Using aggregate data to generate job quality profiles

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Presentation outline

1) Overview of the multi-dimensionality of quality of employment
2) Recent attempts to create job quality profiles using working conditions surveys
3) Data gaps and an alternative approach
4) Constructing indices via occupational classifications
5) Creating job quality profiles at the occupational level
6) An exploratory assessment of trends in occupational job quality in Canada

Multi-dimensionality of quality of employment

Eurofound: Job Quality Indices

Physical environment
- Posture-related (ergonomic)
- Ambient (vibration, noise, temperature)
- Biological and chemical

Work intensity
- Quantitative demands
- Pace determinants and interdependency
- Emotional demands

Working time quality
- Duration
- Atypical working time
- Working time arrangements
- Flexibility

Social environment
- Adverse social behaviour
- Social support
- Management quality

Skills and discretion
- Cognitive dimension
- Decision latitude
- Organisational participation
- Training

Prospects
- Employment status
- Career prospects
- Job security
- Downsizing

Earnings

Quality of Employment Framework | UNECE

Capturing the multifaceted nature of quality of employment

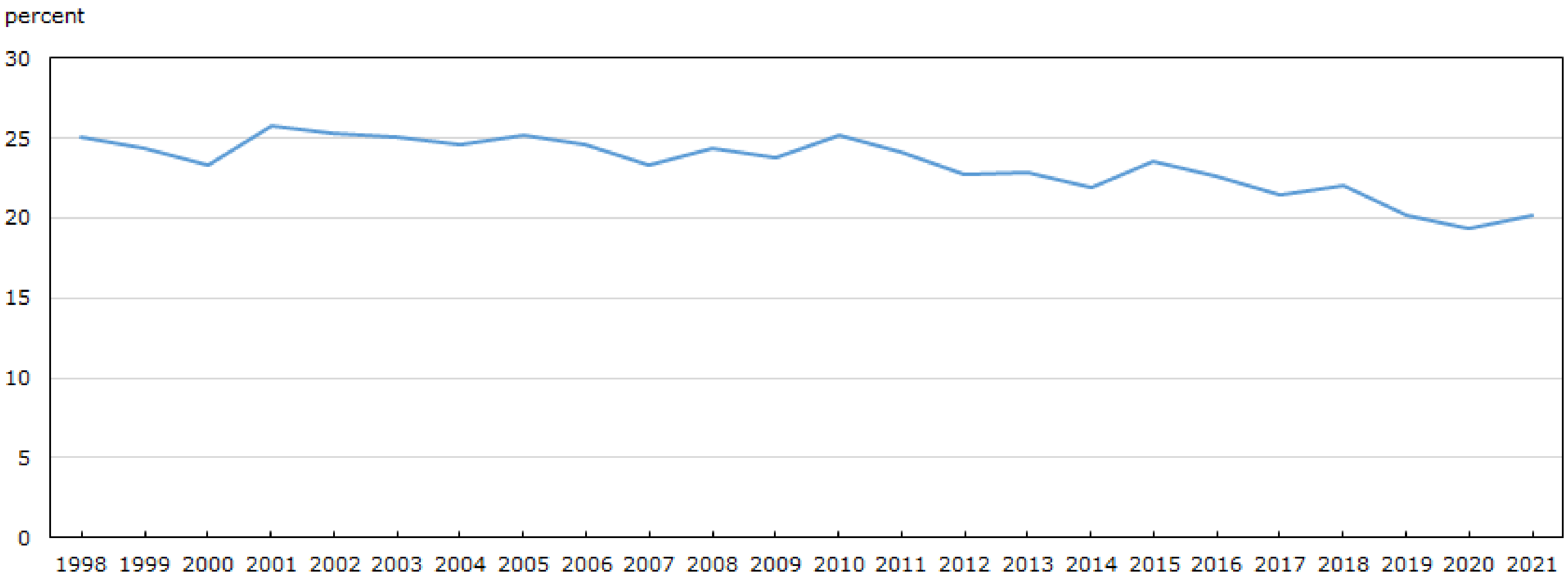
- Single indicator
  - Pro: Clear meaning and policy implications
  - Con: Difficult to evaluate the overall quality of a job

