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Abstract

The world of work is constantly evolving because jobs are created and destroyed, a process that is increasingly becoming conspicuous due to significant technological advances, notably in ICT and computing. Invariably, poor national skills profiles hurt the economy, impede the efficient and timely accumulation of advanced or highly technical skills, and potentially degrade job mobility and wage growth. Thus, understanding the structure of the labor market in the context of occupational skills is essential. This paper provides a skills-based characterization of the labor market and assesses how skills are distributed across the working population, emphasizing key gender differences, and highlighting spatial disparities. It also explains the observed gender pay gap using skills-augmented Mincerian regression models and the 2015 Labor Force Survey.

Results indicate the following: 1) Six in every ten workers in the Philippines are mostly employed in elementary occupations and in the agricultural, forestry, and fishery sectors. The said workers' occupational skill sets are mostly composed of social and basic skills. 2) Some in-demand jobs in the IT-BPM and manufacturing sectors require specific skills bundle that include analytical skills such as systems analysis, systems evaluation, operations analysis, programming, and technology and design. 3) Hard-to-fill (HTF) jobs, mostly in health and wellness, manufacturing, construction, banking and finance, and IT-BPM, require specific skills. While the average social, basic, and management skills in these jobs are like those of in-demand jobs, the analytical skills required are substantially higher than those of the in-demand jobs. 4) HTF jobs are close to very few jobs that share similar skills sets, an indication of the quality of jobs available and/or being created in the economy. 5) Tertiary education and basic skills (both endowments and returns) narrow the pay gap. 6) Highly specific basic and analytical skills narrow the pay gap as well. Highly specific basic skills include Mathematics and Science while highly specific analytical skills include systems analysis, systems evaluation, operations analysis, programming, and technology and design.

Moving forward, 1) There is a need to investigate 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 programs can be leveraged to tackle in-demand jobs in some 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. 5) There is a need to continue developing programs that encourage women's labor force participation and 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 should be integrated in the Philippine statistical systems.

Keywords: skills specificity, occupational skills, gender pay gap

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Labor Market Structures, Pay Gap, and Skills in the Philippines

Connie Bayudan-Dacuycuy and Lawrence B. Dacuycuy*

1. Introduction

While the Philippines has experienced economic growth from 2012-2019, achieving inclusive growth remains elusive. This can be partly attributed to the state of human capital and skills development in the country, which is reflected in the recently concluded 2018 PISA that highlighted the learning inadequacies in reading, Mathematics, and Science. As one of the informative metrics, the 2020 Human Capital Index conveys an alarming stylized fact: an 18-year-old expected years of schooling is only 7.5 years. The inadequacy of basic skills in the country's workforce has serious implications on the ability of the country to respond aggressively to shifting workforce quality trends. Deemed as a legacy country, the Philippines has been assessed as an economy with a strong production base that faces risks in light of the Fourth Industrial Revolution (FIRe) due to weaker performance in key areas that involve the drivers of production, namely: technology and innovation, human capital, global trade and investment, institutional framework, sustainable resources, and demand environment (WEF, 2018). Several pressing challenges have also been identified in the country's institutional framework, human capital, and technology/innovation capacities (WEF, 2018). These issues and challenges have been articulated in the Philippine Development Plan 2017-2022. The Plan has outlined the overall and sector-specific strategic frameworks towards the *matatag*, *maginhawa* at *panatag na buhay* as articulated in the Ambisyon Natin 2040 and has identified two key strategies, namely: the expansion of economic opportunities and the acceleration of human capital development.

The world of work is constantly evolving because jobs are created and destroyed, a process that is increasingly becoming conspicuous due to significant technological advances, notably in ICT and computing. Invariably, poor national skills profiles hurt the economy, impede the efficient and timely accumulation of advanced or highly technical skills, and potentially degrade job mobility and wage growth. Skills development strategies that mitigate search frictions and facilitates timely adjustments in response to labor market realities and dynamics can potentially reduce poverty, increase productivity, which leads to labor mobility and wage growth, and improve matching outcomes in labor markets. Thus, understanding the structure of the labor market in the context of occupational skills is essential.

This paper provides a skills-based characterization of the labor market. Following the framework by Lazear (2009) and implementing the procedure developed by Rinawi and Backes-Gellner (2019), this paper assesses how skills are distributed across the working population, emphasizing key gender differences, and highlighting spatial disparities. Key measures such as the average distance and occupational skills specificity are computed. We crosswalk occupations identified in the Occupational Network (O*NET) database with occupational titles included in the Philippine Standard Occupation Classification (PSOC) and use the importance ratings associated with matched occupations that broadly encompass social, analytical, management, basic, and mechanical skills. This paper investigates the patterns in

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the skills of workers across occupations (including occupations that are considered in-demand and hard-to-fill jobs), regions, education, and gender. It also explains the observed gender pay gap using skills-augmented Mincerian regression models and the 2015 Labor Force Survey.

This paper has the following sections: Section 2 discusses the antecedent economic literature essential for weaving together a complex set of concepts. Methodologies for constituting the data and generating specificity measures and other statistics are also discussed. Section 3 zeroes in on the skill-based characterization of the occupational structure of the labor market. Section 4 highlights the results of the Oaxaca-Blinder pay gap decomposition exercises. The last section provides the conclusion and identifies key takeaways.

2. Methodology: Concepts, measures, and data

2.1. Review of related literature

Models on human capital and job search are used to analyze wage outcomes and explain job mobility (Gathmann and Schonberg 2010). Central to these models is the role of skills-durable investments acquired through school attendance or on the job training (Autor and Handel, 2013). Skills may be general like education and experience or specific, which can be characterized within firms or occupations (Gathmann and Schonberg 2010). The labor market implications of acquiring specific skills have sparked concerns due to the tradeoff between risks and returns (Eggenberger, Rinawi and Backes-Gellner, 2017). Investments in specific skills are viewed risky as it may become difficult for workers to adapt to changes brought about by new technologies (Hanushek, et al 2017). However, such skills are viewed to generate higher returns, plausibly due to higher productivity gains arising from the match between skills and job-specific requirements (Wasmer, 2006). To a certain extent, research on skills specificity has flourished due to its implications for job mobility (Robinson, 2018), wage growth (Gathmann and Schonberg, 2007), and wage inequality (Violante, 2002).

An earlier conceptual version of specificity can be found in Becker's (1962) traditional human capital theory. Based on this theory, specific skills are deemed useful only within a firm while general skills are useful across occupations. However, studies that have distinguished between general and vocational education have also pointed out the presence of skill heterogeneity within educational, occupational, and industrial affiliation categories (Rinawi and Backes-Gellner, 2019)[2]. This largely points to the inadequacy of firm-based human capital specificity. Consequently, researchers have focused on occupation-based human capital specificity that capitalizes on the idea that for workers to produce output, they need to accomplish tasks using skills relevant to the occupation. While Robinson (2018) views workers being endowed with low dimensional vectors of skills that are transferable across occupations, Yamaguchi (2012) views occupations as bundles of tasks. 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). Mihaylov and Gartje (2019) develops measures to classify occupations into non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual tasks. The framework is anchored on the International Standard Classification of Occupations (ISCO), the utilization of which allows replicability in other countries. They

[2] Labor market dynamics and inefficiencies also play a role in the promotion of a particular skill. Wasmer (2009) established that in a labor market with matching frictions, workers may invest more in specific human capital than general human capital. Enabling mechanisms include higher worker protection provisions and poor matching. Wasmer (2009) notes that poor matching manifested by low probability of finding a job increases the relative return to specific skills.

find that 16% of ISCO occupations are in danger of being adversely affected by automation. Like Mihaylov and Tijdens (2019), Generalao (2019) uses this approach to provide a system for assigning skills to tasks found in the Philippine Standard Occupation Classification.

It is well-known that the occupation-based human capital specificity literature has emerged from the theoretical approach found in Lazear (2009), who assumes that individual skills are general skills but may become specific to occupations once different skills have been combined and weighted within firms. For example, persuasion and complex problem-solving skills are used in different occupations although complex problem-solving skills may be more relevant among software developers while persuasion skills may be more relevant among lawyers. At the basic level, 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.

A metric that is closely related to specificity is 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 (2010) have aptly provided an example by comparing outcomes when a carpenter becomes a cabinet maker and when a carpenter becomes a baker. Less human capital will be lost when a carpenter transitions to his new job as a cabinet maker than as a baker since the skills needed in carpentry and cabinet making are more similar than the skills needed in carpentry and baking. Thus, the distance metric can be useful in characterizing the labor market structure using information associated with nearby occupations. This allows the use of distance as an explanatory variable for explaining wage gains or losses in the event of job transitions (Gathmann and Schonberg, 2010; Poletaev and Robinson, 2008).

*2.2. Crosswalking the Philippine Standard Occupational codes with the O*NET codes*

In the Philippines, skills data are not collected in any of the nationally representative surveys that contain the Philippine Standard Occupational Classification (PSOC) codes. Due to this, a crosswalk strategy is employed to develop skills-based metrics related to the labor market. Crosswalking 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, which is based on 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[3] in each occupation The worker characteristics domain[4] has three components: skills, knowledge, and education. 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 occupation are determined by analysts (see Handel, 2016).

Linking national databases to the O*NET database is not a new strategy. For example, Canada relies on the Employment Social Development Canada's essential skill groupings. The applications, information, and research value of the O*NET database are also appreciated in

[3] See https://www.onetonline.org/

[4] Worker characteristics include abilities, occupational interests, work values, and work styles. Skills, knowledge, and education fall under worker requirements. Experience requirements include experience and training, skills, entry requirements, and licensing Occupational requirements include generalized work activities, detailed work activities, organizational context, and work context.

the UK (Hillage and Cross, 2015) and in developing economies like India Vashisnt and Dubey (2018). The crosswalking of survey data in the 4-digit PSOC codes with that of the O*NET database appears feasible. Since the occupations are rated by non-Filipinos, we could interpret the importance scores as targets that can be used to provide an approximation of where our skill distributions converge to.

There are several nationally representative datasets, such as the Labor Force Survey (LFS), the Listahanan, and the Census of Population and Housing (CPH) that can be crosswalked with the O*NET database. However, a comparison of these datasets reveals that the 2015 LFS contains 289 PSOC codes, the Listahanan contains 327, and the CPH contains 451. To include as many occupations as possible into the computation of relevant metrics, the 2015 CPH PSOC codes are crosswalked with the O*NET database. Out of the 451 CPH codes, there were 20 that had no match (see Table 1) and there were 29 codes assigned the average values of separate O*NET codes (e.g., PSOC Physicists and Astronomers was assigned the average of Physicist and Astronomers). There were 152 PSOC codes matched to the O*NET codes (e.g., the code for Pharmacists is used in the PSOC and O*NET; Film, Stage and Related Directors and Producers in the PSOC is matched to Producers and Directors in the O*NET). There were 10 codes that had no matches but were eventually assigned O*NET codes based on the detailed examples of occupations found in the 2012 PSOC manual.

Table 1: Details on crosswalking the 2015 CPH PSOC codes with the O*NET codes

	Freq.	Percent	
Matched	152	33.7	
Reconciled PSOC codes and O*NET codes	240	53.22	Example: 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
PSOC codes do not match with O*NET codes, assignment done	10	2.22	Example: Aged Care Service Managers in PSOC is matched *with* Administrative Services Managers in the O*NET; Traditional and Complementary Medicine Professionals *with* Naturopathic Physicians Creative and Performing Artists Not Elsewhere Classified with Makeup Artists, Theatrical and Performance Handicraft Workers in Wood, Basketry and Related Materials, Textile, Leather and not elsewhere classified *with* Craft Artists Pelt Dressers, Tanners and Fellmongers *with* Sewers, Hand Window Cleaners/ Other Cleaning Workers *with* Janitors and Cleaners, Except Maids and Housekeeping Cleaners Street and Related Service Workers *with* Door-to-Door Sales Workers, News and Street Vendors, and Related Workers
Average of the importance data assigned to the PSOC code	29	6.43	Example: 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
PSOC codes not matched with O*NET, no assignment done	20	4.43	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 Treaters, 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

Source: Authors' compilation based on the crosswalked 2015 CPH and O*NET database.

