

# Labor market structures and pay gap in the Philippines: An occupational skills-based characterization

CONNIE BAYUDAN-DACUYCUY AND LAWRENCE DACUYCUY

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Philippine Institute for Development Studies

*Surian sa mga Pag-aaral Pangkaunlaran ng Pilipinas*

## Background & motivation

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- **A mega trend.** Due to significant and disruptive technological advances, the world of work is constantly evolving.
- **Primacy of skills development.** Poor national skills profiles hurt the economy, reduce dynamic complementarities and degrade job mobility and wage growth.
- **Better outcomes.** Skills development strategies can potentially reduce poverty and increase productivity, improving search and matching outcomes in labor markets.
- **Advocacy.** Focus on occupational skills to highlight useful metrics for labor market characterization.

## What does the literature say?

**Relevance of human capital.** Role of skills - durable investments acquired through school attendance or on the job training (Autor and Handel, 2013).

**Tradeoffs in investments in specific skills:** 1) Investing in specific skills may promote specialization and inflexibility (Hanushek, et al 2017); 2) generate higher returns, due to higher productivity gains arising from the match between skills and job-specific requirements (Wasmer, 2006).

**Occupation-based human capital specificity:** for workers to produce output, they need to accomplish tasks using skills relevant to the occupation.

- Low dimensional vectors of skills that are transferable across occupations (Robinson 2018) or occupations as bundles of tasks (Yamaguchi 2012).
- The task approach is a dominant strategy to classify jobs based on task content and skill requirements (Autor, Levy, and Murnane 2003; Autor and Handel, 2013).

## *What does the literature say?*

**Relevance of skills specificity.** Job mobility (Robinson, 2018); wage growth (Gathmann and Schonberg, 2007); wage inequality (Violante, 2002).

**Need for classification schemes.** Mihaylov and Gartje (2019) developed measures to classify occupations (non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual tasks) using International Standard Classification of Occupations (ISCO)

- 16% of ISCO occupations were in danger of being adversely affected by automation.

## *What does the literature say?*

**Concept of specificity.** Individual skills are general skills but may become specific to occupations once different skills have been combined and weighted within firms (Lazear (2009) and Rinawi (2019)).

**Concept of distance:** Like specificity, the conceptual value of distance depends on the distinction between general and specific skills. The former does not depreciate while the latter is lost when a worker leaves his occupation.

- Gathmann and Schonberg's (2010) example: the carpenter, baker, and cabinet maker.
- The distance between carpenters and cabinet makers is shorter compared to that of carpenters and bakers.

## Characterizing the labor market

- Specificity and distance can be used to characterize the labor market.
- Understanding the structure of the labor market in the context of general and specific skills is essential.
- The specificity metric can help achieve such objective since it can identify how skills are bundled within occupations.
- Specificity can also be used to frame future initiatives in crafting skills and training development programs, leading to improvements in the national skills profile.
- Distance can explain wage gains or losses in the event of job transitions (Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008).

## *Methods to organize the skills data*

No skills data are collected in any of the nationally representative surveys that contain the PSOC codes.

Two methods through which a skill characterization of occupations could be carried out: direct and indirect methods (Robinson. 2018).

- Direct method uses ratings data to characterize occupations (Poletaev & Robinson, 2008)
- Indirect method uses factor analysis to extract information from the raw data of tasks (Gathmann and Schoenberg 2010; Poletaev and Robinson 2008).

Using the indirect method:

Extracted the tasks enumerated in the PSOC Code.

## Methods to organize the skills data

Applied factor analysis to the extracted tasks (around 590 -ing words in the PSOC Code, coded 1 if listed under the occupation code, 0 otherwise)

Became problematic:

- **Identified factors.** Analysis of the rotated factors indicated that there were around 233 tasks that have high factor loadings in the 60 retained factors.
- **Classification.** Tasks under each retained factors appear sensible. For example, tending, storing, delivering, raising, harvesting, planting cultivating, and sowing are identified tasks under factor 1 while monitoring technical report, observing people, grading papers, evaluating, teaching, instructing, conferring, attending, and assigning are tasks under factor 2.
- **Mapping challenge.** There is a challenge of mapping these 60 factors into broad types of skills (e.g., Should factor 1 represent manual or motor skills? Should factor 2 represent communication or mentoring skills?)
- **Attrition.** In addition, around 10% of the occupations did not have under its lists any of the 233 tasks and will, thus, be precluded from the analysis.