- Indices
  - Pro: Captures a broader dimension of quality of employment
  - Cons:
    - Overall quality of employment index typically not recommended (Eurofound, 2012, p.15)
    - If using an index representing a single dimension (e.g. working time) jobs could still score differently on other aspects

- Job quality profiles
  - Pro: Multi-dimensional, captures overall quality of jobs
  - Con: More challenging to measure change over time

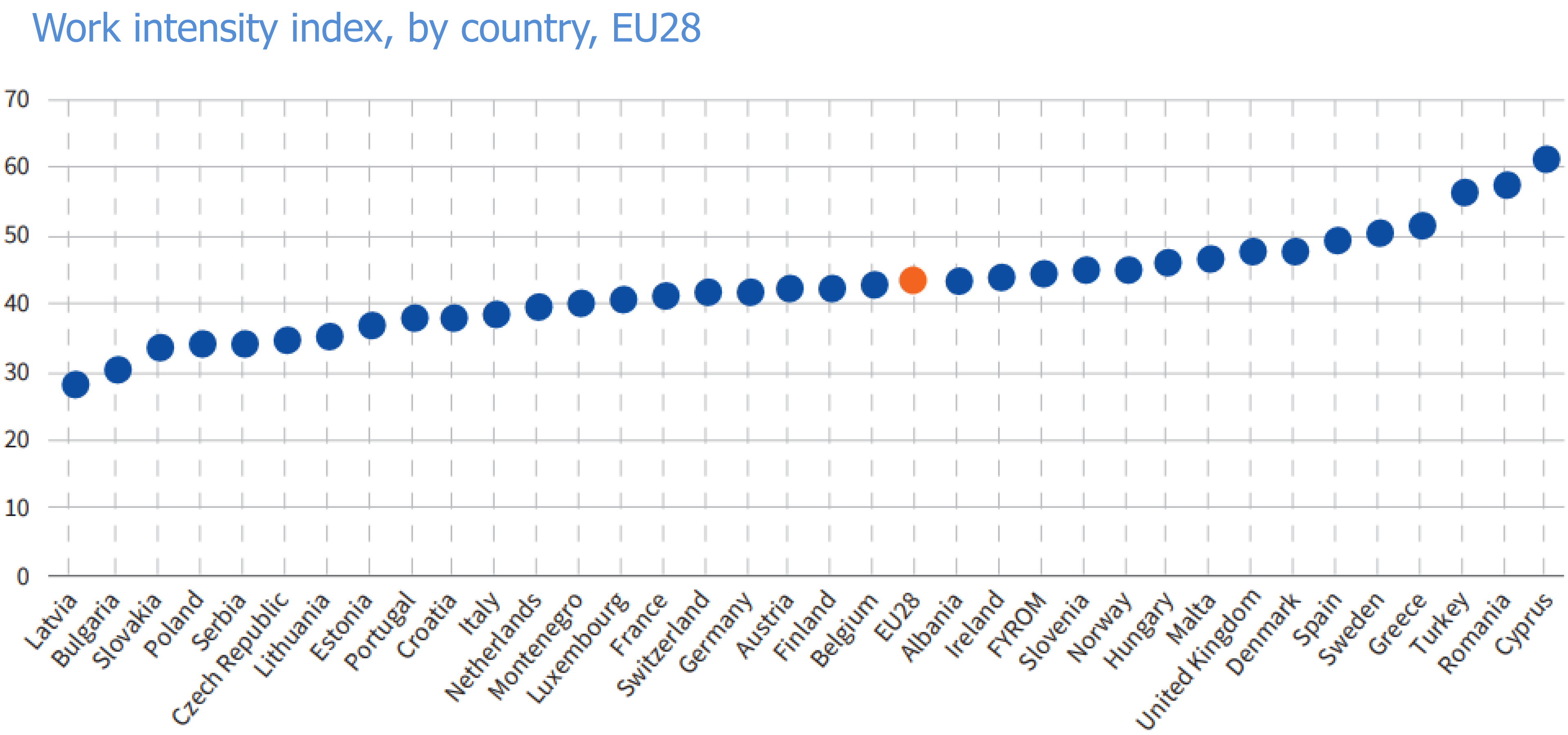
Example 1: Single indicator

Percentage of employees 15 years and over earning less per hour than the low-pay threshold, Canada, 1998 to 2021



Notes: The low pay threshold is two-thirds the median usual hourly wage. Due to rounding, estimates and percentages may differ slightly between different Statistics Canada products, such as analytical documents and data tables.
Source: Statistics Canada, Labour Force Survey, custom tabulation.