The literature has advanced two methods through which a skill characterization of occupations could be carried out, namely, the direct and indirect methods (Robinson. 2018). The direct method uses ratings data to characterize occupations (Poletaev & Robinson, 2008) while the indirect method uses factor analysis to extract information from the raw data of tasks

(Gathmann and Schoenberg 2010; Poletaev and Robinson 2008). For this paper, we follow the the former. This means that the O*NET's importance data can be used to determine whether all or some of the 35 O*NET's skills data are used in each occupation. Using the crosswalked PSOC codes, skills with importance data>=45 are coded 1 (0 otherwise) to constitute the skills bundle in each occupation. The idea is that if the skill is considered important in the occupation, then it is demonstrated/used by workers to fulfill the task in that occupation.

2.3. Measuring occupational specificity

Following Rinawi and Backes-Gellner (2019), there are three steps in computing the occupational specificity measure. First, each occupation is characterized in terms of skill requirements. Using the crosswalked PSOC codes, skills with importance data>=45 are coded 1 (0 otherwise) to constitute the skills bundle in each occupation. Second the ranked order of skills is determined using the labor market information. To do this, the crosswalked data are merged with the 2015 Census of Population and Housing. 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). From table 2, the greatest number of workers use active listening (93% of the total employed), critical thinking (89.3%), speaking (89%), coordination (81%), and monitoring skills (76%). Meanwhile, the bottom 5 skills include those involved in technology design (0.3%), programming (0.6%), installation (1.5%), equipment selection (2.2%), and Science (2.5%).

Table 2: Skills and number of workers

Skills	Total number of workers	Rank	% to total employed
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
Basic: Mathematics	5828115	22	15.8
Management: Personnel 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

Skills	Total number of workers	Rank	% to total employed
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
Basic: 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: Authors' compilation based on the crosswalked 2015 CPH and O*NET database.

Third, the occupational specificity measure is computed as $specificity\ of\ occupation\ i = \frac{sum\ of\ ranks\ of\ skills\ in\ occupation\ i}{number\ of\ skills\ in\ occupation\ i}$. To illustrate, assume that occupations 1 and 2 both use active listening, coordination, monitoring. Assume a fourth skill, which is time management skills 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). In this illustration, 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.

From table 3, elementary occupations like cleaning workers, farmers, clerks, and fillers have low specificity. Looking into their skills, building structure cleaners and building caretakers use active listening only while shelf fillers use active listening, critical thinking, speaking and coordination. These are general skills, or skills that are used by most of the working population (see Table 2). Meanwhile, occupations involved in engineering, mechanics/assembly, and ICT have skills bundles that are specific. For example, electronics engineers use general skills, but they also use skills that a smaller percentage of the working population would rely on, which include those in analytical, management, and mechanical.

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	Apiarists 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

Top 20 occupations	Specificity	Bottom 20 occupations	Specificity
Miners and Quarriers	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

Source: Authors' compilation based on the crosswalked 2015 CPH and O*NET database.

2.4. Broad skills categories

The 35 skills are assigned to broader skill groups, namely social, basic, analytical, management, and mechanical (see Table 4 for the specific skills included per broad category). Given that the importance data have been converted into binary data (importance data>=45 are coded 1, 0 otherwise), the composition of skill bundles used in occupations can now be determined. To illustrate, 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, 0.2, 0.4, 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. For example, the occupation related to sewing and embroidery have high importance data on two skills: 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%). To resolve this issue, the skills bundle is weighted using the number of skills in each broad category. To illustrate, occupation 1 will have the following weighted skills bundle: analytical is 0.06 (=unweighted bundle*weight or 1/2*1/9) and management skill is 0.1 (=1/2*1/5). If the 6 other skills fall under basic skills, occupation 2 will have the following weighted skills bundle: analytical is 0.18 (=4/10*4/9) and basic is 0.51 (=6/10*6/7).

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

Source: Authors' compilation based on the crosswalked 2015 CPH and O*NET database.
Note: Figures in parentheses are number of skills in each category.

2.5. Measuring distance

To come up with a distance measure between occupations, we leverage the idea that occupations requiring workers to perform similar tasks require similar skills and are more likely to be close to one another. For this exercise, we use the importance data in the crosswalked PSOC codes and the Euclidian distance is used to compute the skills-based distance between occupations. To illustrate, assuming two occupations (1 and 2) and two skills vectors (a and b), then $distance_{12} = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2}$. The distance measure takes the set of real numbers as domain and maps it to 0 if occupations 1 and 2 use the same skills. It is equal to a nonnegative, nonzero number if occupations 1 and 2 use different set of skills. We 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 $distance_{12} = \max(distance_{12}, distance_{21})$.

To illustrate, the furthest and closest occupations to software developers and shopkeepers are shown in Table 1A in the appendix**.** In the vector space, software developers[5] are the farthest from salespersons, repairers/mechanics, laborers, cleaners, caretakers, and operators and the closest to only one occupation, application programming. Shopkeepers[6] are the farthest from repairers, mechanics, engineers, operators, technicians, and professionals and the closest to sales assistants/representatives, salespersons, and vendors.

3. Skills-based characterization of the Philippine labor market

3.1. Occupations and the specificity of skills

Results indicate that Filipino workers are using mostly general skills. Around 62% of the working population are working as service and clerical and support workers; service and sales workers; skilled agricultural, fishery and forestry workers; and as workers in elementary occupations (see Table 5). The average specificity of occupations in these 1-digit aggregation is 0.39, indicating that these comprise of occupations that use general skills.

Table 5: Employment and specificity, by 1-digit occupation codes

Category	% of total employment	% of own subpopulation		Average specificity
		Male	Female	
Managers	6.82	4	12	0.78
Professionals	6.65	4	12	0.72
Technicians and associate professionals	4.7	4	6	0.65
Clerical support workers	6.79	4	11	0.45
Service and sales workers	16.8	12	25	0.47
Skilled agricultural, forestry and fishery workers	15.93	22	5	0.29
Craft and related trades workers	9.67	12	5	0.6
Plant and machine operators and assemblers	10.27	15	2	0.63
Elementary occupations	22.38	22	23	0.35

Source: Authors' computation based on the crosswalked 2015 CPH and O*NET database.
Note: The specificity measure is computed as the respective averages of specificity scores of occupations under each major occupational category. Total, male and female employment are 36966328, 24305979 and 12660349, respectively.

[5] skills include basic (active learning, active listening, critical thinking, Mathematics, reading comprehension, speaking, and writing), social skills (monitoring, coordination, social perceptiveness), analytical (complex problem solving, judgement and decision making, systems analysis, systems evaluation, operations analysis, programming), management (time), and mechanical (quality control)
[6] skills include basic (active listening, critical thinking, reading comprehension, speaking, and writing), social (coordination, negotiation, persuasion, service orientation, and social perceptiveness), and analytical (judgement and decision making)

Two out of five male and female workers are involved in occupations requiring general skills. Around 22% of male workers are involved in elementary occupations and another 22% in the agricultural, forestry and fishery. These occupations use general skills such as basic, social, and management skills. Around 23% of female workers are also involved in elementary occupations and 25% are in services and sales.

Gendered patterns are observed in the workers' involvement in occupations that are using specific skills. More male workers are involved in craft and related trades, and plant and machine operation and assembly (12% versus female workers' 5%). These occupations use not only general skills (basic, social, and management skills) but specific skills (analytical and mechanical skills) as well. Meanwhile, more female workers are involved in managerial and professional work (24% versus female workers' 8%), both of which involve analytical skills.

Around six out of ten Filipinos have jobs that mostly use general skills. This speaks of the quality of jobs created and will likely be created in the economy. Looking into the 4-digit PSOC codes with employment share of at least 1% of the total working population, the top panel of table 2A in the appendix indicates that out of the 431 occupations, there are 25 with employment of at least 1% and these already account for 60% of the total employment. Workers under these occupations include farmers, domestic cleaners/helpers, drivers, clerks, shopkeepers, security guards, waiters, and shelf fillers.

This can also be noted in the disaggregation by gender. Around 66% of the male working population are working in 25 occupations, which have the following average weighted skill bundles: 16% social skills, 20% basic skills, 2% analytical, 2% management, and 3% mechanical. Meanwhile, around 67% of the female working population are working in the same number of occupations, which have the following average average skills bundle: 25% social skills, 23% basic skills, 4% analytical, 3% management, and 0% mechanical. These occupations have skill bundles that are mostly composed of social and basic skills and the average specificity of these 25 occupations is low. It is around 0.40, 0.41, and 0.45 for the total, male, and female working populations, respectively.

The sheer number of farmers, domestic cleaners/helpers, drivers, clerks, shopkeepers, security guards, waiters, and shelf fillers are alarming because the country has enjoyed growth since 2012. This puts forth not only the issue of the lack of inclusive growth, but the quality of jobs generated in the economy as well. ICT developments have paved the way for new business models that can further increase the supply of workers in certain occupations with general skills. Motorcycle drivers and taxi/van drivers can continue to account for a large portion of the working population, which in 2015 is around 10%, considering the popularity of ride hailing services such as Grab. Shopkeepers and retail/wholesale trade managers can also continue to increase due to the proliferation of online grocery shopping, which requires online shoppers.

Among the in-demand jobs, the IT-BPM and manufacturing are looking to fill in jobs with more specific skills (analytical) while hotel/restaurant/tourism, wholesale and retail trade, and health and wellness looking to fill in jobs requiring general skills. Some of the jobs with low specificity (identified above) remain to be in-demand as reported in the DOLE's JobsFit 2022 Labor Market Information Report. In-demand jobs refer to "active occupations/job vacancies posted or advertised recurrently by and across establishments/industries" (DOLE 2017, p.57). Matching these in-demand jobs to the skills in the crosswalked data (upper panel of Table 6, see Table 3A in the appendix for details) shows that these 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%).

Among the top employment generators, IT-BPM and manufacturing are looking to fill jobs with more analytical skills. These 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. Such occupations require highly specific skills.

Table 6: Characteristics of in-demand and hard-to-fill jobs

Sector: In demand	Specificity	Distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
Agribusiness (28)	0.58	0.60	35	0.13	0.25	0.08	0.07	0.07
Banking and Finance (3)	0.50	0.55	22	0.14	0.31	0.05	0.06	0.00
Construction (11)	0.70	0.59	41	0.11	0.21	0.08	0.10	0.10
Health and Wellness (10)	0.53	0.57	23	0.22	0.33	0.04	0.06	0.00
Hotel, Restaurant and Tourism (22)	0.49	0.58	25	0.21	0.25	0.04	0.07	0.01
IT-BPM (9)	0.60	0.60	17	0.16	0.36	0.11	0.07	0.01
Manufacturing (9)	0.62	0.56	31	0.08	0.29	0.08	0.06	0.06
Mining (2)	0.84	0.66	24	0.14	0.23	0.14	0.05	0.17
Ownership, Dwellings and Real Estate (4)	0.53	0.56	32	0.19	0.30	0.07	0.07	0.01
Power and Utilities (2)	0.82	0.65	8	0.15	0.27	0.16	0.06	0.12
Transportation (5)	0.42	0.54	39	0.19	0.28	0.02	0.07	0.00
Wholesale and Retail Trade (11)	0.53	0.58	20	0.17	0.33	0.06	0.09	0.00
Average	0.60	0.59	26	0.16	0.28	0.08	0.07	0.05

Sector: Hard-to-fill	Specificity	Distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
Agribusiness (2)	0.77	0.66	3	0.18	0.33	0.17	0.08	0.01
Banking and Finance (4)	0.58	0.59	20	0.18	0.34	0.07	0.08	0.00
Construction (7)	0.68	0.61	18	0.18	0.31	0.10	0.07	0.05
Health and Wellness (10)	0.68	0.61	10	0.22	0.30	0.12	0.09	0.00
Hotel, Restaurant and Tourism (6)	0.67	0.61	13	0.22	0.32	0.11	0.12	0.00
IT-BPM (4)	0.76	0.67	8	0.13	0.32	0.27	0.04	0.01
Manufacturing (9)	0.70	0.62	18	0.13	0.28	0.14	0.08	0.02
Mining (3)	0.85	0.69	4	0.16	0.30	0.23	0.12	0.01
Ownership, Dwellings and Real Estate (1)	0.91	0.63	3	0.11	0.29	0.34	0.03	0.02
Power and Utilities (1)	0.83	0.66	5	0.07	0.32	0.22	0.08	0.03
Wholesale and Retail Trade (3)	0.62	0.61	12	0.11	0.33	0.16	0.06	0.00
Average	0.73	0.63	10	0.15	0.31	0.18	0.08	0.01

Source: Authors' computation based on the crosswalked 2015 CPH and O*NET database.
Note: Figures in () are number of observations. Jobs are based on the JobsFit 2020 Labor Market Information Report.