## Crosswalking with the O\*NET codes

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**Crosswalk strategy:** assigns the job tasks, skills, and other content of the Occupational Information Network (O\*NET) database to the occupation codes of a survey data at the 4-digit SOC level.

- The O\*NET database, uses the Content Model to organize occupational information (Hillage and Cross 2015), contains measures that pertain to the importance of abilities, skills, interests, knowledge, and work activities, content, styles, and values in each occupation. The worker characteristics domain has three components, namely, skills, knowledge, and education.
- For skills: There are 35 skills descriptors that fall in the following categories: basic skills, complex problem-solving skills, resource management skills, social skills, systems skills, and technical skills.
- The importance of these skills in each of the occupations are determined by analysts (see Handel, 2016).

## *Crosswalking with the O\*NET codes*

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A strategy used in Canada and India.

The role of the O\*NET database is to render deliberate the inclusion of skills that are required in occupations. Since they are rated by non-Filipinos, we could interpret the importance scores as target skill importance parameters to provide an approximation of where our skill distributions converge to.

# Crosswalking the Philippine Standard Occupational codes with the O\*NET codes

LFS, the Listahanan, CPH that can be crosswalked against the O\*NET database.

- The 2015 LFS contains 289 PSOCs, the Listahanan contains 327 PSOCs, and the CPH contains 451 PSOCs.

**Table 1:** Details on the crosswalking strategy done in the 2015 CPH PSOC codes

	Freq.	Percent	
Matched	152	33.7	
Reconciled PSOC codes and O*NET codes	240	53.22	<p>Example:</p> <p>Hotel Managers matched with 11-9081.00 Lodging Managers                      Restaurant Managers matched with 11-9051.00 Food Service Managers                      Retail and Wholesale Trade Manager matched with 11-2022.00 Sales Managers</p>
PSOC codes do not match with O*NET codes, assignment done	10	2.22	<p>Example:</p> <p>Aged Care Service Managers in PSOC is matched <i>with</i> Administrative Services Managers in the O*NET;                      Traditional and Complementary Medicine Professionals <i>with</i> Naturopathic Physicians                      Creative and Performing Artists Not Elsewhere Classified <i>with</i> Makeup Artists, Theatrical and Performance                      Handicraft Workers in Wood, Basketry and Related Materials, Textile, Leather and not elsewhere classified <i>with</i> Craft Artists                      Pelt Dressers, Tanners and Fellmongers <i>with</i> Sewers, Hand                      Window Cleaners/ Other Cleaning Workers <i>with</i> Janitors and Cleaners, Except Maids and Housekeeping Cleaners                      Street and Related Service Workers <i>with</i> Door-to-Door Sales Workers, News and Street Vendors, and Related Workers</p>
Average of the importance data assigned to the PSOC code	29	6.43	<p>Example:</p> <p>Physicists and Astronomers assigned the average of 19-2012.00 Physicists and 19-2011.00 Astronomers                      Mathematicians and Actuaries assigned the average of 15-2021.00 Mathematicians and 15-2011.00 Actuaries</p>
PSOC codes not matched with O*NET, no assignment done	20	4.43	<p>Legislators, Senior Government Officials, Traditional Chiefs and Heads Of Villages, Senior Officials Of Special-Interest Organizations, Process Control Technicians Not Elsewhere Classified, Information and Communications Technology User Support Technicians, Astrologers, Fortune-Tellers and Related Workers, Personal Services Workers Not Elsewhere Classified, Charcoal Makers and Related Workers, Minor Forest Product Gatherers, Wood Treeters, Stationary Plant and Machine Operators Not Elsewhere Classified, Hand and Pedal Vehicle Drivers, Drivers Of Animal-Drawn Vehicles and Machinery, Garbage and Recycling Collectors, Refuse Sorters, Sweepers and Related Laborers, Odd Job Persons, Water and Firewoods Collector, Elementary Workers Not Elsewhere Classified</p>

# Measuring occupational specificity

1. Skills with importance data  $\geq 45$  are coded 1 (0 otherwise) to constitute the skills bundle in each occupation.

2. The ranked order of skills is determined using the labor market information. To do this, the crosswalked data are merged with the 2015 CPH. This facilitates the computation of the total number of workers using each skill, which will serve as the labor market skills weight. The skills are then ranked from 1 (the greatest number of workers) to 35 (least number of workers).

