, demographic and sorting variables explain the gender wage gap. Demographic and sorting variables include age, education, numeracy and literacy scores, on-the-job training, and country, sector, and occupation controls. Bars indicate the share of unconditional wage gap explained by a given set of variables. Statistical significance levels: *** p<0.01;** p<0.05;* p<0.1.

Quantifying the Risk of Automation: Potential Impact on Jobs

Probability of Job Automation as a Function of Job Tasks

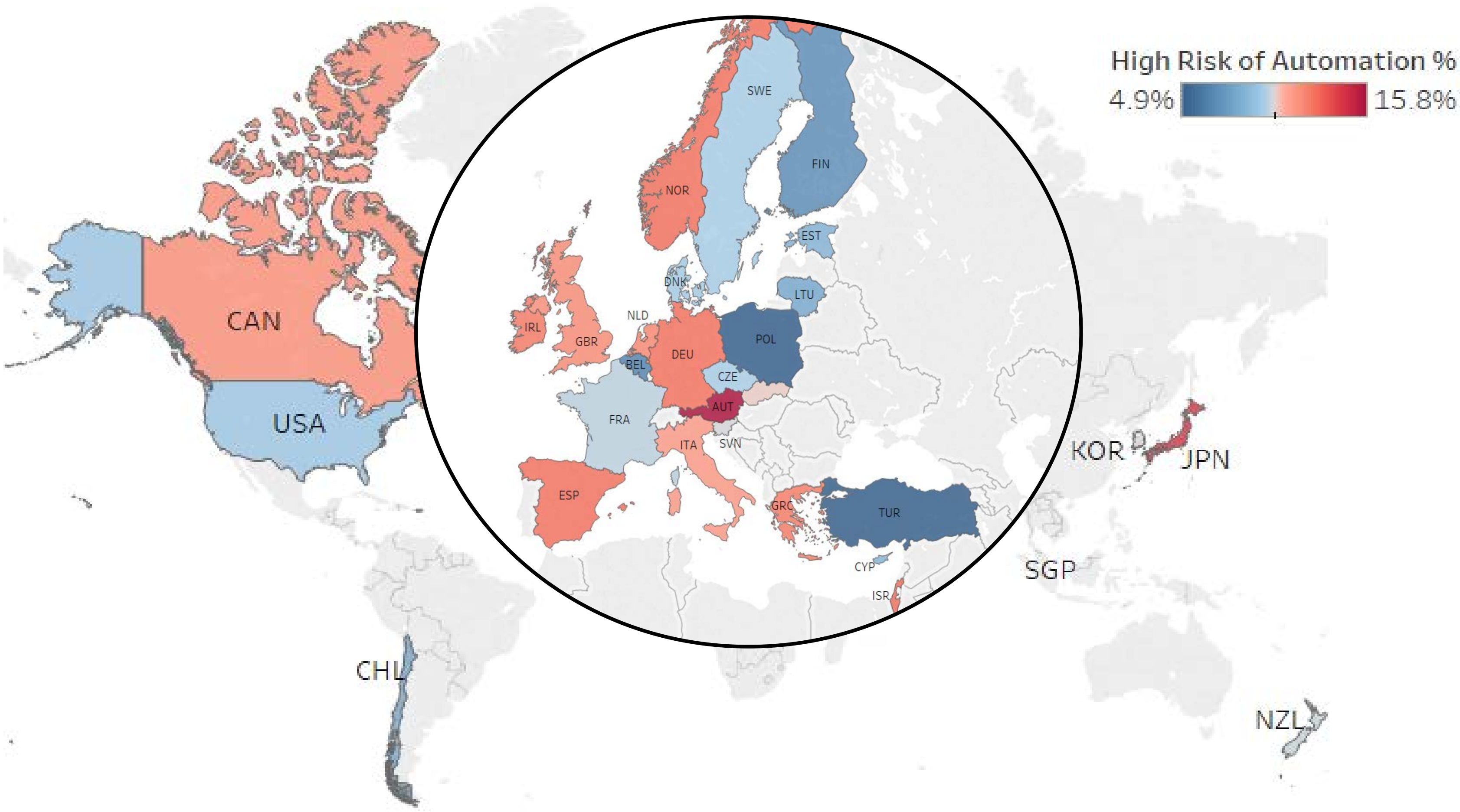
- Current literature draws upon occupational level data for predicting the susceptibility of workers to automation
- **Frey and Osbourne (2017)** estimate probability of automation at the current state of technology for occupations in the O*NET database
- Using **Expectation-Maximization (EM) algorithm**, we relate occupation level probabilities to individual task characteristics (Arntz, Gregory and Zierahn, 2017)
- This allows us to predict differences in the susceptibility to automation at the **individual level** and therefore between genders

Women at Higher Risk of Automation- 26 Million Female Jobs at High Risk in OECD countries