Hotel/restaurant/tourism, wholesale and retail trade, and health and wellness have in-demand of jobs requiring general skills, which consist of lower analytical skills and higher social and basic skills (versus other in-demand jobs). A quick assessment reveals that there are numerous occupations that bundle skills the same way. The list includes bartenders, clerk, waiter, cashier, beautician, bagger, weaver, cleaner/helper, laborer, and room attendant. This is worrisome given that developments in information, communication, and technology have dramatically reshaped the world of work. Such developments have undeniably highlighted occupations that are geared towards more intensive use of ICT, data analytics, and high value adding social skills[7]. 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 (HTF) jobs in the DOLE's JobsFit 2022 Labor Market Information Report.

Most HTF jobs require specific skills. By sector, HTF jobs are found in the IT-BPM, health/wellness, agribusiness, mining, and power and utilities. Hard-to-fill jobs refer to "job vacancies which the employer/company is having difficulty or taking longer time to fill in because job applicants are not qualified and/or there is no supply of job applicants for the job vacancy" (DOLE 2017, p.57). Matching these in-demand jobs to the skills in the crosswalked data (lower panel of Table 6, see Table 4A in the appendix for details) show that these jobs are mostly in health and wellness (20%), manufacturing (18%), construction (14%), banking and finance (8%), and IT-BPM (8%). It can be noted that these jobs require specific skills, and the average social, basic, and management skills in these jobs are relatively similar to those of in-demand jobs. However, the average mechanical skills are lower while the analytical skills are substantially higher in HTF jobs than in-demand jobs. These are also jobs that have high average distance, implying highly dissimilar skill sets compared with the nearby occupations. This could be an indication of the quality of jobs being created in the economy.

With respect to the sectors, 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.

3.2. Regional distributions of skills

Skill distributions vary spatially. The National Capital Region (NCR), CALABARZON and Central Luzon have the highest percentage of workers that are engaged in jobs requiring high skills. (Table 7). The National Capital Region (NCR), CALABARZON and Central Luzon have the greatest number of workers that belong to the top 40% skill quintiles. This implies that these regions have more workers that use the social, fundamental, analytical, management, and mechanical skills more than other regions. Among these three regions, the NCR has the highest proportion of workers involved in occupations that use the social, fundamental, analytical, and management skills while CALABARZON has the greatest number of workers involved in occupations that use mechanical skills.

[7] WEF (2018) identifies software and applications developers and analysts, sales and marketing professionals, managing directors and chief executives, data analysts and scientists, sales representatives, wholesale and manufacturing, technical and scientific products, general and operations managers, human resources specialists, financial and investment advisers, assembly and factory workers, and database and network professionals as emerging job roles.

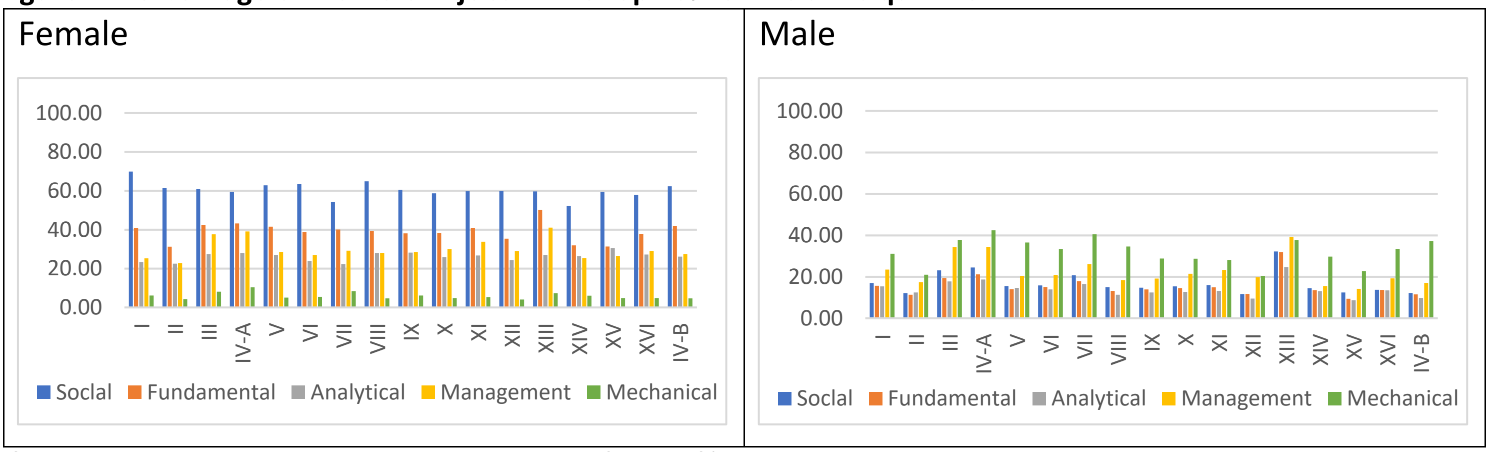
Table 7: Proportion of workers in the top 40% quintiles, by broad skills category

Region	Social skills	Fundamental skills	Analytical skills	Management skills	Mechanical skills
I Ilocos Region	5.20	4.65	4.66	4.19	4.59
II Cagayan Valley	3.05	2.51	2.98	2.45	2.32
III Central Luzon	12.34	12.04	12.50	14.18	12.82
IV-A CALABARZON	16.20	16.38	16.58	18.32	17.91
V Bicol Region	4.67	4.48	4.91	4.10	5.45
VI Western Visayas	7.02	6.56	6.61	5.92	7.15
VII Central Visayas	7.25	7.36	7.09	7.00	8.53
VIII Eastern Visayas	3.57	3.22	3.35	2.93	4.03
IX Zamboanga Peninsula	2.69	2.59	2.82	2.45	2.87
X Northern Mindanao	3.98	3.87	3.97	3.82	3.84
XI Davao Region	4.18	4.20	4.29	4.44	4.12
XII SOCCSKSARGEN	3.34	3.12	3.11	3.40	2.76
NCR	18.67	21.79	19.03	20.04	14.52
Cordillera Autonomous Region	1.59	1.47	1.74	1.25	1.57
ARMM	2.05	1.63	2.07	1.70	2.05
XIII Caraga	1.97	1.96	2.21	1.88	2.42
IV-B MIMAROPA	2.24	2.18	2.09	1.94	3.04
Number of workers in the top 40% quintiles	12427982	9645848	7189923	10655819	9218993

Source: Authors' computation based on the crosswalked 2015 CPH and O*NET database.
Note: Each entry represents the proportion of workers in the top skill quintiles relative to the total workers in the top 40% quintiles (Q4 and Q5 subpopulations). Estimates on total employment were computed using the 2015 Census of Population and Housing.

Gendered differences in skills are also observed across regions. A larger percentage of female workers are engaged in jobs that require high level of skills. This is true for all broad skills category except for mechanical skills. Looking into the top quintiles (quintiles 4 and 5) of the weighted skills scores, most female workers are engaged in jobs with high social skills (Figure 1). Ilocos Region has the largest percentage of female workers with high social skills (around 70%) although the other regions are not very far behind (between 60-65%). Female workers with jobs that have high fundamental skills ranges from 31% (ARMM) to 50% (NCR). Those with jobs that have high management skills ranges from 22% (Cagayan Valley) to 41% (NCR). Those in Central Luzon and CALABARZON have percentages (38% and 39%, respectively) that are comparable with that of the NCR. Meanwhile, female workers with jobs that have high analytical skills have a narrow range, from 23% (Cagayan Valley) to 30% (ARMM).

Figure 1: Percentage of workers in jobs in the top 40% of the skills quintile



Source: Authors' computation based on the crosswalked 2015 CPH and O*NET database.
Note: Estimates pertain to the proportion of males to total working males (all quintiles) in a particular region. I Ilocos Region, II Cagayan Valley, III Central Luzon, IV-A CALABARZON, V Bicol Region, VI Western Visayas, VII Central Visayas, VIII Eastern Visayas, IX Zamboanga Peninsula, X Northern Mindanao, XI Davao Region, XII SOCCSKSARGEN, XIII NCR, XIV Cordillera Administrative Region, XV Autonomous Region of Muslim Mindanao ARMM, XIV Caraga, IV-B MIMAROPA

Male workers are involved in jobs with high mechanical skills and the percentage ranges from 21% (Cagayan Valley) to 41% (CALABARZON). This contrasts with the female workers across regions, with less than 9% of them engaged in jobs with high mechanical skills. In terms of high social and fundamental skills, the percentage of male workers in the NCR are the highest at around 32%. The percentage of these workers in the rest of the regions fluctuate within a narrow band of 9-16%. Some regions like Central Luzon, CALABARZON, and NCR have higher percentage of male workers engaged in jobs with high management skills (34-38%) relative to other regions like Cagayan Valley, SOCCSKSARGEN, CAR, and ARMM (14-17%). NCR has the biggest percentage of male workers engaged in jobs with high analytical skills (39%) and SOCCSKSARGEN and ARMM have the smallest (around 10%).

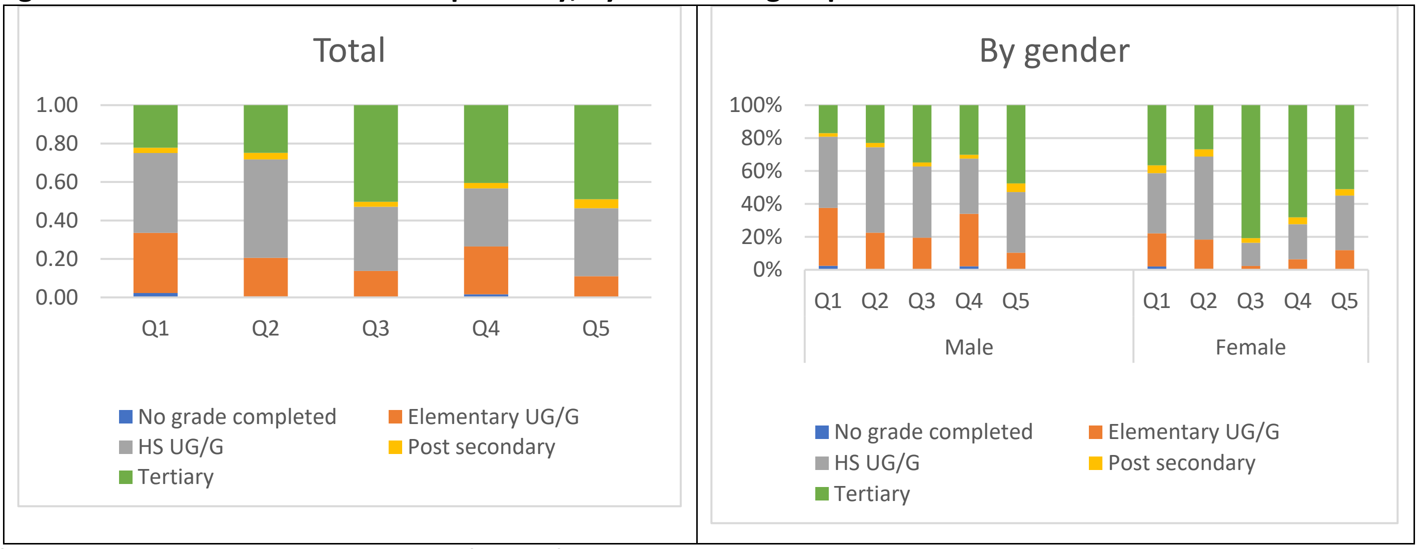
3.3. Skills and education

Although the percentage of workers with tertiary education is higher for high levels of specificity, there are also workers with tertiary education who are engaged in jobs that have low levels of specificity (e.g., those using basic skills). At high levels of specificity, around 40% and 49% have tertiary education (Q4 and Q5, respectively) although the percentage of workers with less than tertiary education is just as high. In addition, a noticeable percentage of workers with tertiary education (around 20%) are engaged in jobs with low levels of specificity (Q1 and Q2).