3. Occupational specificity measure is computed

$$\text{specificity of occupation } i = \frac{\text{sum of ranks of skills in occupation } i}{\text{number of skills in occupation } i}$$

- Occupations 1 and 2 both use active listening, coordination, monitoring.
- Assume a fourth skill, which is time management sk in occupation 1 and programming skills in occupation 2.
- The specificity of occupation 1 is 4.75 (computed as  $(1 + 4 + 5 + 9)/4$ ) while that of occupation 2 is 11 (computed as  $(1 + 4 + 5 + 34)/4$ ).
- Occupation 2 is more specific than occupation 1.
- We divided the occupation specificity by the maximum specificity so that the measure lies between 0 and 1.

**Table 2: Skills and number of workers**

Skills	Total number of workers	Rank	% to total employe
Basic: Active listening	34409638	1	93.1
Basic: Critical thinking	33016068	2	89.3
Basic: Speaking	32887791	3	89.0
Social: Coordination	29943633	4	81.0
Social: Monitoring	28086383	5	76.0
Social: Social perceptiveness	23231851	6	62.8
Analytical: Judge and decision-making	20671798	7	55.9
Basic: Reading comprehension	20110464	8	54.4
Management: Time	19813673	9	53.6
Social: Service orientation	19790823	10	53.5
Analytical: Complex problem solving	15937954	11	43.1
Basic: Writing	15935695	12	43.1
Social: Persuasion	12412216	13	33.6
Basic: Active learning	12185679	14	33.0
Social: Negotiation	9415414	15	25.5
Mechanical: Operation monitoring	8613103	16	23.3
Social: Instructing	8122330	17	22.0
Mechanical: Operation and control	6802203	18	18.4
Basic: Learning strategies	6585856	19	17.8
Analytical: Systems analysis	6142594	20	16.6
Analytical: Systems evaluation	6018272	21	16.3
Analytical: Mathematics	5828115	22	15.8
Management: Financial resources	5136889	23	13.9
Mechanical: Quality control	4351725	24	11.8
Mechanical: Equipment maintenance	2991384	25	8.1
Management: Financial resources	2897488	26	7.8
Mechanical: Troubleshooting	2861320	27	7.7
Mechanical: Repairing	2840359	28	7.7
Management: Material resources	2359533	29	6.4
Analytical: Operations analysis	1092808	30	3.0
Analytical: Science	919852	31	2.5
Mechanical: Equipment selection	818075	32	2.2
Mechanical: Installation	550068	33	1.5
Analytical: Programming	229960	34	0.6
Analytical: Technology and design	124685	35	0.3

Source: CPH crosswalked against the O\*NET database

‡ **Table 3: Top and Bottom 20 Occupations, by specificity**

Top 20 occupations	Specificity	Bottom 20 occupations	Specificity
Electronics Engineers	1.000	Building Structure Cleaners	0.061
Engineering Professionals Not Elsewhere Classified	0.970	Window Cleaners	0.061
Systems Administrators	0.970	Other Cleaning Workers	0.061
Physical and Engineering Science Technicians Not Elsewhere Classified	0.967	Vehicle Cleaners	0.061
Building and Related Electricians	0.965	Cleaners and Helpers in Offices, Hotels and Other Establishments	0.061
Cabinetmakers and Related Workers	0.962	Building Caretakers	0.061
Woodworking Machine Tool Setters and Operators	0.956	Shoemakers and Related Workers	0.122
Wood Processing Plant Operators	0.956	Stock Clerks	0.153
Metal Polishers, Wheel Grinders and Tool Sharpeners	0.928	Shelf Fillers	0.153
Mining Engineers, Metallurgists and Related Professionals	0.911	Subsistence Mixed Crop and Livestock Farmers	0.183
Air Conditioning and Refrigeration Mechanics	0.908	Oysters and Mussels Producers	0.183
Agricultural and Industrial Machinery Mechanics and Repairers	0.908	Apiculturists and Sericulturists	0.183
Systems Analysts	0.908	Eggs Producers	0.183
Information and Communications Technology Operations Technicians	0.892	Dairy Farmer	0.183
Database Designers and Administrators	0.889	Other Market Gardeners and Crop Growers, Not Elsewhere Classified	0.183
Information and Communications Technology Installers and Servicers	0.885	Prawn Producers	0.183
Miners and Quarryers	0.883	Duck Raisers	0.183
Mining and Quarrying Laborers	0.883	Subsistence Livestock Farmers	0.183
Mobile Farm and Forestry Plant Operators	0.880	Animal Producers Not Elsewhere Classified	0.183
Mechanical Engineers	0.880	Subsistence Crop Farmers	0.183

Note -. Authors' computations using 2015 Census of Population and Housing data.