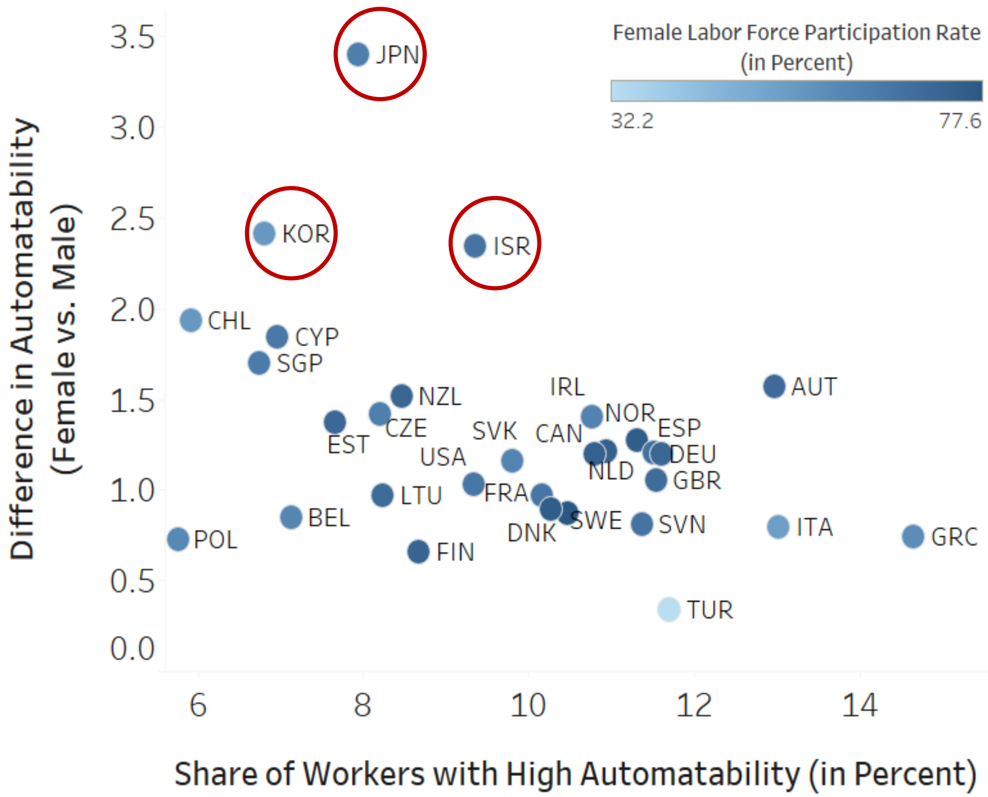
Note. The probability of automation is estimated using an Expected Maximization algorithm that relates individual characteristics (age, education, training, among others) and job task characteristics to occupational-level risk of automation. Differences in probability of automation and share of workers with high automatability across gender are statistically significant at 1% level. High automatability is defined as having probability of automation >= 0.7. Number of individuals at high risk based on sample of 30 countries.

Share of Females at High Risk of Automation Varies Across Countries



Note. The probability of automation is estimated using an Expected Maximization algorithm that relates individual characteristics (age, education, training, among other) and job task characteristics to occupational level risk of automation. High automatability is defined as having probability of automation >= 0.7.

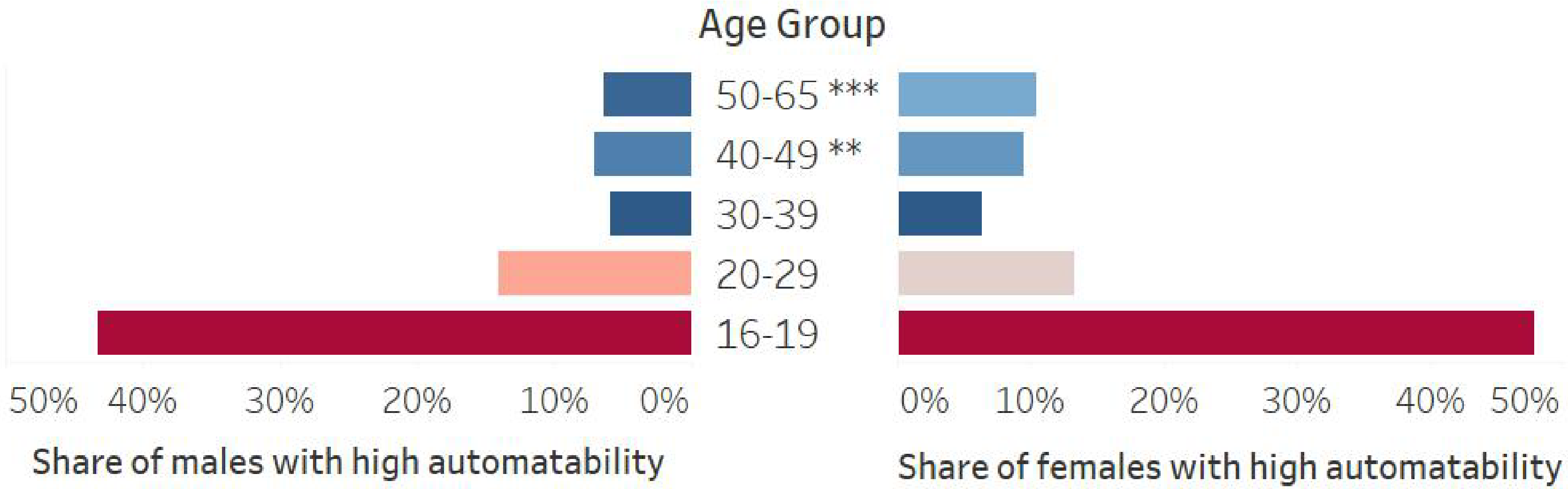
Significant Cross-Country Heterogeneity in the Gender Gap in Likelihood of Automation



Note. The probability of automation is estimated using an Expected Maximization algorithm that relates individual characteristics (age, education, training, among other) and job task characteristics to occupational level risk of automation. High automatability is defined as having probability of automation >= 0.7. Difference in automatability = (Share of females with high automatability) / (Share of males with high automatability).