Broken down by gender, female workers engaged in jobs that require highly specific skills are better educated than male workers. Around 68%, and 51% of female workers have tertiary education in specificity quintiles 4^{th} and 5^{th}, respectively. These percentages are substantially bigger compared with that of male workers at 35%, 30% and 48%, respectively.

Despite this, there is a higher percentage of female workers who have tertiary education and are engaged in jobs with low specific skills. At low levels of specificity, around 30-40% of female workers have tertiary education. These percentages are bigger compared with that of male workers in the same specificity quintiles (between 17-23%).

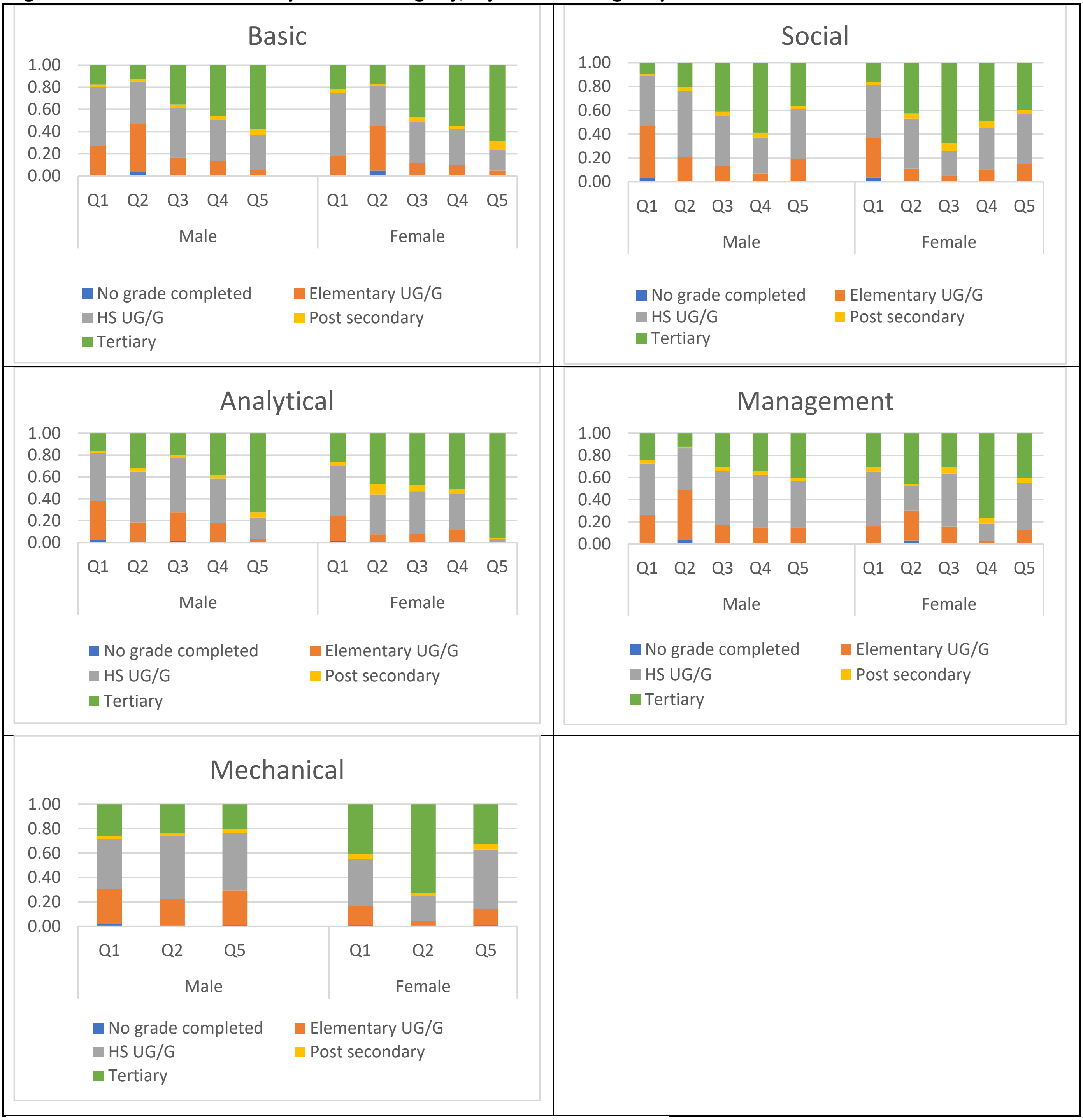
Figure 2: Quintile of skills bundle specificity, by education group



Source: Authors' computation based on the 2015 Census of Population and Housing.

With respect to broad skills category, a sizeable percentage of male and female workers with less than tertiary education is engaged in jobs with low levels of skills. However, these workers *are also engaged in jobs that require high skills levels.* This is observed in social skills, where around 60% of male and female workers (Q5) have less than tertiary education; and in management skills, where around 42% of male and female workers (Q5) have less than tertiary education. Across the social skill quintile and education groups, there are similar percentages of male and female workers.

Figure 3: Quintile of skills by broad category, by education group



Source: Authors' computation based on the crosswalked 2015 CPH and O*NET database.

A sizeable percentage of workers with tertiary education is engaged in jobs with high levels of skills although the percentage of female workers is higher than those of their male *counterparts.* Around 55% and 68% of female workers engaged in jobs with high basic skills ((Q4 and Q5) are highly educated. These are higher than those male workers at 46% and 58%, respectively. A similar observation can be noted in the highest level of analytical skills (Q5), with around 96% of female workers being highly educated. This is higher than male workers (76%). In terms of jobs with high management skills (Q4), around 77% of female workers are highly educated and this is higher than male workers (34%). In fact, across quintiles of management skills, a sizeable percentage of male workers has less than tertiary education and this is more pronounced in lower management skill level.

4. Gender pay gap, labor market structures, and skills

Recent reports have indicated that the gender wage gap in the Philippines shifted in favor of women (see ILO, 2018; ADB, 2013). 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 the pay gap does 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.

To do this, we use the Oaxaca-Blinder decomposition method, which decomposes the wage gap into three measurable components, namely: endowment, coefficient, and interaction effects. This methodology identifies whether predictors are gap-narrowing or gap-widening by accounting for their respective endowment and coefficient effects. Our decompositions are carried out from the perspective of male workers[8].

Consider two regression functions, denoted by

$$w_i^F = x_i^{F\prime}\beta_F + \epsilon_i^F, i = 1,2,\dots,N_F \quad (1)$$

$$w_i^M = x_i^{M\prime}\beta_M + \epsilon_i^M, i = 1,2,\dots,N_M \quad (2)$$

By assumption, both error terms ϵ_i^F and ϵ_i^M are mean zero stochastic components. We use the same regressors, implying that $dim(x_i^F) = dim(x_i^M)$. The mean pay of female and male workers are specified as follows:

$$\bar{w}^F = E[w_i^F] = \bar{x}^{F\prime}\beta_F \quad (3)$$

$$\bar{w}^M = E[w_i^M] = \bar{x}^{M\prime}\beta_M \quad (4)$$

Where $\bar{x}^F$ and $\bar{x}^M$ represent vectors of mean characteristics for female and male workers, respectively.

The observed mean wage gap, ΔEw is given by

$$\Delta Ew = E[w_i^F] - E[w_i^M] \quad (5)$$

The idea is to decompose the observed wage gap. Given that our reference group is male workers, we can have the following:

$$\Delta Ew = \bar{x}^{F\prime}\beta_F - \bar{x}^{M\prime}\beta_M \quad (6)$$

[8] It is not our intention to characterize statistical discrimination further empirically.

To get the terms that would identify the contribution of characteristics and coefficients, we add and subtract $\bar{x}^{F\prime}\beta_M, \bar{x}^{M\prime}\beta_F$. To eliminate other terms and constitute the interaction component, we add and subtract $\bar{x}^{M\prime}\beta_M$, and $\bar{x}^{F\prime}\beta_F$.

$$\Delta Ew = (\bar{x}^{F\prime}\beta_F - \bar{x}^{M\prime}\beta_M) + (\bar{x}^{F\prime}\beta_M - \bar{x}^{F\prime}\beta_M) + (\bar{x}^{M\prime}\beta_F - \bar{x}^{M\prime}\beta_F) + (\bar{x}^{M\prime}\beta_M - \bar{x}^{M\prime}\beta_M) + (\bar{x}^{F\prime}\beta_F - \bar{x}^{F\prime}\beta_F)$$

Rearranging,

$$\Delta Ew = (\bar{x}^{F\prime} - \bar{x}^{M\prime})\beta_M + \bar{x}^{M\prime}(\beta_F - \beta_M) + \bar{x}^{F\prime}(\beta_F - \beta_M) - \bar{x}^{M\prime}(\beta_F - \beta_M) \quad (7)$$

We have the familiar Oaxaca-Blinder decomposition formula cast in terms of its threefold representation.

$$\bar{w}^F - \bar{w}^M = \underbrace{\left(\bar{x}^{F'} - \bar{x}^{M'}\right)\beta_M}_{Endowment} + \underbrace{\bar{x}^{M'}(\beta_F - \beta_M)}_{Coefficient} + \underbrace{\left(\bar{x}^{F'} - \bar{x}^{M'}\right)(\beta_F - \beta_M)}_{Interaction} \quad (8)$$

The first component $\left(\bar{x}^{F'} - \bar{x}^{M'}\right)\beta_M$ accounts for group differences in terms of predictors, weighted by the coefficient estimates associated with male workers. $\bar{x}^{F'}\beta_M$ represents the wage of the average male worker when the average attribute of female workers was used instead. The difference between $\bar{x}^{F'}\beta_M$ and $\bar{x}^{M'}\beta_M$ represents the expected change in male pay. Known as the endowment effect, it essentially measures the expected change in the pay outcome of male workers if they have the females' predictor levels (Jann, 2008). Consider the k[th] predictor. Suppose $(\bar{x}^{F,k} - \bar{x}^{M,k})\beta_{M,k} > 0$. This implies that said predictor's endowment effect is gap-narrowing. Male workers stand to gain if their average characteristic is the same as females'. Otherwise, such a predictor is gap-widening. The second component $\bar{x}^{M'}(\beta_F - \beta_M)$ accounts for differences between female and male worker coefficients, or coefficient effects, weighted by the average male worker attributes. It essentially measures the expected change in the pay outcome of male workers if they are rewarded the same way as female workers. Consider the k[th] predictor. Suppose $\left(\beta_{F,k} - \beta_{M,k}\right)\bar{x}^{M,k} > 0$. This implies that said predictor's coefficient effect is gap-narrowing. Male workers stand to gain if their k[th] attribute has been similarly rewarded relative to female. Otherwise, such a predictor is gap-widening. The last one is the interaction effects, $\left(\bar{x}^{F'} - \bar{x}^{M'}\right)(\beta_F - \beta_M)$. It simply accounts for joint endowment and coefficient effects.