# Broad skills categories

The 35 skills are assigned to broader skill groups: social, basic, analytical, management, and mechanical and aggregated.

The importance data have been converted into binary data (importance data  $\geq 45$  are coded 1, 0 otherwise).

- If occupation 1 uses 10 skills, of which 2 are basic skills, 4 are analytical skills, and 4 are mechanical, then occupation 1 has a skill bundle of 0.2, 0.4, 0, 0, and 0.4.
- However, an occupation with only 1 or 2 skills will show up with a very high percentage in certain skills category. The occupation related to sewing and embroidery have high importance data on time management (management skill) and judgement/decision making (analytical skill). Thus, this occupation will have a higher percentage of analytical skills than another occupation with high importance data in 10 skills, 4 of which are analytical skills (50% vs. 40%).
- In the end, the skills bundle is weighted using the number of skills in each broad category.

**Table 4:** Broad skills categories and skills components

Basic skills (7)	critical thinking, active learning, active listening, reading comprehension, speaking, writing, and learning strategies
Social skills (7)	coordination, monitoring, instructing, negotiation, persuasion, service orientation and social perceptiveness
Analytical skills (9)	Science, Mathematics, complex problem solving, systems analysis, systems evaluation, judgement and decision making, operations analysis, programming, and technology and design
Management skills (5)	management of financial resources, material resources, personnel resources, and time, and quality control
Mechanical skills (7)	equipment maintenance, equipment selection, installation, operation and control, operation monitoring, repairing, and troubleshooting

Note: Figures in parentheses are number of skills in each category.



# Measuring distance

Leverage the idea that occupations requiring workers to perform similar tasks require similar skills and are more likely to be close to one another.

Use the importance data in the crosswalked PSOC codes and the Euclidian distance is used to compute the skills-based distance between occupations.

2 occupations (1 and 2) and 2 skills vectors (a and b), then  $distance_{12} = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2}$ .

0 if similar, 1 if dissimilar

Normalize this by dividing the computed distance by the maximum distance for each occupation.

Doing this will yield asymmetric distances between two occupations ( $distance_{12} \neq distance_{21}$ ) given the presence of other occupation (n) with  $distance_{1n} \neq distance_{2n}$ .

Thus, we take a more conservative approach by choosing  $distance_{12} = \max(distance_{12}, distance_{21})$ .

Table 1A: Distance of selected occupations to other occupations

	Occupations that are far	Distance	Occupations that are close	Distance
Software Developers (Specificity: 0.79)	Contact Center Salespersons	1.00	Applications Programmers	0.00
	Agricultural and Industrial Machinery Mechanics and Repairers	0.97		
	Air Conditioning and Refrigeration Mechanics	0.97		
	Miners and Quarryers	0.97		
	Mining and Quarrying Laborers	0.97		
	Aircraft Engine Mechanics and Repairers	0.97		
	Fashion and Other Models	0.96		
	Concessionaires and Loggers	0.95		
	Food and Beverage Tasters and Graders	0.94		
	Window Cleaners	0.94		
	Cleaners and Helpers In Offices, Hotels and Other Establishments	0.94		
	Building Structure Cleaners	0.94		
	Other Cleaning Workers	0.94		
	Building Caretakers	0.94		
	Vehicle Cleaners	0.94		
	Bicycle and Related Repairers	0.93		
	Mobile Farm and Forestry Plant Operators	0.93		
	Kitchen Helpers	0.92		
	Protective Services Workers Not Elsewhere Classified	0.91		
	Ship Engineer	0.91		
Shoemaking and Related Machine Operators	0.90			
Managing Directors and Chief Executives	0.90			
Weaving and Knitting Machine Operators	0.90			
Precision-Instrument Makers and Repairers	0.90			
Heavy Truck and Lorry Drivers	0.90			
Crane, Hoist and Related Plant Operators	0.90			
Shopkeepers (Specificity: 0.45)	Aircraft Engine Mechanics and Repairers	1.00	Shop Sales Assistants	0.29
	Agricultural and Industrial Machinery Mechanics and Repairers	0.98	Debt Collectors and Related Workers	0.27
	Air Conditioning and Refrigeration Mechanics	0.98	Commercial Sales Representatives	0.22
	Physical and Engineering Science Technicians Not Elsewhere Classified	0.97	Street Vendors (Excluding Food)	0.00
	Engineering Professionals Not Elsewhere Classified	0.93	Street Food Salespersons	0.00
	Ship Engineer	0.93	Street and Related Service Workers	0.00
	Systems Administrators	0.93	Door To Door Salespersons	0.00
	Electronics Engineers	0.87	Stall and Market Salespersons	0.00
	Chemical Products Plant and Machine Operators	0.85		
	Building and Related Electricians	0.85		
	Underwater Divers	0.85		
	Chemists	0.85		
	Chemical Engineers	0.85		