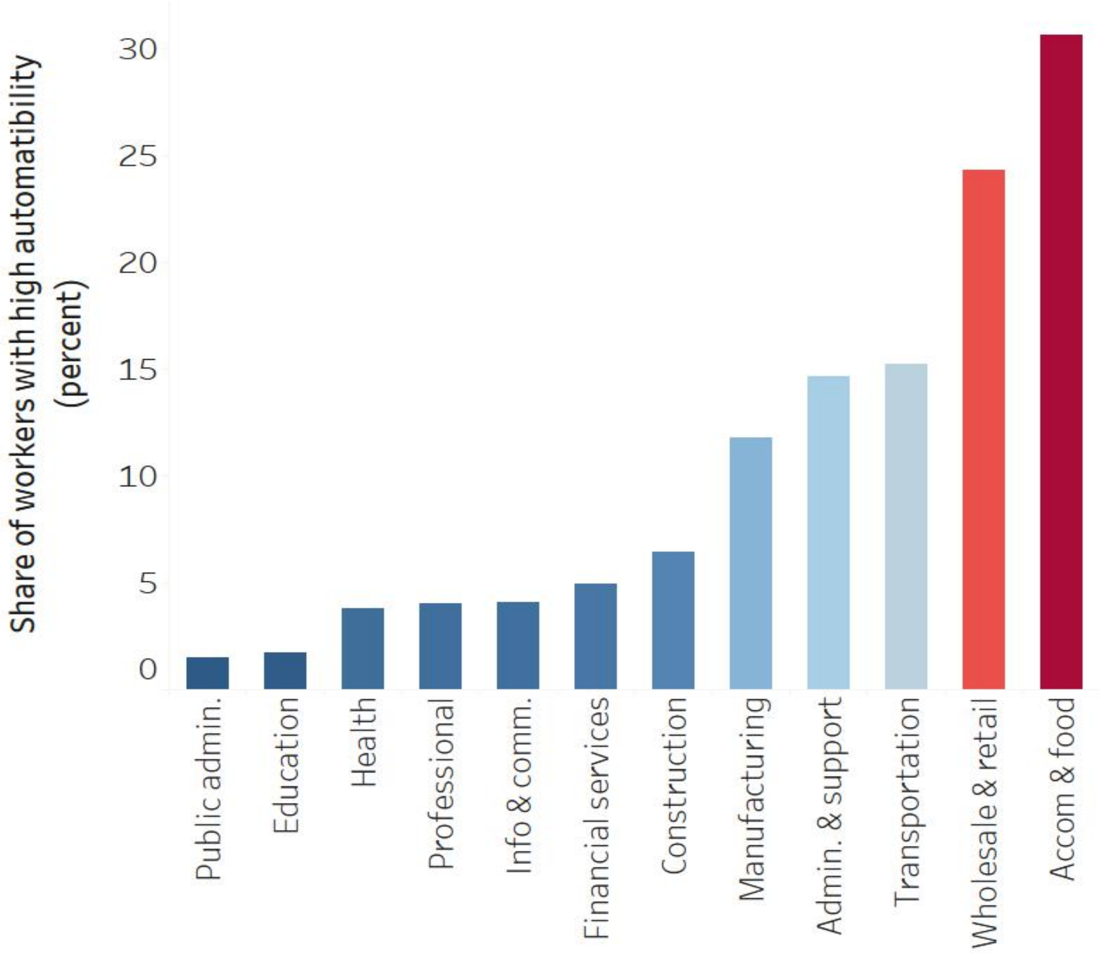
Older Women at Significantly Higher Risk for Automation

Low-skilled, less-educated women most at risk



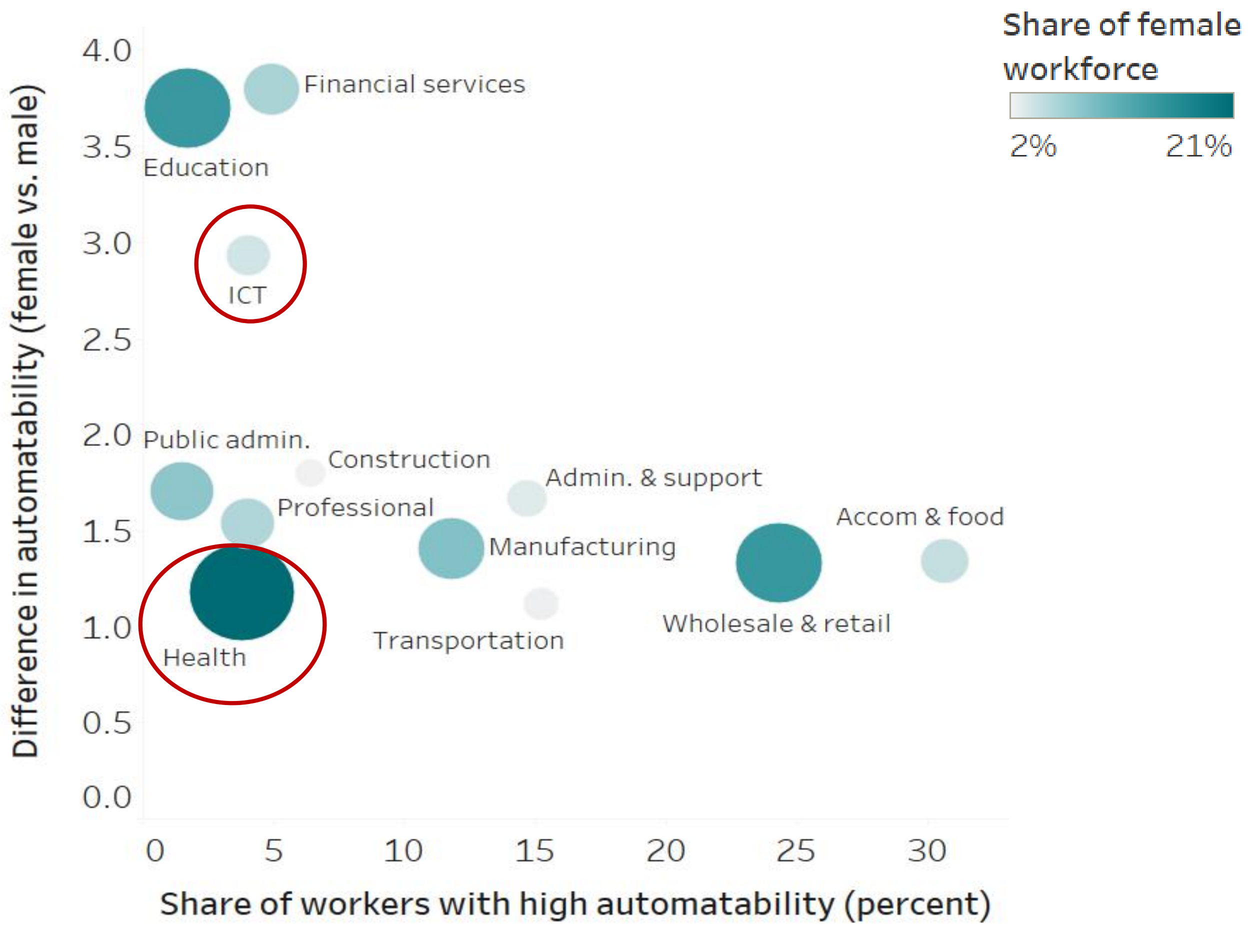
Note. The probability of automation is estimated using an Expected Maximization algorithm that relates individual characteristics (age, education, training, among other) and job task characteristics to occupational level risk of automation. High automatability is defined as having probability of automation >= 0.7. Statistical significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Some Sectors Face a Higher Risk of Automation