To identify the contributions of various predictors, we use a Mincerian wage function, regressing the respective logarithm of pay for female and male workers against known regressors that include skills, location, and personal attributes. For all decomposition estimates, male workers represent the base category. To interpret the effects of skills, specificity, average distance and educational attainment, the estimates have been exponentiated[9].

The objective of any decomposition exercises is to look for clues on how to narrow the pay gap in a counterfactual way. In terms of overall results, the endowment effect works to narrow the pay gap (first panel, column 2, Table 8). This means that replicating female workers' profiles (educational, other personal, and locational endowments) benefits male workers. Positive contributions to this gap-narrowing effect primarily come from the educational attainment, and

[9] We use Ben Jann's Stata program `Oaxaca.ado' to carry out the Oaxaca – Blinder threefold decomposition procedure. The 'eform' option was used to convert estimates based on log pay regressions into levels.

social, analytical, and management skills. On the other hand, adjusting male workers' basic and mechanical skills to match those of females would result to a decrease of 3.2% and 2.1% in the male's pay, respectively. This implies that male workers' attributes in terms of basic and mechanical skills can reduce the wage gap even without replicating the basic and mechanical skill endowments of female workers.

Table 8: Pay gap decomposition

Base specification: Broad Skills			
At least attended college	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
Specification: Skills x Specificity			
Personal	1.003	0.959	1.003
At least attended college	1.130	1.044	1.087
Social	1.105	0.860	0.768
Basic	1.046	1.349	1.268
Analytical	1.008	1.044	1.056
Management	1.011	0.991	0.998
Mechanical	0.998	0.944	1.051
Private	1.075	1.006	1.016
Geographical	1.028	1.028	0.996
Specification: Skills x Average Distance			
Personal	1.003	0.917	1.002
At least attended college	1.153	1.037	1.074
Social	1.158	0.852	0.782
Basic	0.954	1.778	1.370
Analytical	1.036	1.046	1.068
Management	1.005	1.052	1.006
Mechanical	0.986	0.999	1.001
Private	1.074	1.005	1.014
Geographical	1.029	1.034	0.997

Source: Authors' computation using the 2015 Labor Force Survey, all quarters

Even if female workers' endowments in social, analytical, management skills are pay gap-narrowing, the way the labor market rewards such skills may introduce a different scenario (first panel, column 3, Table 8). Most of the estimates in the table are greater than 1, indicating favorable labor market returns to skills and education. The female educational attainment is moderately rewarded in the labor market and results indicate that the male pay will increase by 3.7% had males' college attendance rates are on par with their female counterparts. As a predictor, tertiary degree/units are gap-narrowing, both in terms of its endowment and coefficient effects.

Despite being viewed as more socially skilled, the returns to the social skills of female workers are much lower than their male counterparts. Replicating such female wage structures with respect to social skills may instead result in a wider pay gap and as such, male workers are better off relying on their social skill returns. Results indicate that if male workers are rewarded the same way as female's social skills are rewarded, their pay would be lower by 15%. Female wage structures that pertain to the rest of the skills categories enhance the gap-narrowing effects of endowments. However, no skill compresses the pay gap as significantly as the basic skills. Male pay would increase by 85% if their basic skill profile is identical to females', substantially narrowing the pay gap (first panel, column 2, Table 8).

To investigate the effects of the occupational structure in the labor market, we investigate the interaction between skills and the specificity metric (second panel, Table 8). Based on the pay regression results, the effects of the weighted skills are positive. This means that the more specific skills are rewarded more by the market. In terms of the pay gap, the endowment effects of the specificity of the females' skills, except for mechanical, is gap-reducing. The returns to the specificity of basic and analytical skills are gap-reducing, implying that the females' endowment of these skills is better rewarded in the market. Males' specific social, management, and mechanical skills are better rewarded, however.

Average distance denotes the degree to which a given occupation is different from the other occupations in terms of skill requirements. The higher the value of this measure, the more different are the skill sets between the reference occupation relative to other occupations. Based on the pay regression results, the effects of the weighted skills are positive. This means that the more dissimilar the skills in an occupation are (compared with the skills of other occupations close to it), the higher the pay will be. As the males' social and mechanical skill sets become differentiated, male workers receive better rewards. The pay gap related to the coefficient effect becomes wide when male workers are rewarded the returns to females' social and mechanical skill sets. On the other hand, as the females' basic, analytical, and management skills become differentiated, the female workers receive better rewards in the labor market. In this case, the pay gap becomes narrow when male workers are rewarded the returns to female's basic, analytical, and management skills.

To summarize, the reversal in the wage gap has put forward some interesting results that pertain to how the occupational skills and 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 highly rewards tertiary education as indicated by its robust endowment and coefficient effects.
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. Labor market structures also play a role in reducing pay gap. The returns to highly specific occupational skills, especially those that are related to basic and analytical skills, narrow the pay gap. Highly specific basic skills include Mathematics and Sciences while highly specific analytical skills include systems analysis, systems evaluation, operations analysis, programming, and technology and design. Skills that are different from the skills of nearby occupations narrow the pay gap as well.

5. Summary and few takeaways

This paper provides a skills-based characterization of the labor market. Following the framework by Lazear (2009) and implementing the procedure developed by Rinawi and Backes-Gellner (2019), the paper has computed some metrics, such as the distance and specificity of skills. To do this, a crosswalking strategy is done (e.g., matching of the PSOC in the 2015 CPH with the occupation codes in the O*NET). The metrics are then used to characterize the Philippine labor market using the 2015 CPH and to analyze the gender pay gap in 2015. To implement the latter, augmented Mincerian regression models are estimated using all quarters of the 2015 Labor Force Survey. Results indicate the following:

1. Six in every ten workers in the Philippines are mostly employed in elementary occupations and in the agricultural, forestry, and fishery sectors. The said workers' occupational skill sets are mostly composed of social and basic skills. Some of these workers such as bartender, clerk, waiter, cashier, beautician, bagger, weaver, cleaner/helper, laborer, and room attendant remain in-demand (as reported in the JobsFit 2022 LMIR) have skill bundles that are characteristically general in nature. These are in-demand jobs in the hotel/restaurant/tourism, construction, health and wellness, and wholesale and retail trade sectors.
2. Some in-demand jobs in the IT-BPM and manufacturing sectors require specific skills bundle that include analytical skills such as systems analysis, systems evaluation, operations analysis, programming, and technology and design.
3. Hard-to-fill (HTF) jobs, mostly in health and wellness, manufacturing, construction, banking and finance, and IT-BPM, require specific skills. While the average social, basic, and management skills in these jobs are similar to those of in-demand jobs, the analytical skills required are substantially higher than those of the in-demand jobs.
4. HTF jobs are close to very few jobs that share similar skills sets, an indication of the quality of jobs available and/or being created in the economy.
5. In 2015, there is a pay gap in favor of women. The following variables are found to narrow the gap: tertiary education and basic skills (both endowments and returns).
6. Accounting for the occupational structure in the labor market, highly specific basic and analytical skills narrow the pay gap. Highly specific basic skills include Mathematics and Science while highly specific analytical skills include systems analysis, systems evaluation, operations analysis, programming, and technology and design.

Moving forward, there is a need to investigate 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. In an input-output setting, the formation and evolution of skills or learned competencies depend on the complex interaction of dynamics in home and school learning environments, learning attitudes, investments, instructional interventions, educational philosophies, and other related factors (Heckman and Mosso, 2014). We could also learn from the voluminous economics education literature that deals with school performance, environments, and leaners' attitudes and circumstances. It is well-documented that boys remain disadvantaged in the education front, have high drop-out rates, and have relatively low mean performance in the National Achievement Tests for both Grades 6 and 10 (David et, 2018). The inability to achieve competencies by dropping out of school has serious implications on the workers' abilities to take advantage of online training opportunities, including certification courses in massive open online courses (MOOCs such as Coursera and EdX) that continue to offer upskilling and reskilling strategies.

Given the high drop-out rates attributable to the lack of interest and poverty, the participation of educationally disadvantaged boys or young men may be facilitated by the availability of jobs with low-skill requirements such as jobs classified as elementary occupations. The availability of this labor market option depresses the overall skill quality of the Philippine workforce and has serious negative implications for economic growth. Thus, minimizing educational disparities at young ages may bode well for the efficacy of skill development programs. Solutions advocated by David et al (2018) and bolder educational perspectives espoused by Pacqueo and Orbeta (2020) may be useful for turning the tide. These include several initiatives that help improve home learning environments, enable multi-period investments in children especially those in disadvantaged households, promote the value of education consistently and intergenerationally through coherent media campaigns, calibrate the amount boys will receive from the 4Ps to increase attendance rates, enable gendered approaches to learning, and promote the involvement of communities in designing learning activities and determining learning outcomes for young children.

The importance of tertiary education cannot be overemphasized in enhancing the readiness of the country's future workforce. Philippine higher educational institutions (PHEIs) provide learning environments that develop cognitive and non-cognitive skills, which can translate or enhance general and specific skills needed in the workplace. Several PHEIs have already shifted to the Outcome Based Education curriculum, which identifies learning outcomes and establishes learning support environments that are conducive to the formation of professional learning communities. These will develop competencies that are aligned to the skill requirements of the FIRe and of some emerging sectors such as the creative economy.

Some universities may be rigid in revising their curriculum programs, although some private universities already offer innovative courses that address the needs of the future work and are locating in technoparks to intensify collaboration and to facilitate interaction with manufacturing giants. One program innovation is to offer professional courses, which necessarily strengthen linkages between the academe and industry. School-to-labor market transition programs such as apprenticeships should be enhanced as well.

TVET programs can be leveraged to tackle in-demand jobs in some sectors. These training programs are very useful especially to workers who wish to shift their career paths but do not have the necessary skills and training to respond to these HTF jobs. In consultation with industry experts, TVETs can then craft training programs that are aligned to the needs of the industry, giving them the impetus to improve their facilities and resources accordingly. There is a need to ensure the adequate supply of qualified trainers who can serve the sector-specific skills needs. To increase the pool of competent trainers, TVETs can also consider tapping into the industry experts as trainers.

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. While ICT developments have paved the way to high value adding jobs, new business models facilitated by platforms can further increase the supply of workers in certain occupations with general skills. Motorcycle drivers and taxi/van drivers can continue to account for a large portion of the working population considering the popularity of ride hailing services such as Grab. Shopkeepers and retail/wholesale trade managers, as online shoppers, can also continue to increase due to the proliferation of online shopping. Thus, a national upskilling program is imperative to ensure that these workers can participate in other market opportunities in the future. The design of this upskilling program can benefit from working not only with local stakeholders but with experts from other countries that have successful skills programs. Learning from the experience of the SkillsFuture in Singapore, for example, can help the country assess how its current resources match with the requirements to design, implement, maintain, and monitor such program.

There is a need to continue developing programs that encourage women's labor force participation and address job intermittencies resulting from care work. Firms are likely to view the provision of training to workers with intermittent market attachments as a risky investment. Thus, women may be faced with slower earnings growth and limited job mobility prospects. As the population ages, women will again be heavily involved in the care economy. Thus, developing programs for the care economy (childcare and elderly care) is imperative. Equally imperative is the integration of Filipino values and culture in the design and implementation of these programs.

Leveraging women's better educational achievements may help mitigate skills gap in highly technical occupations. Some of the newly created jobs now are more sophisticatedly analytical and require high level soft and social skills. Leveraging women's educational profile and cognizant of the fact that there are dynamic complementarities in the evolution of skills, programs that promote or provide incentives to women specializing in science, technology, and innovation may yield significant economic benefits and may advance the employment agenda.