## Which occupations are Filipinos mostly involved in?

	# of occupations with employment of at least 1%	% of employment to total working population	Skills bundle	Ave. Specificity
Total	25/431	60%	Mostly composed of social and basic skills. Workers under these occupations include farmers, domestic cleaners/helpers, drivers, clerks, shopkeepers, security guards, waiters, and shelf fillers	Low, 0.40
Male	25/431	66%	16% social skills, 20% basic skills, 2% analytical, 2% management, and 3% mechanical.	Low, 0.41
Female	25/431	66%	25% social skills, 23% basic skills, 4% analytical, 3% management, and 0% mechanical.	Low, 0.45



## By geographical location:

- The NCR has the highest proportion of workers involved in occupations that use the social, fundamental, analytical, and management skills
- CALABARZON has the greatest number of workers involved in occupations that use mechanical skills.
- No other regions except for Regions III and IV-A come close to the NCR's record. Some industrial parks and freeport zones are in Region III while most economic processing zones, technoparks, and industrial estates are in Region IV-A.

## By gender:

	Low	High
Basic skills	50% of males vs 60% of females	16% of males vs 40% of females
Analytical skills	27% of males vs 64% of females	14% of males vs 26% of female
Mechanical skills	65% of male vs 6% of female	32% vs 90%

## By gender and geographical differences:

- 50% of all females in the NCR have jobs that have high basic skills requirements.
- 32% of all males in the NCR match the same outcome.

## By educational attainment:

- A large percentage of workers with at least tertiary education are involved in occupation using specific skills.
- A large percentage of workers with elementary and secondary level of education are involved in occupations using general skills bundle.

# in-demand jobs

- In-demand jobs refer to active occupations/job vacancies posted or advertised recurrently by and across establishments/industries (DOLE, 2017).
- In-demand jobs are mostly in agribusiness (24%), hotel/restaurant/tourism (19%), construction (9%), health and wellness (9%), wholesale and retail trade (9%), IT-BPM (8%), and manufacturing (8%).

<p>IT-BPM and manufacturing are looking to fill jobs with more analytical skills.</p>	<p>jobs include software quality assurance analysts and IT support staff. In agribusiness, there is a clear need for technical experts, managers, pathologist, biologist, engineer, and quality control technicians.</p>	<p>Require highly specific skills (programming, technical design, operations analysis/control, Science and Math)</p>
<p>Hotel/restaurant/tourism, wholesale and retail trade, and health and wellness are in-demand of jobs requiring general skills, which consist of lower analytical skills and higher social and basic skills (versus other in-demand jobs).</p>	<p>bartenders, clerk, waiter, cashier, beautician, bagger, weaver, cleaner/helper, laborer, and room attendant.</p>	<p>Require general skills (active listening, speaking, coordination, social perceptiveness, critical thinking)</p>

Worrisome given that developments in information, communication, and technology have dramatically reshaped the world of work, more intensive use of ICT, data analytics, and high value adding social skills. These requires the formation and development of skills that the country’s education and training systems have problems generating, as validated by the list of hard-to-fill jobs in the DOLE’s JobsFit 2022 Labor Market Information Report.