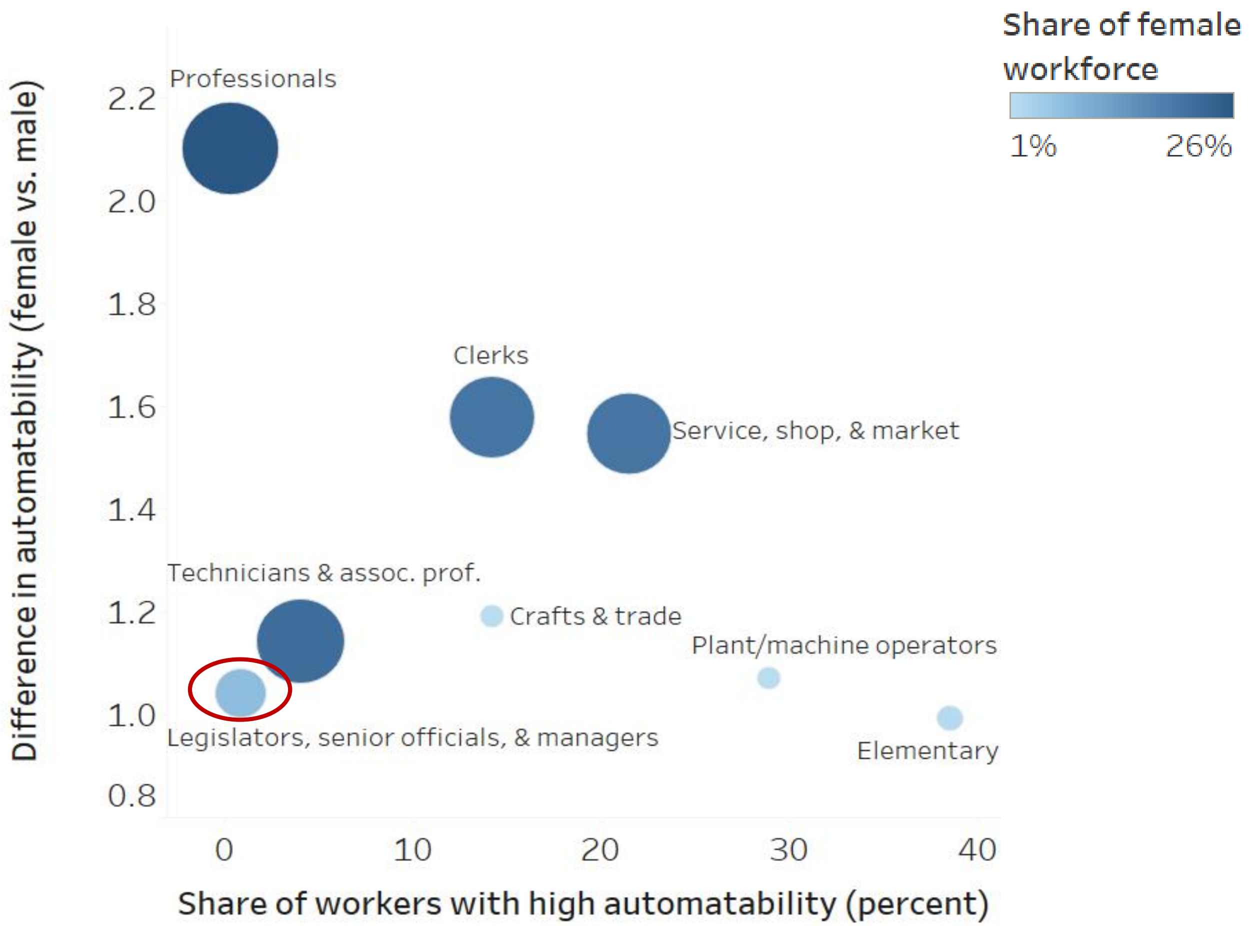
Note. High automatability is defined as having probability of automation > 0.7.
The figure includes both male and female workers in a sector.

Women are Overrepresented in Sectors at Low Risk of Automation, But Still Face Higher Risk than Men…



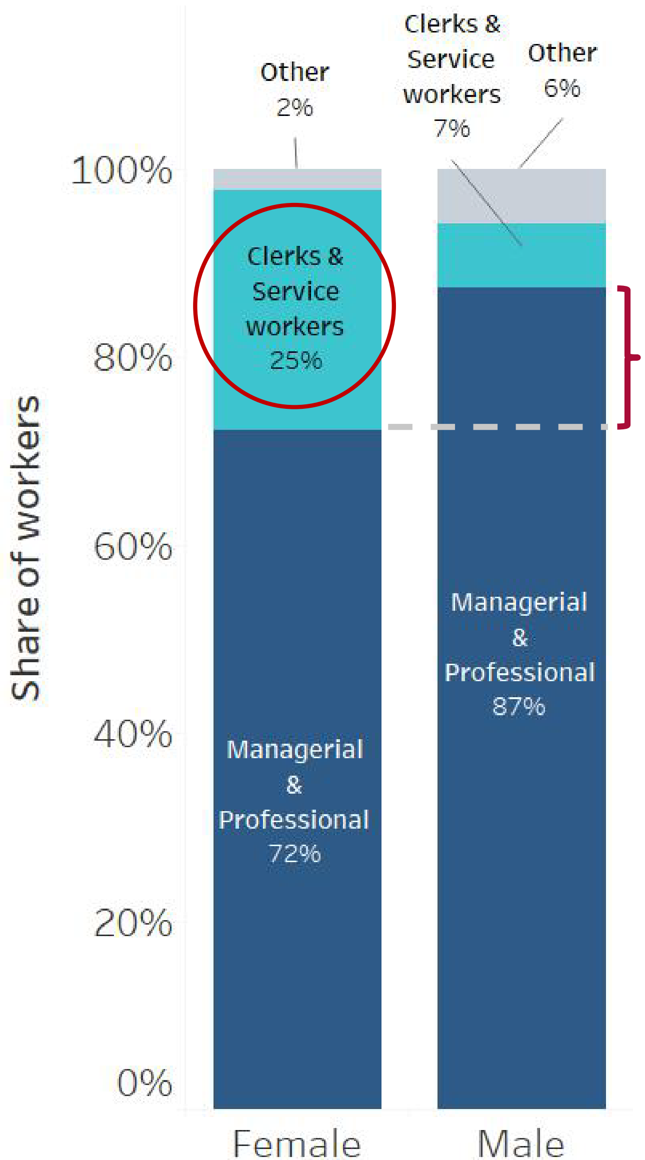
Note. Difference in automatability = (Female probability of automation) / (Male probability of automation). Size of bubble indicates share of female workforce.