Best practices for collecting, analyzing, and updating labor market information should be integrated in the Philippine statistical systems. The digital revolution is transforming how data are gathered, analyzed, and updated. The World Bank has an active partnership with LinkedIn to generate timely information on skills. It has conducted a nationally representative survey of the Philippine urban economy under the Skills Toward Employment and Productivity program. Replicating the structure of the ONET may be costly but it has features that enrich human resource interventions, track labor market developments and dynamics, and inform future statistical directions, particularly in ascertaining the quality, composition, and evolution of skill sets in both formal and informal sectors, and the high technology sector.

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APPENDIX

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 Quarriers	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		
	Bus and Tram Drivers	0.89		
	Freight Handlers	0.89		
	Woodworking Machine Tool Setters and Operators	0.89		
	Wood Processing Plant Operators	0.89		
	Dairy Farmer	0.88		
	Duck Raisers	0.88		
	Mixed Crop and Livestock Farm Laborers	0.88		
	Other Field Crop Farmers	0.88		
	Animal Producers Not Elsewhere Classified	0.88		
	Rice Farmers	0.88		
	Eggs Producers	0.88		
	Other Aqua Products Producers	0.88		
	Tree and Shrub Crop Growers	0.88		
	Prawn Producers	0.88		
	Poultry Producers	0.88		
	Garden and Horticultural Laborers	0.88		
	Mixed Crop and Animal Producers	0.88		
	Sugarcane Farmers	0.88		
	Vegetable, Legumes and Root Crops Farmers	0.88		
	Subsistence Mixed Crop and Livestock Farmers	0.88		
	Livestock Farmer	0.88		
	Other Market Gardeners and Crop Growers, Not Elsewhere Classified	0.88		
	Milkfish and Tilapia Producers	0.88		
	Crop Farm Laborers	0.88		
	Oysters and Mussels Producers	0.88		
	Seaweeds Producers	0.88		
	Chicken Farmer	0.88		
	Hog Raising Producers	0.88		
	Apiarists and Sericulturists	0.88		
	Corn Farmers	0.88		
	Livestock Farm Laborers	0.88		
	Coconut Farmers	0.88		
	Subsistence Crop Farmers	0.88		
	Subsistence Livestock Farmers	0.88		
	Gardeners, Horticultural and Nursery Growers	0.88		
	Fibre Preparing, Spinning and Winding Machine Operators	0.88		
	Religious Professionals	0.88		

Occupations that are far	Distance	Occupations that are close	Distance
Religious Associate Professionals	0.88		
Building Frame and Related Trades Workers Not Elsewhere Classified	0.88		
Building Construction Laborers	0.88		
Rubber Products Machine Operators	0.88		
Shoemakers and Related Workers	0.88		
Underwater Divers	0.88		
Civil Engineering Laborers	0.88		
Metal Polishers, Wheel Grinders and Tool Sharpeners	0.87		
Fishermen Not Elsewhere Classified	0.87		
Fishery and Aquaculture Laborers	0.87		
Deep-Sea Fishery Workers	0.87		
Subsistence Fishers, Hunters, Trappers and Gatherers	0.87		
Inland and Coastal Waters Fishery Workers	0.87		
Hunters and Trappers	0.87		
Hand Packers	0.87		
Announcers On Radio, Television and Other Media	0.87		
Riggers and Cable Splicers	0.87		
Metal Processing Plant Operators	0.87		
Packing, Bottling and Labelling Machine Operators	0.86		
Sewing Machine Operators	0.86		
Service Station Attendants	0.86		
Ships' Deck Crews and Related Workers	0.86		
Motor Vehicle Mechanics and Repairers	0.86		
Building and Related Electricians	0.86		
Manufacturing Laborers Not Elsewhere Classified	0.86		
Domestic Cleaners and Helpers	0.85		
Hand Launderers and Pressers	0.85		
Musical Instrument Makers and Tuners	0.85		
Personnel and Careers Professionals	0.85		
Printers	0.85		
Actors	0.85		
Bleaching, Dyeing and Fabric Cleaning Machine Operators	0.84		
Textile, Fur and Leather Products Machine Operators Not Elsewhere Classified	0.84		
Metal Finishing, Plating and Coating Machine Operators	0.84		
Information and Communications Technology Installers and Servicers	0.84		
Metal Production Process Controllers	0.84		
Laundry Machine Operators	0.84		
Coding, Proof-Reading and Related Clerks	0.84		
Metal Molders and Coremakers	0.84		
Well Drillers and Borers and Related Workers	0.84		
Sports Coaches, Instructors and Officials	0.84		
Fumigators and Other Pest and Weed Controllers	0.83		
Car, Taxi and Van Drivers	0.83		
Plastic Products Machine Operators	0.83		
Firefighters	0.83		
Education Managers	0.83		
Physiotherapy Technicians and Assistants	0.83		
Clerical Support Workers Not Elsewhere Classified	0.83		
Paper Products Machine Operators	0.83		
Pulp and Papermaking Plant Operators	0.83		
Beauticians and Related Workers	0.83		
Structural Metal Preparers and Erectors	0.83		
Locomotive Engine Drivers	0.83		
Lifting Truck Operators	0.83		
Stonemasons, Stone Cutters, Splitters and Carvers	0.83		
Client Information Workers Not Elsewhere Classified	0.82		
Railway Brake, Signal and Switch Operators	0.82		
Other Language Teachers	0.82		
Steam Engine and Boiler Operators	0.82		
Shotfirers and Blasters	0.82		
Physical and Engineering Science Technicians Not Elsewhere Classified	0.82		
Paramedical Practitioners	0.82		
Cashiers and Ticket Clerks	0.82		
Police Inspectors and Detectives	0.82		
Incinerator and Water Treatment Plant Operators	0.82		
Fur and Leather Preparing Machine Operators	0.81		
Medical Secretaries	0.81		

	Occupations that are far	Distance	Occupations that are close	Distance
	Medical Records and Health Information Technicians	0.81		
	Electrical Power-Line Installers and Repairers	0.81		
	Ambulance Workers	0.81		
	Stall and Market Salespersons	0.81		
	Shopkeepers	0.81		
	Street Food Salespersons	0.81		
	Street and Related Service Workers	0.81		
	Street Vendors (Excluding Food)	0.81		
	Door To Door Salespersons	0.81		
	Glass and Ceramics Plant Operators	0.81		
	Waiters	0.81		
	Athletes and Sports Players	0.81		
	Spray Painters and Varnishers	0.81		
	Motorcycle Drivers	0.81		
	Power Production Plant Operators	0.80		
	Insulation Workers	0.80		
	Welders and Flame Cutters	0.80		
	Metal Working Machine Tool Setters and Operators	0.80		
	Blacksmiths, Hammersmiths and Forging Press Workers	0.80		
	Librarians and Related Information Professionals	0.80		
	Print Finishing and Binding Workers	0.80		
Shopkeepers	Aircraft Engine Mechanics and Repairers	1.00	Shop Sales Assistants	0.29
(Specificity: 0.45)	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'S 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		
	Managing Directors and Chief Executives	0.84		
	Incinerator and Water Treatment Plant Operators	0.84		
	Mechanical Engineers	0.84		
	Chemical Engineering Technicians	0.84		
	Chemical and Physical Science Technicians	0.84		
	Miners and Quarriers	0.84		
	Mining and Quarrying Laborers	0.84		
	Chemical Processing Plant Controllers	0.83		
	Petroleum and Natural Gas Refining Plant Operators	0.82		
	Electronics Engineering Technicians	0.82		
	Electrical Engineering Technicians	0.82		
	Medical and Pathology Laboratory Technicians	0.82		
	Software and Applications Developers and Analyst Not Elsewhere Classified	0.81		
	Wood Processing Plant Operators	0.81		
	Woodworking Machine Tool Setters and Operators	0.81		
	Information and Communications Technology Operations Technicians	0.81		
	Mechanical Engineering Technicians	0.81		
	Software Developers	0.81		
	Applications Programmers	0.81		
	Musical Instrument Makers and Tuners	0.81		
	Mining Engineers, Metallurgists and Related Professionals	0.81		
	Motor Vehicle Mechanics and Repairers	0.80		
	Aircraft Pilots and Related Associate Professionals	0.80		

Table 2A: Broad skills and employment

Both male and female (36966328)	Unweighted					Weighted						
Occupation	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Specificity	% of emp to total
Rice Farmers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	5.33
Crop Farm Laborers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	4.52
Domestic Cleaners and Helpers	0.75	0.00	0.00	0.25	0.00	0.38	0.00	0.00	0.05	0.00	0.44	4.30
Retail and Wholesale Trade Managers	0.26	0.30	0.22	0.22	0.00	0.26	0.30	0.11	0.22	0.00	0.79	4.18
Motorcycle Drivers	0.27	0.36	0.18	0.18	0.00	0.14	0.21	0.04	0.07	0.00	0.42	4.13
Mixed Crop and Livestock Farm Laborers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	3.21
Corn Farmers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	2.98
Civil Engineering Laborers	0.17	0.25	0.25	0.08	0.25	0.06	0.11	0.08	0.02	0.11	0.63	2.67
Car, Taxi and Van Drivers	0.17	0.42	0.08	0.17	0.17	0.06	0.30	0.01	0.07	0.05	0.49	2.51
General Office Clerks	0.30	0.50	0.00	0.20	0.00	0.15	0.36	0.00	0.08	0.00	0.37	2.34
Stall and Market Salespersons	0.45	0.45	0.09	0.00	0.00	0.38	0.32	0.01	0.00	0.00	0.45	2.31
Shopkeepers	0.45	0.45	0.09	0.00	0.00	0.38	0.32	0.01	0.00	0.00	0.45	2.31
Inland and Coastal Waters Fishery Workers	0.00	0.33	0.22	0.00	0.44	0.00	0.14	0.04	0.00	0.25	0.75	2.08
Carpenters and Joiners	0.17	0.42	0.17	0.17	0.08	0.06	0.30	0.03	0.07	0.01	0.44	1.80
Security Guards	0.22	0.67	0.00	0.11	0.00	0.07	0.57	0.00	0.02	0.00	0.37	1.75
Building Construction Laborers	0.20	0.40	0.00	0.00	0.40	0.03	0.11	0.00	0.00	0.11	0.51	1.63
Primary School Teachers	0.30	0.35	0.25	0.10	0.00	0.30	0.35	0.13	0.04	0.00	0.67	1.59
Coconut Farmers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	1.56
Contact Center Information Clerks	0.30	0.60	0.00	0.10	0.00	0.15	0.51	0.00	0.02	0.00	0.42	1.50
Waiters	0.36	0.36	0.18	0.09	0.00	0.24	0.21	0.04	0.02	0.00	0.42	1.44
Street Food Salespersons	0.45	0.45	0.09	0.00	0.00	0.38	0.32	0.01	0.00	0.00	0.45	1.42
Vegetable, Legumes and Root Crops Farmers	0.20	0.60	0.00	0.20	0.00	0.03	0.26	0.00	0.04	0.00	0.18	1.31
Building Caretakers	0.00	1.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.06	1.27
Shelf Fillers	0.25	0.75	0.00	0.00	0.00	0.04	0.32	0.00	0.00	0.00	0.15	1.18
Stonemasons, Stone Cutters, Splitters and Carvers	0.33	0.33	0.11	0.17	0.06	0.33	0.29	0.02	0.10	0.01	0.60	1.08
Average (Total)						0.14	0.27	0.02	0.04	0.02	0.40	(60.40)