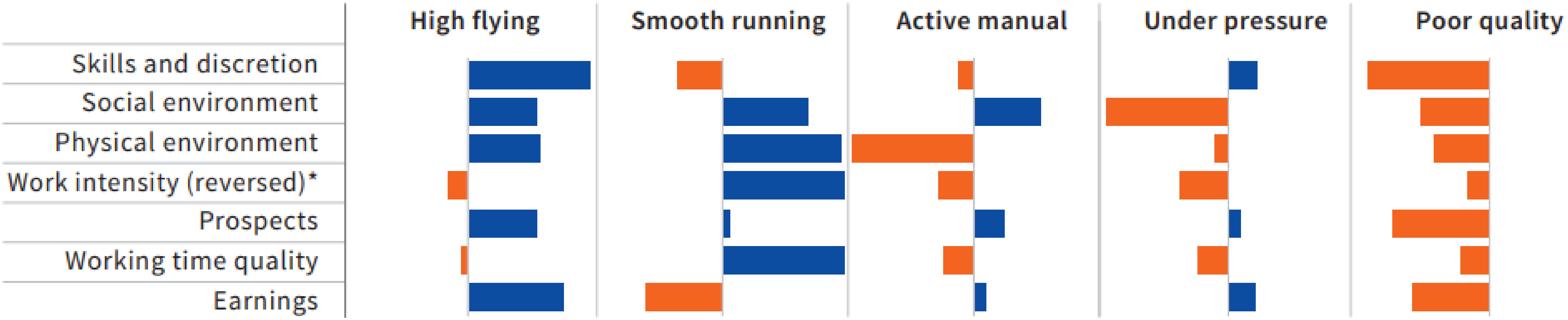
Example 2: Work dimension index



Source: Eurofound, 2017, p. 48

Job quality profiles (1)

- Eurofound (2017)
  - Based on data from the 6th European Working Conditions Survey (EWCS)
  - Created quality of employment indices for skills and discretion, social environment, physical environment, work intensity, prospects and working time quality
  - Used Latent Class Analysis (LCA) to identify jobs that were similar in terms of quality of employment.
  - Results show that some jobs score highly on some quality of employment dimensions, but lower on others



Source: Eurofound, 2017, p. 128

Job quality profiles (2)

- Chen and Mehdi (2019)
  - Used data from the Canadian *General Social Survey (GSS): Canadians at work and home*.
  - Regrouped indicators to create indices similar to Eurofound
  - Missing the "physical environment dimension"
- Identified four job quality profiles

Predicted job quality profiles (latent classes) by individual and job characteristics

Covariates	Job quality profiles			
	High overall quality jobs	Good quality jobs, poor working-time quality	Fair quality jobs, poor job resources and benefits	Poor overall quality jobs
	Class 1	Class 2	Class 3	Class 4
	probability			
Reference person (at means)	0.302	0.272	0.141	0.285
Men	0.316	0.268	0.144	0.272
Women	0.287	0.276	0.138	0.299
Ages 18 to 29	0.254	0.263	0.198	0.285
Ages 30 to 44	0.303	0.284	0.149	0.264
Ages 45 to 59	0.325	0.270	0.105	0.299
Ages 60 and older	0.340	0.236	0.121	0.304

Source: Chen and Mehdi, 2019
Note: Partial table shown, model includes other covariates such as immigration status and province.

Data limitations: the Canadian case

- From 2017 to 2024, Statistics Canada did not have a survey covering all dimensions of quality of employment.
  - The Labour Force Survey (LFS) includes some measures of QoE (e.g. wages, long hours), but does not provide a comprehensive picture
  - In 2022, a program of LFS supplements was implemented to address data gaps
    - Short sets of questions covering 1 or 2 topics are collected each month to create regular time series
      - e.g. April 2022: scheduling and hours, November 2022: training, March 2024: career prospects

- Lacking a single data source to produce "job quality profiles"

Linking and aggregating

- No options to link the data sources at the micro level
  - Different time periods, small samples