…in Part, Because They Hold Lower-Level, Less-skilled Positions

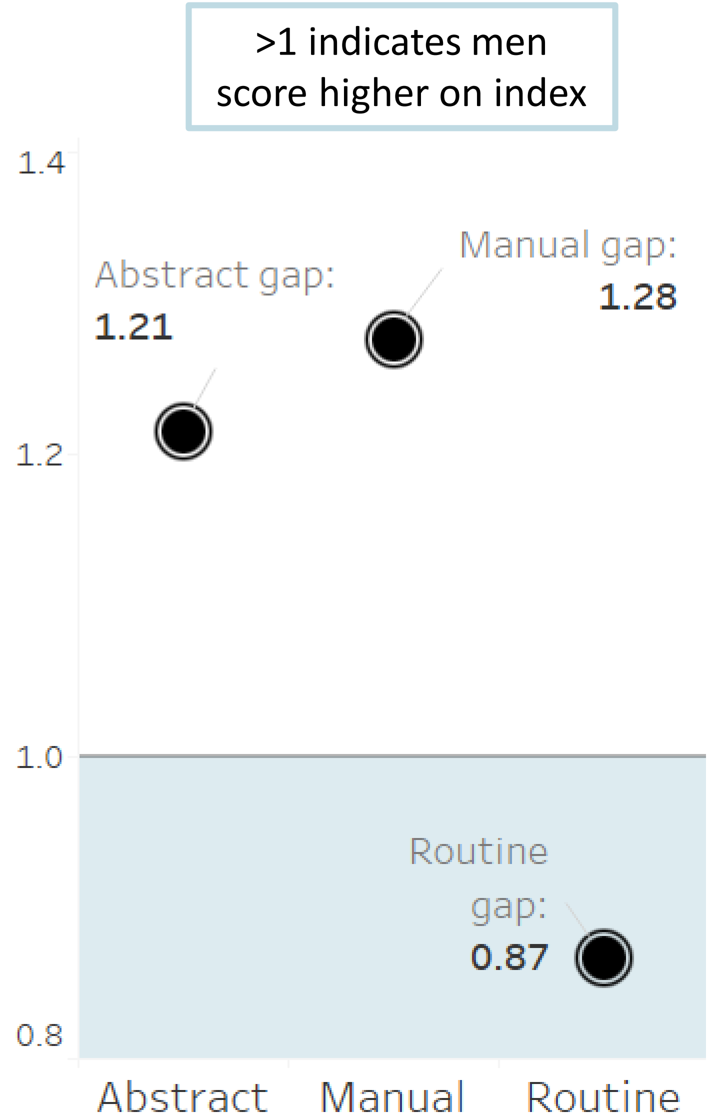


Note. Difference in automatability = (Female probability of automation) / (Male probability of automation). Size of bubble indicates share of female workforce.