Male (24305979)	Unweighted					Weighted						
Occupation	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Specificity	% of emp to total
Rice Farmers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	7.57
Motorcycle Drivers	0.14	0.21	0.04	0.07	0.00	0.27	0.36	0.18	0.18	0.00	0.42	6.18
Crop Farm Laborers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	5.20
Corn Farmers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	4.07
Mixed Crop and Livestock Farm Laborers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	3.96
Civil Engineering Laborers	0.06	0.11	0.08	0.02	0.11	0.17	0.25	0.25	0.08	0.25	0.63	3.94
Car, Taxi and Van Drivers	0.06	0.30	0.01	0.07	0.05	0.17	0.42	0.08	0.17	0.17	0.49	3.76
Inland and Coastal Waters Fishery Workers	0.00	0.14	0.04	0.00	0.25	0.00	0.33	0.22	0.00	0.44	0.75	3.10
Carpenters and Joiners	0.06	0.30	0.03	0.07	0.01	0.17	0.42	0.17	0.17	0.08	0.44	2.71
Security Guards	0.07	0.57	0.00	0.02	0.00	0.22	0.67	0.00	0.11	0.00	0.37	2.45
Building Construction Laborers	0.03	0.11	0.00	0.00	0.11	0.20	0.40	0.00	0.00	0.40	0.51	2.43
Coconut Farmers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	2.23
Retail and Wholesale Trade Managers	0.26	0.30	0.11	0.22	0.00	0.26	0.30	0.22	0.22	0.00	0.79	2.04
Stonemasons, Stone Cutters, Splitters and Carvers	0.33	0.29	0.02	0.10	0.01	0.33	0.33	0.11	0.17	0.06	0.60	1.61
General Office Clerks	0.15	0.36	0.00	0.08	0.00	0.30	0.50	0.00	0.20	0.00	0.37	1.50
Stall and Market Salespersons	0.38	0.32	0.01	0.00	0.00	0.45	0.45	0.09	0.00	0.00	0.45	1.50
Ships' Deck Crews and Related Workers	0.13	0.11	0.03	0.02	0.11	0.25	0.25	0.17	0.08	0.25	0.63	1.48

Occupation	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Specificity	% of emp to total
Vegetable, Legumes and Root Crops Farmers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	1.48
Building Caretakers	0.00	0.14	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.06	1.42
Welders and Flame Cutters	0.00	0.11	0.02	0.04	0.03	0.00	0.40	0.20	0.20	0.20	0.59	1.32
Bus and Tram Drivers	0.07	0.14	0.00	0.09	0.06	0.22	0.33	0.00	0.22	0.22	0.47	1.31
Waiters	0.24	0.21	0.04	0.02	0.00	0.36	0.36	0.18	0.09	0.00	0.42	1.28
Shopkeepers	0.38	0.32	0.01	0.00	0.00	0.45	0.45	0.09	0.00	0.00	0.45	1.18
Contact Center Information Clerks	0.15	0.51	0.00	0.02	0.00	0.30	0.60	0.00	0.10	0.00	0.42	1.05
Messengers, Package Deliverers and Luggage Porters	0.15	0.23	0.01	0.08	0.00	0.30	0.40	0.10	0.20	0.00	0.36	1.02
Average (Total)						0.23	0.47	0.08	0.14	0.08	0.41	(65.81)

Female (12660349)			**Unweighted**					**Weighted**				
Occupation	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills	Specificity	% of emp to total
Domestic Cleaners and Helpers	0.38	0.00	0.00	0.05	0.00	0.75	0.00	0.00	0.25	0.00	0.44	11.05
Retail and Wholesale Trade Managers	0.26	0.30	0.11	0.22	0.00	0.26	0.30	0.22	0.22	0.00	0.79	8.28
Shopkeepers	0.38	0.32	0.01	0.00	0.00	0.45	0.45	0.09	0.00	0.00	0.45	4.47
General Office Clerks	0.15	0.36	0.00	0.08	0.00	0.30	0.50	0.00	0.20	0.00	0.37	3.96
Primary School Teachers	0.30	0.35	0.13	0.04	0.00	0.30	0.35	0.25	0.10	0.00	0.67	3.90
Stall and Market Salespersons	0.38	0.32	0.01	0.00	0.00	0.45	0.45	0.09	0.00	0.00	0.45	3.87
Crop Farm Laborers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	3.21
Street Food Salespersons	0.38	0.32	0.01	0.00	0.00	0.45	0.45	0.09	0.00	0.00	0.45	2.58
Contact Center Information Clerks	0.15	0.51	0.00	0.02	0.00	0.30	0.60	0.00	0.10	0.00	0.42	2.36
Cashiers and Ticket Clerks	0.14	0.21	0.04	0.07	0.00	0.27	0.36	0.18	0.18	0.00	0.43	2.29
Nursing Professionals	0.25	0.29	0.20	0.08	0.01	0.25	0.29	0.29	0.13	0.04	0.80	2.05
Sewing, Embroidery and Related Workers	0.00	0.00	0.05	0.10	0.00	0.00	0.00	0.50	0.50	0.00	0.49	1.99
Secondary Education Teachers	0.30	0.35	0.13	0.04	0.00	0.30	0.35	0.25	0.10	0.00	0.67	1.88
Mixed Crop and Livestock Farm Laborers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	1.78
Waiters	0.24	0.21	0.04	0.02	0.00	0.36	0.36	0.18	0.09	0.00	0.42	1.74
Shelf Fillers	0.04	0.32	0.00	0.00	0.00	0.25	0.75	0.00	0.00	0.00	0.15	1.70
Hand Launderers and Pressers	0.38	0.00	0.00	0.05	0.00	0.75	0.00	0.00	0.25	0.00	0.44	1.52
Household Service Providers	0.22	0.30	0.01	0.07	0.00	0.33	0.42	0.08	0.17	0.00	0.43	1.42
Sales and Marketing Managers	0.27	0.32	0.11	0.15	0.00	0.27	0.32	0.23	0.18	0.00	0.77	1.28
Health Care Assistants	0.22	0.30	0.01	0.07	0.00	0.33	0.42	0.08	0.17	0.00	0.43	1.23
Beauticians and Related Workers	0.10	0.18	0.01	0.03	0.00	0.29	0.43	0.14	0.14	0.00	0.30	1.17
Commercial Sales Representatives	0.28	0.34	0.03	0.05	0.00	0.33	0.40	0.13	0.13	0.00	0.49	1.09
Shop Sales Assistants	0.40	0.34	0.01	0.05	0.00	0.40	0.40	0.07	0.13	0.00	0.51	1.04
Rice Farmers	0.03	0.26	0.00	0.04	0.00	0.20	0.60	0.00	0.20	0.00	0.18	1.03
Average (Total)						0.33	0.39	0.12	0.15	0.00	0.45	(66.90)

Table 3A. In-demand jobs

Sector		Specificity	Ave distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
Agribusiness	Marine Biologist	0.81	0.66	7	0.25	0.29	0.20	0.08	0.01
	Plant Pathologist	0.81	0.66	7	0.25	0.29	0.20	0.08	0.01
	Marketing Officer	0.70	0.60	14	0.14	0.37	0.19	0.04	0.00
	Quality Control Technician	0.97	0.77	4	0.10	0.26	0.18	0.03	0.26
	Land Surveyor	0.58	0.57	5	0.04	0.47	0.11	0.05	0.00
	Heavy Equipment Mechanic	0.91	0.78	7	0.11	0.28	0.10	0.03	0.28
	Marketing Specialist	0.60	0.62	7	0.33	0.29	0.09	0.04	0.00
	Horticultural Worker	0.74	0.61	4	0.29	0.33	0.08	0.15	0.00
	Purchaser	0.74	0.61	4	0.29	0.33	0.08	0.15	0.00
	Hand Tractor Operator	0.88	0.61	54	0.00	0.05	0.08	0.07	0.30
	Fish Feeder	0.75	0.55	105	0.00	0.14	0.04	0.00	0.25
	Fisherman	0.75	0.55	105	0.00	0.14	0.04	0.00	0.25
	Slaughterer	0.37	0.52	17	0.14	0.21	0.04	0.07	0.00
	Fish and Marine Products Processor	0.37	0.52	17	0.14	0.21	0.04	0.07	0.00
	Food Processor	0.37	0.52	17	0.14	0.21	0.04	0.07	0.00
	Sales Representative/Sales Officer	0.49	0.57	18	0.28	0.34	0.03	0.05	0.00
	Seaweed Farmer	0.18	0.54	82	0.03	0.26	0.00	0.04	0.00
	Poultry Producer	0.18	0.54	82	0.03	0.26	0.00	0.04	0.00
	Piggery Worker/Technician	0.18	0.54	82	0.03	0.26	0.00	0.04	0.00
	Packer	0.31	0.62	55	0.00	0.00	0.00	0.20	0.00
Banking and Finance	Appraiser	0.54	0.56	8	0.11	0.37	0.06	0.06	0.00
	Bank Teller	0.53	0.54	31	0.18	0.34	0.06	0.05	0.00
	Cashier	0.43	0.56	27	0.14	0.21	0.04	0.07	0.00
Construction	Field Engineer	0.87	0.69	0	0.24	0.28	0.20	0.20	0.00
	Building Construction Engineer	0.87	0.69	0	0.24	0.28	0.20	0.20	0.00
	Cabinetmaker	0.96	0.60	42	0.00	0.13	0.15	0.05	0.30
	Bricklayer and Related Worker	0.60	0.51	49	0.01	0.19	0.13	0.07	0.01
	Purchaser	0.74	0.61	4	0.29	0.33	0.08	0.15	0.00
	Dump Truck Loader	0.88	0.61	54	0.00	0.05	0.08	0.07	0.30
	Pipe Fitter	0.79	0.57	24	0.13	0.18	0.05	0.09	0.18
	Painter bi	0.32	0.51	73	0.08	0.16	0.01	0.10	0.00
	Molding and Casting Worker	0.76	0.56	66	0.01	0.27	0.01	0.06	0.18
	Administrative Clerk	0.37	0.54	39	0.15	0.36	0.00	0.08	0.00
	Laborer/Helper	0.51	0.56	95	0.03	0.11	0.00	0.00	0.11
Health and Wellness	Midwifery Professional	0.72	0.63	17	0.21	0.35	0.13	0.09	0.00
	Respiratory Therapist	0.70	0.61	17	0.30	0.35	0.08	0.09	0.00
	Ballet Instructor	0.70	0.62	11	0.30	0.35	0.08	0.09	0.00
	Radiology Technician	0.67	0.60	1	0.29	0.33	0.08	0.04	0.03
	Barber	0.54	0.55	7	0.26	0.44	0.03	0.05	0.00
	Hairdresser	0.54	0.55	7	0.26	0.44	0.03	0.05	0.00
	Nail Technician	0.30	0.55	54	0.10	0.18	0.01	0.03	0.00
	Beautician	0.30	0.55	54	0.10	0.18	0.01	0.03	0.00
	Hospital Attendant	0.43	0.55	19	0.22	0.30	0.01	0.07	0.00
	Clerk	0.37	0.54	39	0.15	0.36	0.00	0.08	0.00
Hotel, Restaurant and Tourism	Food Production Coordinator	0.82	0.62	6	0.24	0.28	0.14	0.20	0.01
	Culinary Worker	0.80	0.60	5	0.26	0.30	0.11	0.22	0.00
	Chambermaid	0.67	0.61	5	0.30	0.35	0.08	0.09	0.00
	Hotel Housekeeping Attendant	0.67	0.61	5	0.30	0.35	0.08	0.09	0.00
	Hotel Manager	0.76	0.66	10	0.27	0.32	0.07	0.23	0.00