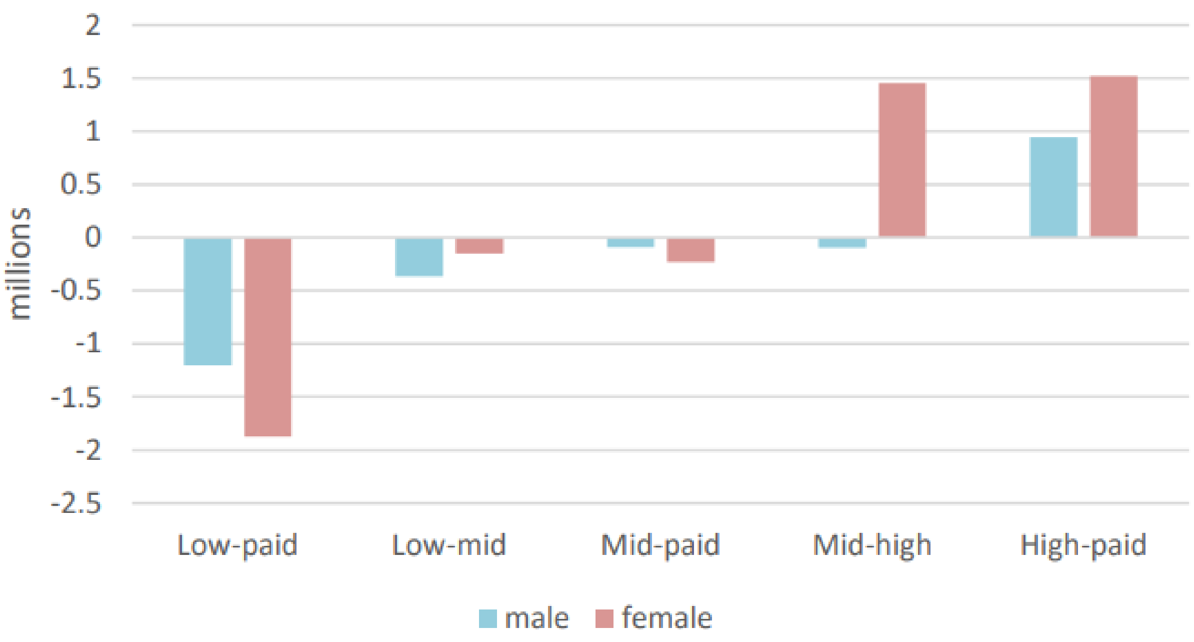
- What if there is a way to combine this information at an aggregate level?

  - Occupational classifications
    - Common to many surveys
    - Occupational categories are based on the nature of tasks, duties and skills, and are likely to be associated with similar quality of employment outcomes.

Prior analysis using occupational characteristics

- Torrejón Pérez *et al.* (2023)
  - Calculated average hourly earnings for industry by occupation cells at t=0.
  - Jobs are classified into five quintiles of "quality" based on these average earnings
  - Number of jobs in each cluster is calculated at t+n

Employment change, EU27, 2019Q4-2021Q4, by gender



Source: Torrejón Pérez *et al.*, 2023, p.25

Data sources with occupational information relevant to Canada

- 2016 General Social Survey (GSS)
  - Dedicated quality of employment modules covering most QoE dimensions
    - Except physical environment
  - Smaller sample size, older data

- LFS & LFS supplements
  - Large sample size, high-quality sampling frame
  - Recent estimates
  - Proxy responses

- O*NET
  - Based on data collected in the United States, provides occupation-level information on skill use, knowledge requirements, as well as work activities and the work environment
  - Regularly updated based on surveys and expert knowledge

Experimental approach

- Use of the National Occupational Classification system (NOC).
  - Classification specific to Canada (equivalent to ISCO)

- Selected most recent data, whenever possible

- Based on Eurofound and UNECE dimensions, identify closest corresponding measures to construct indices

Examples of measures

Work intensity	Data source
Enough time to get job done	GSS - How often can you complete your assigned workload during your regular working hours?
	GSS - How often do you consider your workload manageable?
Tight deadlines	O*NET - Time pressure

Skills and discretion	Data source
Training paid for or provided by the employer	LFS supplement

Physical environment	Data source
Vibrations	O*NET - Wholebody vibration
Loud noise	O*NET - Sounds, Noise Levels Are Distracting or Uncomfortable

Creating the database of occupational scores

- Converted occupational classifications to create a common denominator across data sources (e.g. SOC to NOC)

- Calculated an average for each occupational category
  - Occupational scores do not always have a clear meaning – objective is to differentiate occupations on a particular dimension.
  - E.g. permanent job =1, temporary job=0
    - Occupational average A: 0.25 vs B: 0.50
    - Occupational score indicates higher probability of having a permanent job in Occupation B.