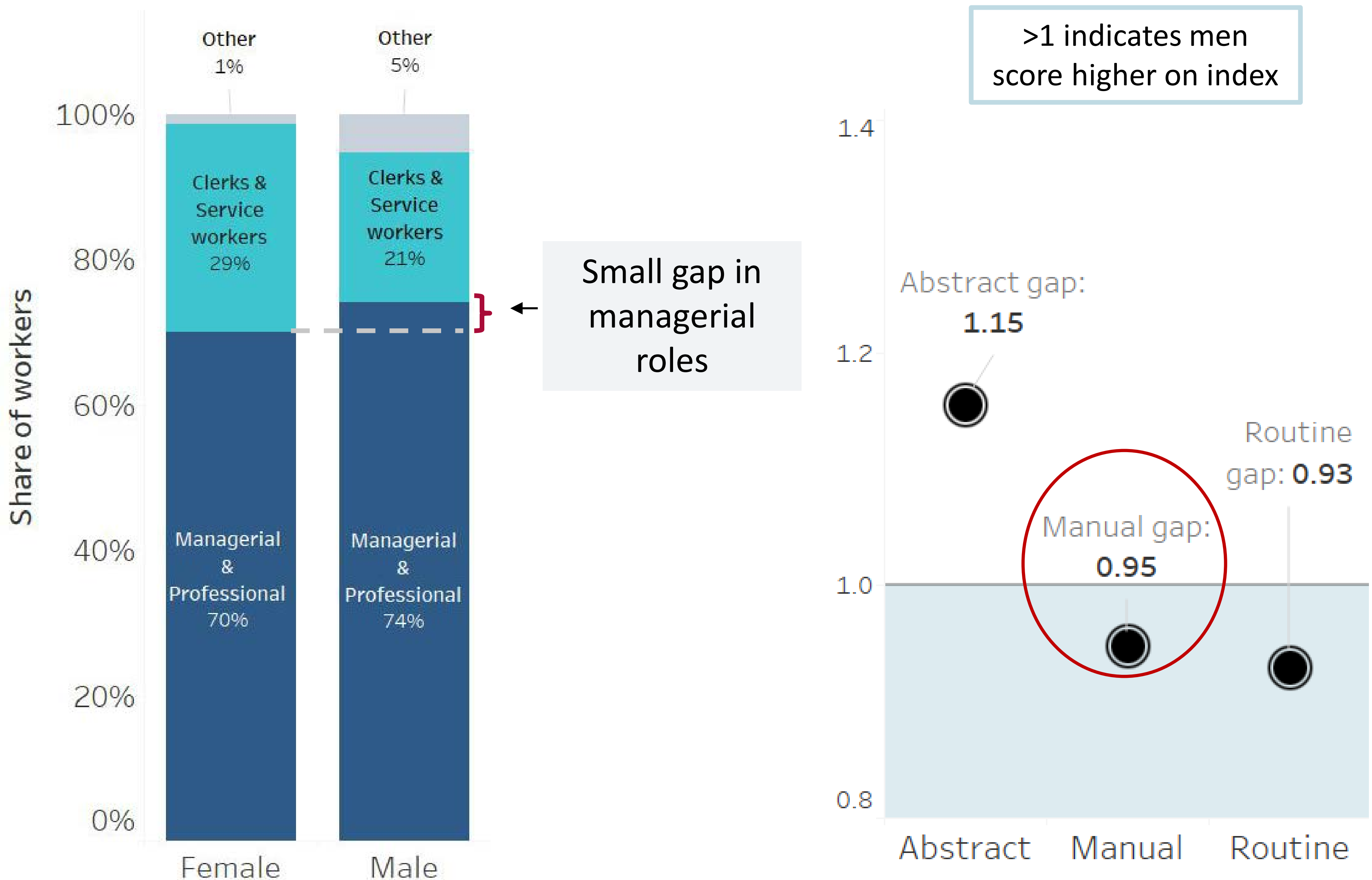
Zooming in: ICT Sector



Significant differences in occupational distribution



Zooming in: Healthcare Sector

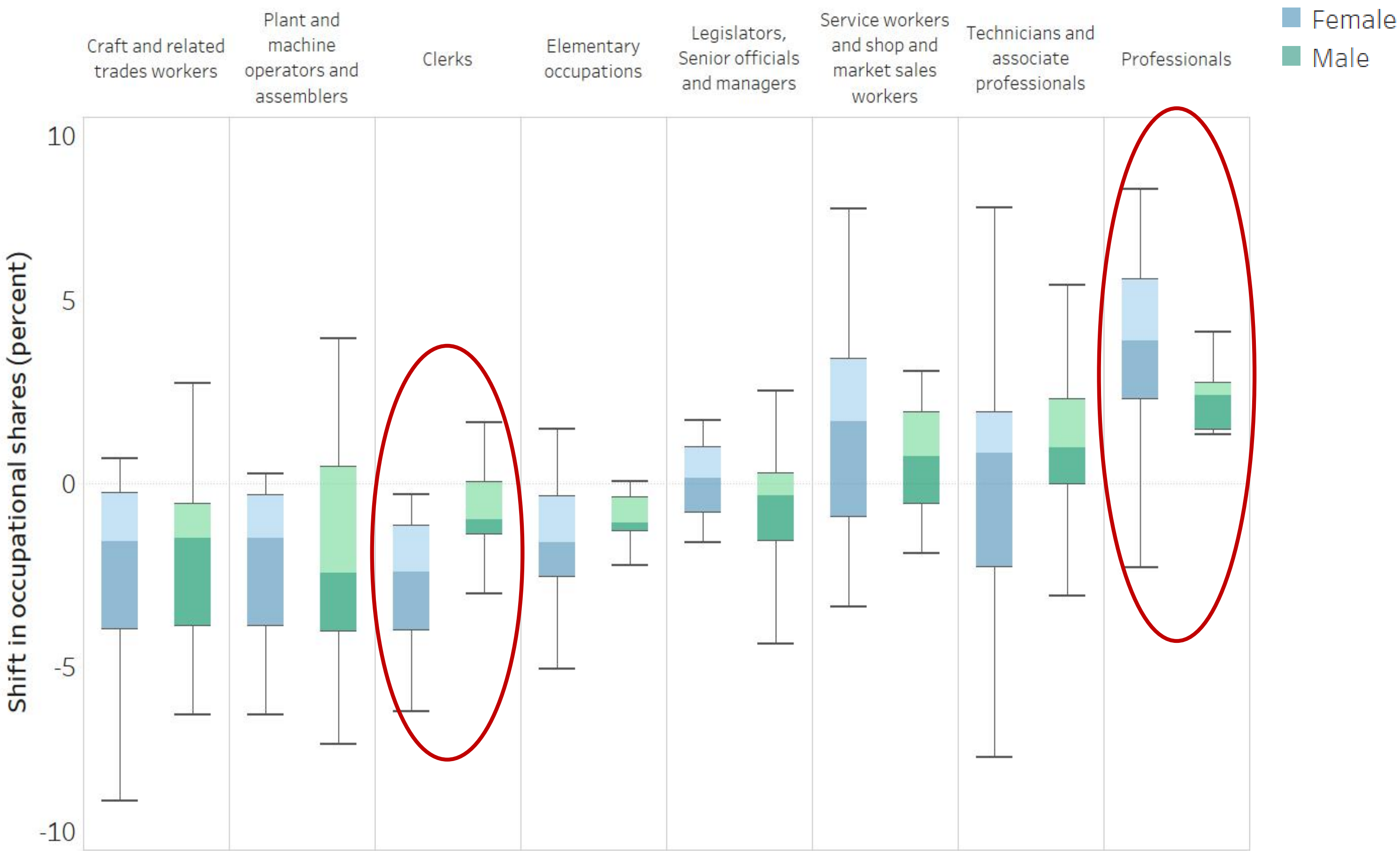


Important to note

Caveats

- Estimates presents a lower bound for the potential impact of automation
- Estimates based on technological feasibility of automation as opposed to the economic feasibility
- Opportunities and challenges associated with the gig economy not fully captured

Bright Spot: Women have Shifted into More Technical and Professional Occupations (1994-2016)