Sector		Specificity	Ave distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
	Head Waiter	0.42	0.56	26	0.24	0.21	0.04	0.02	0.00
	Service Crew	0.42	0.56	26	0.24	0.21	0.04	0.02	0.00
	Hotel and Restaurant Staff/Crew	0.42	0.56	26	0.24	0.21	0.04	0.02	0.00
	Waiter/Waitress	0.42	0.56	26	0.24	0.21	0.04	0.02	0.00
	Cashier	0.43	0.56	27	0.14	0.21	0.04	0.07	0.00
	Baker	0.52	0.51	30	0.02	0.32	0.04	0.07	0.01
	Human Resource Assistant	0.46	0.54	32	0.19	0.37	0.03	0.06	0.00
	Sales Representative/Sales Officer	0.49	0.57	18	0.28	0.34	0.03	0.05	0.00
	Bartender	0.55	0.56	12	0.38	0.32	0.03	0.05	0.00
	Hotel Front Desk Clerk (English, Chinese and Korean Language Proficient)	0.56	0.56	16	0.38	0.22	0.03	0.11	0.00
	Log Scaler	0.65	0.65	65	0.00	0.08	0.01	0.03	0.18
	Bell Boy	0.36	0.51	20	0.15	0.23	0.01	0.08	0.00
	Butler	0.43	0.55	19	0.22	0.30	0.01	0.07	0.00
	Domestic Cleaner and Helper	0.44	0.58	25	0.38	0.00	0.00	0.05	0.00
	Clerk	0.37	0.54	39	0.15	0.36	0.00	0.08	0.00
	Room Attendant	0.06	0.61	54	0.00	0.14	0.00	0.00	0.00
	Utility Personnel	0.06	0.61	54	0.00	0.14	0.00	0.00	0.00
IT-BPM	Software Quality Assurance Analyst	0.82	0.71	1	0.04	0.29	0.36	0.04	0.00
	IT Support Staff	0.89	0.67	0	0.01	0.33	0.30	0.04	0.06
	Finance Consultant	0.70	0.61	15	0.29	0.33	0.12	0.09	0.00
	Sales Manager	0.77	0.65	12	0.27	0.32	0.11	0.15	0.00
	Human Resource Assistant	0.46	0.54	32	0.19	0.37	0.03	0.06	0.00
	Sales Representatives/Sales Officer	0.49	0.57	18	0.28	0.34	0.03	0.05	0.00
	Data Entry/Encoder Clerk	0.39	0.56	17	0.00	0.45	0.01	0.10	0.00
	Health Care Service Worker	0.43	0.55	19	0.22	0.30	0.01	0.07	0.00
	Electronic Mail and Chat Support Agent	0.42	0.55	35	0.15	0.51	0.00	0.02	0.00
Manufacturing	Automotive Brakes System Service Technician	0.82	0.59	15	0.07	0.32	0.22	0.04	0.06
	Instrumentation and Control Technician	0.83	0.61	12	0.07	0.23	0.16	0.04	0.16
	Bricklayer and Related Worker	0.60	0.51	49	0.01	0.19	0.13	0.07	0.01
	Quality Control Inspector	0.55	0.52	27	0.05	0.26	0.06	0.06	0.04
	Pipe Fitter	0.79	0.57	24	0.13	0.18	0.05	0.09	0.18
	Executive Sales Agent	0.49	0.57	18	0.28	0.34	0.03	0.05	0.00
	Data Entry/Encoder Clerk	0.39	0.56	17	0.00	0.45	0.01	0.10	0.00
	Weaver	0.47	0.55	7	0.14	0.47	0.01	0.02	0.00
	CNC Machinist	0.66	0.53	113	0.02	0.21	0.01	0.07	0.12
Mining	Mining Manager	0.80	0.67	9	0.26	0.30	0.21	0.08	0.00
	Mining Laborer	0.88	0.66	39	0.01	0.15	0.06	0.01	0.34
Ownership, Dwellings and Real Estate	Urban Planner	0.81	0.60	4	0.07	0.32	0.22	0.08	0.03
	Human Resource Assistant	0.46	0.54	32	0.19	0.37	0.03	0.06	0.00
	Painter	0.32	0.51	73	0.08	0.16	0.01	0.10	0.00
	Sales and Marketing Assistant	0.51	0.57	17	0.40	0.34	0.01	0.05	0.00
Power and Utilities	Health Inspector	0.77	0.59	6	0.26	0.30	0.21	0.03	0.01
	Engine Cadet	0.88	0.71	9	0.03	0.23	0.11	0.08	0.23
Transportation and Storage	Ticket Teller	0.43	0.56	27	0.14	0.21	0.04	0.07	0.00
	Human Resource Assistant	0.46	0.54	32	0.19	0.37	0.03	0.06	0.00
	Ticket Issuing/Travel Clerk	0.52	0.56	25	0.38	0.32	0.03	0.05	0.00
	Automotive Painter	0.32	0.51	73	0.08	0.16	0.01	0.10	0.00
	Administrative Clerk	0.37	0.54	39	0.15	0.36	0.00	0.08	0.00
Wholesale and Retail Trade	Marketing Officer	0.70	0.60	14	0.14	0.37	0.19	0.04	0.00

Sector		Specificity	Ave distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
	Fashion Consultant	0.77	0.66	16	0.27	0.32	0.11	0.15	0.00
	Conference and Event Planner	0.74	0.62	8	0.29	0.24	0.08	0.24	0.00
	Finance Clerk	0.52	0.56	27	0.05	0.40	0.07	0.06	0.00
	Invoice Clerk	0.43	0.56	27	0.14	0.21	0.04	0.07	0.00
	Cashier	0.43	0.56	27	0.14	0.21	0.04	0.07	0.00
	Junior Auditor	0.48	0.57	21	0.06	0.32	0.04	0.07	0.00
	Human Resource Assistant	0.46	0.54	32	0.19	0.37	0.03	0.06	0.00
	Promodizer	0.46	0.55	14	0.19	0.37	0.03	0.06	0.00
	Data Entry/Encoder Clerk	0.39	0.56	17	0.00	0.45	0.01	0.10	0.00
	Sales Clerk	0.51	0.57	17	0.40	0.34	0.01	0.05	0.00

Note: Jobs identified in the Labor Market Information Report that were not matched in the crosswalked data: Rides Operator, Plant Operator, Operations Assistant, Technical Writer, Production Worker, Psychometrician, Design Engineer, Data Analyst, Lay-out Artist, Technical Support Specialist, Video Editor, Order Tracker/Coordinator, Technical Field Specialist, Production Worker, Senior Project Engineer

Table 4A: Characterization of hard-to-fill jobs identified in the JobsFit 2022 Labor Market Information Report

Sector		Specificity	Ave distance	Number of nearby occupations	Social skills	Basic skills	Analytical skills	Management skills	Mechanical skills
Agribusiness	Chemist	0.83	0.66	5.00	0.07	0.32	0.22	0.08	0.03
	Animal Husbandry Professional	0.70	0.66	1.00	0.29	0.33	0.12	0.09	0.00
Banking and Finance	Accounting Manager	0.74	0.65	15.00	0.27	0.32	0.11	0.15	0.00
	Financial Assistant	0.52	0.56	27.00	0.05	0.40	0.07	0.06	0.00
	Credit/Finance Analyst	0.57	0.56	18.00	0.35	0.30	0.05	0.05	0.00
	Associate Auditor	0.48	0.57	21.00	0.06	0.32	0.04	0.07	0.00
Construction	Landscape Artist	0.75	0.63	7.00	0.27	0.32	0.16	0.08	0.00
	Foreman/woman, assembly	0.77	0.59	6.00	0.26	0.30	0.16	0.08	0.01
	Road Grader and Scraper Operator	0.73	0.62	3.00	0.29	0.33	0.12	0.09	0.00
	Surveyor	0.58	0.57	5.00	0.04	0.47	0.11	0.05	0.00
	Air Duct Worker	0.91	0.78	7.00	0.11	0.28	0.10	0.03	0.28
	Real Estate Consultant	0.54	0.57	13.00	0.26	0.32	0.06	0.05	0.00
	Asphalt Roofer	0.47	0.51	85.00	0.02	0.14	0.01	0.09	0.06
Health and Wellness	Psychologist	0.80	0.73	2.00	0.26	0.30	0.21	0.08	0.00
	Dietetic Technician	0.88	0.67	4.00	0.24	0.28	0.20	0.20	0.00
	Nutritionist	0.88	0.67	4.00	0.24	0.28	0.20	0.20	0.00
	Optometrist	0.73	0.63	7.00	0.21	0.26	0.18	0.09	0.00
	Optician	0.73	0.63	7.00	0.21	0.26	0.18	0.09	0.00
	Physical Therapy Technician	0.67	0.61	4.00	0.30	0.35	0.08	0.09	0.00
	2D Echocardiography Technician	0.67	0.60	1.00	0.29	0.33	0.08	0.04	0.03
	Dental Technician	0.52	0.50	48.00	0.05	0.27	0.07	0.06	0.01
	Embalmer	0.40	0.51	8.00	0.13	0.30	0.03	0.07	0.00
	Dental Assistant	0.50	0.49	11.00	0.32	0.40	0.01	0.02	0.00
Hotel, Restaurant and Tourism	Project Architect	0.86	0.65	7.00	0.24	0.28	0.20	0.20	0.00
	Sales Executive	0.70	0.60	14.00	0.14	0.37	0.19	0.04	0.00
	Accounting Manager	0.74	0.65	15.00	0.27	0.32	0.11	0.15	0.00
	Front Office Manager	0.77	0.65	12.00	0.27	0.32	0.11	0.15	0.00
	Butcher	0.37	0.52	17.00	0.14	0.21	0.04	0.07	0.00
	Interpreter	0.59	0.58	10.00	0.25	0.41	0.02	0.11	0.00
IT-BPM	Software Engineer	0.79	0.75	1.00	0.04	0.29	0.36	0.04	0.00
	Mobile App Developer	0.79	0.75	1.00	0.04	0.29	0.36	0.04	0.00
	System Analyst	0.91	0.63	3.00	0.11	0.29	0.34	0.03	0.02
	Executive Assistant	0.56	0.55	25.00	0.35	0.41	0.02	0.05	0.00
Manufacturing	Automotive Engineer	0.88	0.70	3.00	0.17	0.21	0.34	0.03	0.02
	Chemical Engineer	0.85	0.72	2.00	0.24	0.28	0.26	0.03	0.02
	Chemist	0.83	0.66	5.00	0.07	0.32	0.22	0.08	0.03
	Sales Executive	0.70	0.60	14.00	0.14	0.37	0.19	0.04	0.00
	Warehouse Manager/Supervisor	0.79	0.70	8.00	0.26	0.30	0.11	0.22	0.00
	Sewer	0.49	0.55	23.00	0.00	0.00	0.05	0.10	0.00
	Cake Decorator	0.52	0.51	30.00	0.02	0.32	0.04	0.07	0.01
	Interpreter	0.59	0.58	10.00	0.25	0.41	0.02	0.11	0.00
	Glass Cutter	0.67	0.55	70.00	0.00	0.29	0.01	0.03	0.07
Mining	Metallurgical Engineer	0.91	0.69	4.00	0.16	0.27	0.25	0.19	0.01
	Chemist	0.83	0.66	5.00	0.07	0.32	0.22	0.08	0.03
	Psychologist	0.80	0.73	2.00	0.26	0.30	0.21	0.08	0.00
Ownership, Dwellings and Real Estate	Business Process Analyst	0.91	0.63	3.00	0.11	0.29	0.34	0.03	0.02
Power and Utilities	Chemist	0.83	0.66	5.00	0.07	0.32	0.22	0.08	0.03
Wholesale and Retail Trade	Statistician	0.81	0.70	2.00	0.04	0.39	0.27	0.04	0.00
	Account Executive	0.70	0.60	14.00	0.14	0.37	0.19	0.04	0.00
	Messenger	0.36	0.51	20.00	0.15	0.23	0.01	0.08	0.00

Note: Jobs identified in the Labor Market Information Report that were not matched in the crosswalked data: Reports Analyst, Search Engine Optimization Analyst, Computer Hardware Engineer, Mechatronics Engineer, Engineering Manager, Service Engineer, Laboratory Researcher, Budget Analyst, Parts Pricing Analyst, Medical Specialist, Asset Manager, Chemical Analyst, Sales Engineer, Master Mechanic.