- Level of detail limited by data quality
  - E.g. Data quality too low for the most detailed occupational groups

Creating indices

- When possible, indicators were combined within each dataset.
- Otherwise, z-scores of occupational averages were combined at the aggregate level to create a composite score for each occupational category
  - E.g. Prospects index = (*Z*-score (average job security) + *Z*-score(average career prospects) + *Z*-score(probability of job permanence))/3

- All indices expressed in *Z*-scores to ensure comparability.

Final indices

- Physical environment
- Work intensity
- Working time
- Social environment
- Access to training
- Skills and discretion
- Prospects
- Benefits
- Wages

Performing the classification

- Latent Profile Analysis/Latent Class Analysis
  - Supports inferences from a sample to a population
  - Expresses results in terms of the probability that a case belongs to a specific class
  - Models can fail to reach an appropriate level of fit

- K-means clustering
  - No assumptions regarding the nature of the data
  - Forces all cases to fall in a specific class
  - A solution is always found (quality of fit is relative)

✓ K-means clustering more appropriate for this type of analysis

Selecting a solution

- K-means does not provide a single solution
  - Range of options to evaluate quality
    - Weighted sum of squares (minimize within cluster variation)
    - "Silhouette method" (how well each case falls within a cluster)
    - Gap statistic: compares within cluster variation with a distribution that has no clustering

- See UC Business Analytics (2017) for a discussion, and implementation in R.

Description of clusters

- 5 cluster solution identified as the best solution based on 2/3 of methods, and third-best option based on 1 method.

Average standardized scores of quality of employment indices across occupational clusters

	Prospects	Time	Intensity	Social	Discretion	Training	Benefits	Wage	Physical
More challenging physical environment, with lower wages, good social	-0.271	-0.423	0.140	0.256	-0.744	-0.809	-0.416	-0.543	-1.181
More flexible, better physical environment, below-average wages	-0.039	0.413	-0.031	0.141	0.294	0.201	0.223	-0.193	0.510
High quality, higher intensity	0.745	1.020	-0.419	-0.024	1.057	0.811	1.009	1.373	0.949
Low quality, lower intensity	-1.033	-0.569	0.563	-0.211	-0.964	-0.801	-1.643	-1.149	0.006
Good prospects, less flexible, more challenging physical	0.560	-1.224	-0.155	-0.420	-0.012	0.508	0.540	0.423	-0.806

Source: Statistics Canada, Labour Force Survey, General Social Survey & O*NET, author's calculations

Examples of occupations: Cluster 1

- More challenging physical environment, with lower wages, good social

- Ex:
  - Cleaners
  - Heavy equipment operators
  - Labourers in processing, manufacturing and utilities

Examples of occupations: Cluster 2

- More flexible, better physical environment, below-average wages

- Ex:
  - Managers in food service and accommodation
  - Financial, insurance and related administrative support workers
  - Insurance, real estate and financial sales occupations
  - Contractors and supervisors, maintenance trades and heavy equipment and transport operators
  - Supervisors, processing and manufacturing occupations

Examples of occupations: Cluster 3

- High quality, higher intensity

- Ex:
  - Managers in financial and business services
  - Managers in public administration
  - Physical science professionals
  - Computer and information systems professionals

Examples of occupations: Cluster 4

- Low-quality, lower intensity

- Ex:
  - Tourism and amusement services occupations
  - Cashiers
  - Machine operators and related workers in textile, fabric, fur and leather products processing and manufacturing