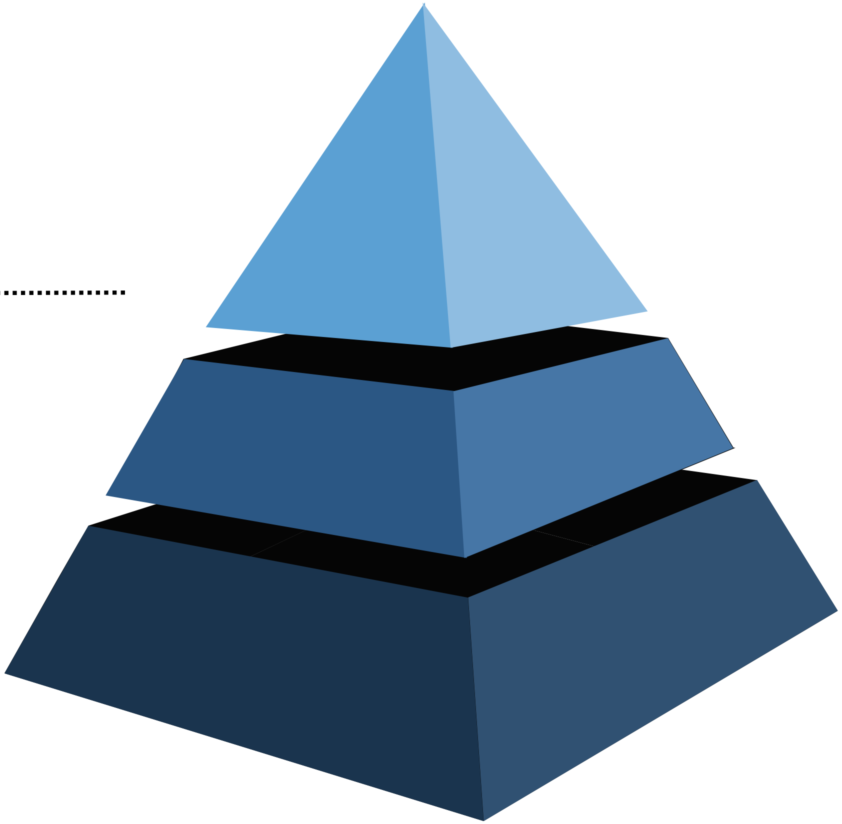
Shift in occupation calculated as difference between share of female (male) workers in occupation X and country Y in 1994, and the share of female (male) workers in same occupation and country in 2016. Top and bottom values of the intervals represent country-specific maximum and minimum values for occupational share differences. Data on 1994 occupational distribution are taken from the International Adult Literacy Survey.

Policy Considerations: Helping Women Transition to a New Future of Work

Empowering women with skills

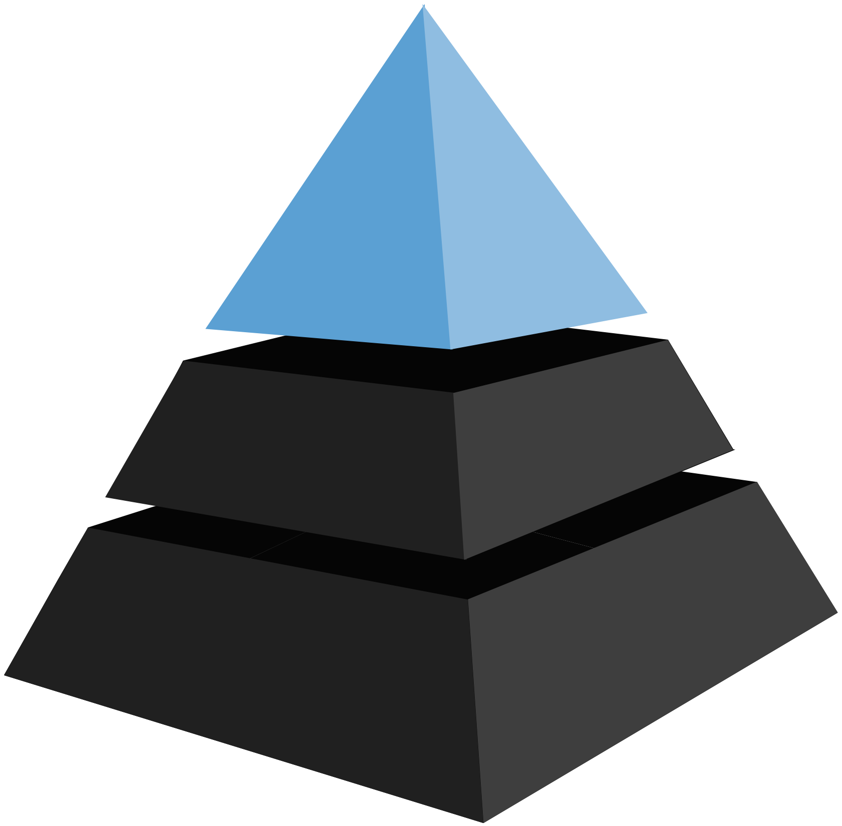
Bringing more women into the workforce (increase FLFP)

Easing transition for workers



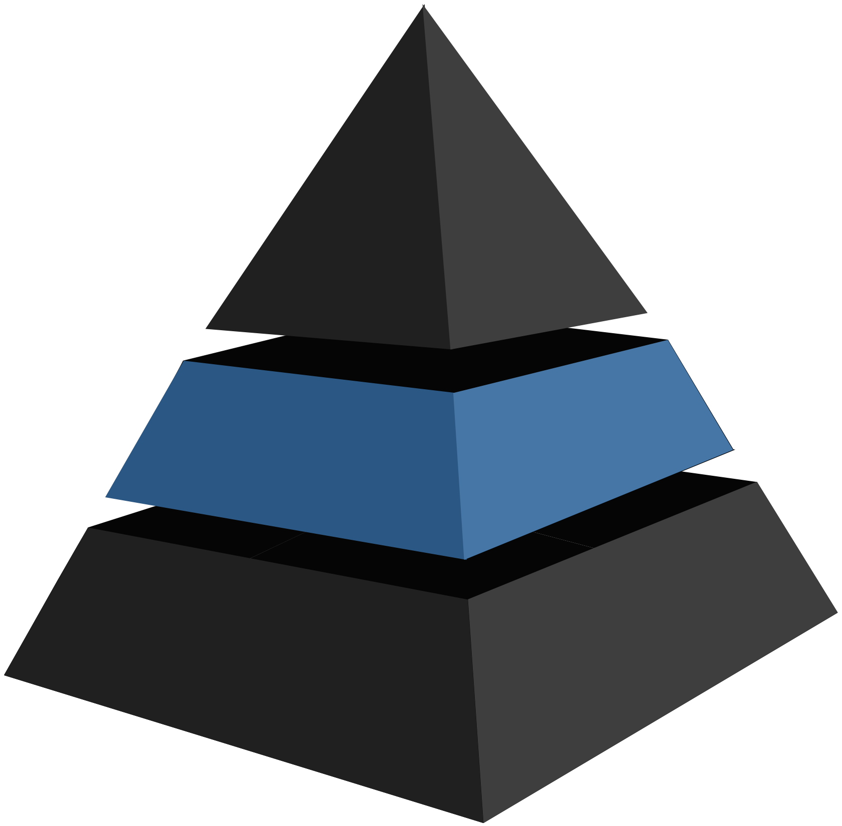
Empowering Women with Skills

- Invest in early education, focusing on STEM fields where women are relatively disadvantaged
    - Girls Who Code (U.S.), Girls in ICT Day (UN)
- Reduce skill mis-matches and encourage lifelong learning
    - Continuing vocational training (CVT) in EU states
- Foster gender parity in management positions
    - Quotas on women’s representation in company boards (e.g., Norway)
- Bridge gender digital divide
    - Gender-specific goals in national ICT policies (e.g., Finland)