## Hard-to-fill jobs

Hard-to-fill (HTF) jobs refer to job vacancies which the employer/company is having difficulty or taking longer time to be filled because job applicants are not qualified and/or there is no supply of job applicants for the job vacancy (DOLE, 2017).

these jobs are mostly in health and wellness (20%), manufacturing (18%), construction (14%), banking and finance (8%), and IT-BPM (8%).

Findings:

1. These jobs require specific skills.
2. The average social, basic, and management skills in these jobs are relatively similar to those of in-demand jobs. **The average mechanical skills are lower while the analytical skills are substantially higher.**
3. These are also occupations that have dissimilar skill sets relative to the skills of nearby occupations, an indication of the quality of jobs being created in the economy.

**By sector:** the average analytical skills requirement of the IT-BPM is the highest, with jobs for software engineer, mobile app developer, and system analyst included as HTF jobs.

Chemist, an HTF job in the agribusiness, mining, and power and utilities sectors, also has high analytical requirements. In the health and wellness front, psychologists, dietetic technicians, nutritionists, optometrists, and opticians are included in HTF jobs that require relatively high analytical skills.

# Gender pay gap, method

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Based on the the 2015 LFS, the mean daily pay of female workers is PhP 345 while that of the male workers is PhP 277, a 25% pay gap in favor of women. While this bodes well to the female working populace, it deserves a systematic analysis to ensure that pay gap do not widen in favor of any gender. This is done in the context of analyzing the contribution of labor market metrics such as skills, specificity, distance.

Oaxaca-Blinder decomposition method, decomposes the gap into:

- The endowment effect: accounts for group differences in terms of predictors, weighted by the coefficient estimates associated with male workers. essentially measures the expected change in the pay outcome of male workers if they have the females' predictor levels (Jann, 2008).
- The coefficient effect: accounts for differences between female and male worker coefficients, or coefficient effects, weighted by the average male worker attributes. (Returns)

Mincerian-style pay functions, regressing the respective logarithm of pay for female and male workers against known regressors that include skills, location, and personal attributes.

## Gender pay gap, findings

The reversal in the wage gap has put forward some interesting results that pertain to how the occupational skills and the metrics to measure labor market structures, like specificity and distance, interact.

1. The female educational and social, analytical, and management skill endowments narrow the wage gap, whether said skills are weighted by specificity or distance measure.
2. The labor market rewards tertiary education highly as indicated by its robust endowment and coefficient effects.

Base specification: Broad Skills				
		Endowment effect	Coefficient effect	Interaction effect
Personal		1.003	0.946	1.003
At least attended college		1.150	1.037	1.074
Social		1.156	0.848	0.792
Basic		0.968	1.815	1.337
Analytical		1.038	1.062	1.089
Management		1.003	1.062	1.004
Mechanical		0.979	1.012	0.990
Private		1.074	1.007	1.019
Geographical		1.029	1.034	0.997

## Gender pay gap, findings

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3. The labor market substantially rewards the female's basic skills, which suggests looking into the formation of basic skills as an effective way to reduce the male's pay deficiency.
4. The labor market structures also play a role in reducing pay gap. The returns to highly specific occupational skills, such as basic and analytical skills, narrow pay gap.
  - Highly specific basic skills include learning strategies while highly specific analytical skills include Mathematics and Sciences, systems analysis, systems evaluation, operations analysis, programming, and technology and design.
5. Skills that are different from the skills of nearby occupations narrow the pay gap as well.

## Takeaways

- 1. There is a need to look into the basic education sector and the kinds of school and home environments that can foster gendered differentiated learnings. Failure to address the issues in the sector can result in the workforce missing out on reskilling and upskilling opportunities that are widely available online.*
- 2. The importance of tertiary education cannot be overemphasized in enhancing the readiness of the country's future workforce.*
- 3. TVET training programs can be expanded to tackle in-demand and hard-to-fill jobs in various sectors.*
- 4. There is a need to assess the quality of jobs being created by the expanding sectors and ensure that reskilling and upskilling programs are in place, both of which facilitate the workers' upward occupational mobility.*

## Takeaways

- 5. There is a need to continue developing programs to encourage women's labor force participation and to address job intermittencies resulting from care work.*
- 6. Leveraging women's better educational achievements may help mitigate skills gap in highly technical occupations.*
- 7. Best practices for collecting, analyzing, and updating labor market information exist and should be integrated in the Philippine statistical systems.*