Examples of occupations: Cluster 5

- Good prospects, less flexible, more challenging physical environment

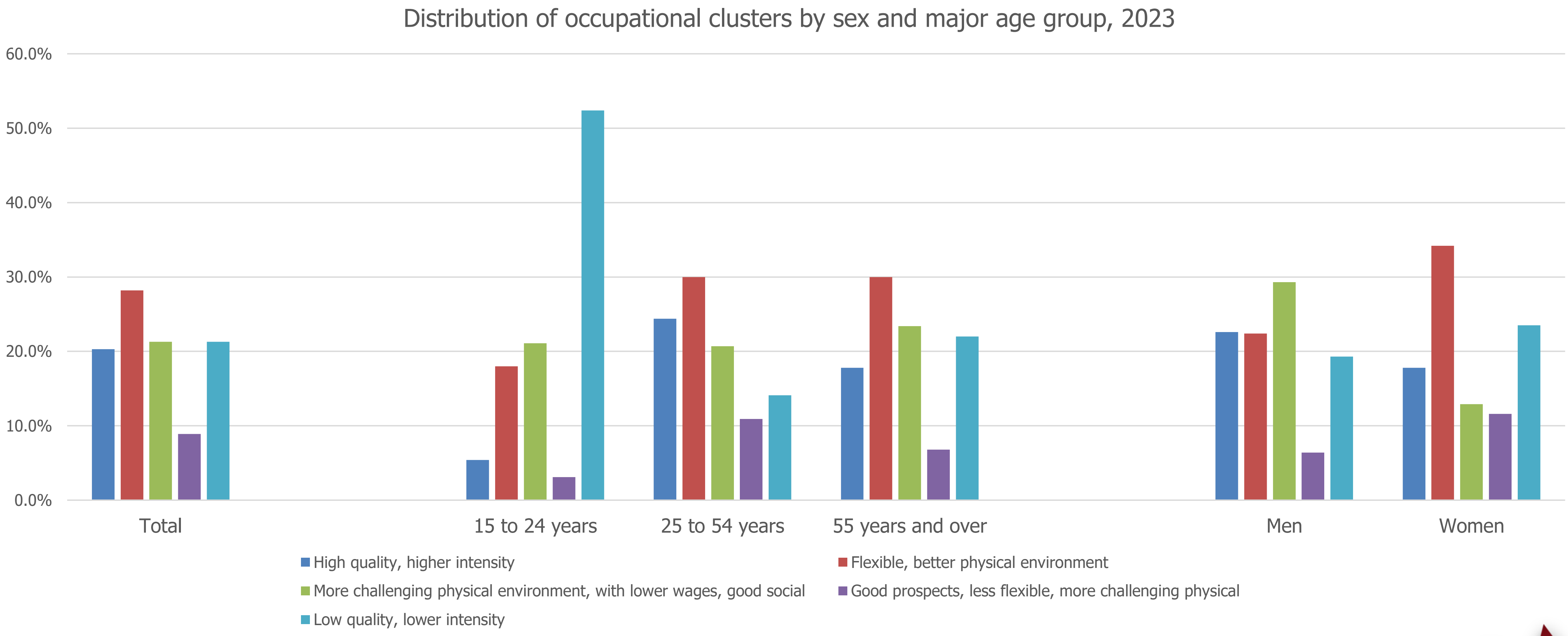
- Ex:
  - Professional occupations in nursing
  - Secondary and elementary school teachers and educational counsellors
  - Machinery and transportation equipment mechanics (except motor vehicle)
  - Contractors and supervisors, mining, oil and gas

Mapping trends in occupational clusters

- Occupational classification merged back to Canadian LFS to map trends in occupational clusters over time and by demographics.

Source: Statistics Canada Labour Force Survey, General Social Survey & O*NET, author's calculations

Distribution by age and sex



Source: Statistics Canada Labour Force Survey, General Social Survey & O*NET, author's calculations

Limitations

- Ignores all sampling error and does not take into account how well the sample or O*NET measures accurately reflect the mean occupational scores in the population.
- Averages mask variations within the occupational group
  - Can be reduced somewhat by doing gender, age analysis using the clusters.
- Scales have an ambiguous meaning – reflects the situation of the "average worker in a given occupation", relative to the "mean of average occupational scores"
- Mixes data sources, O*NET scores may not reflect situation in countries that are not the U.S.A.

Implications and possibles next steps

- Value of compiling quality of employment information by occupation
  - Can inform how changes in occupational structure are associated with shifts in quality of employment

- Possibility of building cross-country database of quality of employment information by occupation

- Validate O*NET scores against survey results across other countries.

- Perform similar analysis in different countries.

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