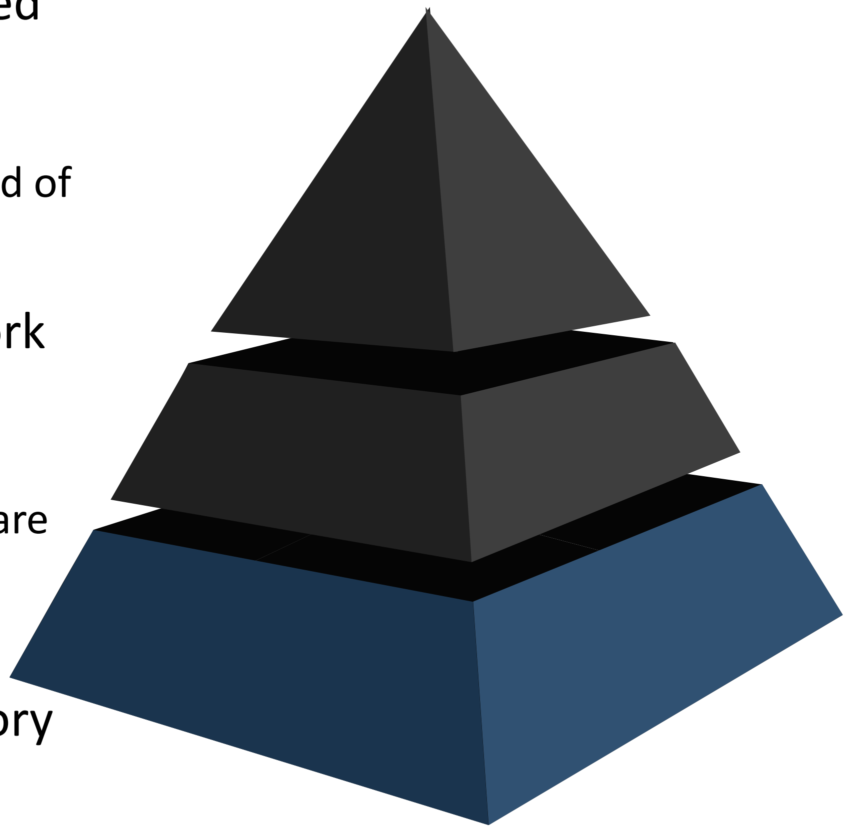
Bringing More Women into the Workforce

- Tackle legal, regulatory, and other barriers
- Help women balance the unpaid care burden
  - Maternity leave policies; affordable child care; flexible work arrangements
- Implement tax policies that do not penalize the secondary earner
  - Replacing family taxation with individual taxation (e.g., Sweden, Canada, Italy)
- Provide tax relief for low-income families
  - Earned income tax credit (e.g., U.S.), or a combination of tax and transfers (e.g., U.K., other G7 countries)



Easing Transition for Workers

- Ensure gender parity in support for displaced workers
  - Individual training accounts (e.g., France and Singapore) linking training to individuals instead of jobs or sectors
- Adapt social protection to new forms of work by creating portable benefits and closing coverage gaps
  - Healthy San Francisco, which provides healthcare coverage independently of employment status
- Protect displaced workers through basic income guarantees or other non-contributory schemes
  - Expanding social pensions and earned income credit



THANK YOU!

APPENDIX

Table 1. Questionnaire Items Used to Construct RTI		
Index Component		Questionnaire item
RTI: Abstract		Read diagrams, maps or schematics
		Write reports
		Solve complex problems
		Persuade or influence people
		Negotiate with people
RTI: Routine	Lack of flexibility	Change sequence of task (inverse)
		Change how to do work (inverse)
		Change speed of work (inverse)
		Change working hours (inverse)
	Lack of learning on the job	Learn work-related things from coworkers (inverse)
		Learn by doing (inverse)
		Keep up to date with new products and services (inverse)
	Manual routine	Hand and finger dexterity
RTI: Non-routine Manual		Perform physical work for long hours
ICT Use		Use internet for understanding issues related to work
		Conduct transactions on the internet
		Use spreadsheet software
		Use a programming language
		Level of computer use

Probability of automation – Expected Maximization algorithm (1)

1. Assign probabilities of automation from Frey and Osborne (2017) using respondent's occupation in the U.S. sample. Each occupation in PIAAC maps to multiple disaggregate occupations used in Frey and Osborne (2017).
2. Assign weights to each disaggregate category and estimate an individual-level regression:

$$Prob(Autom)_{ij} = \sum_{n=1}^{N} \beta_n X_{in} + \epsilon_{ij}$$

where X_{in} contains individual, job, and task characteristics.

3. Reweight the regression using predicted probability of automation (use weighted Generalized Linear Model).
4. Repeat 2-3 until best fit is achieved.
5. Use β_n from the best fit specification to predict probabilities for each individual in the sample.

Probability of automation – Expected Maximization algorithm (2)

- Characteristics predicting **lower probability of automation**:
  - Individual: college degree, higher numeracy, literacy, problem solving skills
  - Job: public sector, firm size (<10 or >1000)
  - Task: cooperating with others, training and influencing others, presenting, planning activities of others, solving complex problems, using high-level mathematics, using programming language, writing reports and articles, reading professional publications, working physically for long hours.
- Characteristics **predicting higher probability of automation**:
  - Individual: less than high school degree, lower numeracy, literacy, problem solving skills
  - Job: private sector, firm size (10-1000)
  - Task: reading diagrams, performing transactions on the Internet, selling, consulting, negotiating, using fingers and hands accurately.