Inter-American Development Bank

Occupations: Labor Market Classifications, Taxonomies, and Ontologies in the 21st Century

Labor Markets Division

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TECHNICAL NOTE Nº (IDB-TN-1513)

September 2018

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Ospino, Carlos.
Occupations: labor market classifications, taxonomies, and ontologies in the 21st century / Carlos G. Ospino Hernandez.
p. cm. — (IDB Technical Note ; 1513)
Includes bibliographic references.
1. Occupations-Classification. 2. Job descriptions. I. Inter-American Development Bank. Labor Markets Division. II. Title. III. Series.
IDB-TN-1513

http://www.iadb.org

Occupations: Labor Market Classifications, Taxonomies, and Ontologies in the 21st Century[1] [2]

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Key words: Occupations, labor markets, taxonomies, ontologies.

JEL Codes: J01

[1] This paper forms part of the deliverables of the Economic and Sector Work, Skills for the XXI Century: Revamping Technical Vocational Education and training in LAC, number RG-E1554.

[2] I am grateful for the invaluable input and suggestions of Graciana Rucci, Carolina Gonzalez-Velosa and Oliver Azuara.

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Abstract

This technical note discusses what occupational catalogs are and how they can be used to inform labor markets public policy. The main classifications, ontologies and computational developments that have allowed generating up-to-date information about labor market participants are studied. Catalogs play a valuable role in providing a standardized language for the activities that people perform in the labor market. It allows the construction of statistical information on employment and wages, to guide job seekers by informing about the opportunities and requirements of vacancies and to guide those who need training to enter the labor market or change careers. The note also discusses the evidence of the use of catalogs in the region and proposes some ideas to take advantage of technological tools to develop catalogs of comparable occupations in Latin America and the Caribbean.

Introduction

What is your current (previous) occupation? It's a common question that comes up in a variety of situations from a household survey, an application form on a job search site, or an elevator pitch to a potential employer. In all cases, the response consists of a series of words or a brief description. Most of us feel at ease interpreting the information provided in the response. However, when a pollster has to enter this response into his or her electronic or manual data entry system, when an official in a country's public employment service wants to use this information to make public policy decisions, or when a human resources department manager wants to evaluate whether a resume meets the minimum requirements to fill a vacancy, this response becomes harder to process. This is where occupational classification systems can provide solutions to such problems.

As a standardized language for describing the work performed by individuals, occupational classification systems fulfill three basic functions: They support statistical information collection, facilitate labor market analysis, and enhance career planning and job searching (Government of Canada 2016 (Government of Canada 2016)). In the first instance, the system allows for efficient response coding and assists in statistical planning and data collection. In the second case, labor statistics can be better captured and interpreted, helping to identify trends, guide policy design and support public and private employment services. Finally, classifications usually contain occupational requirements, competency levels, and very precise occupational characteristics that aid talent management professionals and job seekers in making better decisions.

An example of how occupational classifications support statistical information collection is found in the United States, where employment and wage statistics can be distilled down to the occupational level, having as a condition that an occupation can only be included in its classification if it is possible to gather statistical information about it. Conversely, in Latin America, it is not possible to generate employment statistics at the detailed occupation level since the household surveys from which such information is compiled are not statistically representative at this level of disaggregation. It is partly because, when using the international occupational classification, the occupations covered are not statistically representative as in the United States.

While job search efforts are currently assisted by algorithms that analyze the applicant's information and compare it to the vacancy requirements, the first step in developing such tools is to have a taxonomy from the outset. Taxonomies are what links the workers' various characteristics with the occupational components such as tasks, skills, knowledge requirements, and other job specifications. To this end, taxonomies serve as catalysts for tools that can assist in job management and placement. We now dig deeper into some definitions and examples of occupational classifications and taxonomies.

Overview of occupational classifications and taxonomies

A classification or taxonomy is a systematic array of objects placed into groups or categories according to an established criteria (European Commission 2017). In this paper, the objects relate to the various occupations found in Latin American and the Caribbean labor markets. Occupations and jobs are distinct elements in an occupational taxonomy. A job is defined as a set of tasks and responsibilities performed by a person, for an employer or for oneself (International Labor Office (ILO) 2012). While an occupation is understood as a set of jobs that are carried out, with slight differences, in multiple establishments, and not necessarily within the same industry (Emmel and Cosca 2010).

Table 1 lists the two main types of occupational classification systems that exist in the world. The first one classifies occupations chiefly on the basis of skills needed to perform the job, while the second classifies them on the basis of the similarity of tasks performed in an occupation, regardless of the level of education required. The International Standard Classification of Occupations (ISCO-08) developed by the International Labour Organization (ILO) aligns with the former, while the Standard Occupational Classification (SOC-2018) developed by the United States Bureau of Labor Statistics (BLS) corresponds to the latter.

Table 1. Main Types of Occupational Classification Systems

Main feature	Based on competency levels (Education) required to perform the occupation.	Based on tasks and activities performed by workers in an occupation.
Example	International Standard Classification of Occupations	Standard Occupational Classification
Latest version	2008	2018
Country	International	United States
Developer	International Labour Organization	Bureau of Labor Statistics
Number of occupations at the highest level of detail	436	867
Number of occupations at the highest aggregate level	10	23
There may be different levels of education for the same occupation	No	Yes
Hierarchical (the lower levels are components of the higher levels)	Yes	Yes
Includes non-profit work	Yes	No
Seeks to generate occupational-level statistical information	No	Yes
Years in which it has been updated	1968, 1988, 2008	2000, 2010, 2018

Compiled by author. Source: (International Labor Office (ILO) 2012; Bureau of Labor Statistics 2018)

Each classification system is defined by its classification principles. These dictate how each occupation is included, excluded, ordered, and classified in each country's labor markets. The classifications are intended to be exclusive and exhaustive. Exclusivity allows occupations that are different based on classification principles to be assigned different codes. Exhaustiveness enables all current occupations in labor markets to be incorporated into the classification. For the latter, a special code is usually designated at the lowest level of disaggregation to include occupations that could not be classified in existing categories.

The two most important differences between the SOC-2018 and ISCO-08 are their classification principles and how they treat subsistence workers (Emmel and Cosca 2010). Both systems are based on the tasks performed by workers in each occupation. However, while ISCO classifies most broad groups based on skill levels -- which defines it as an education-based classification system -- SOC classifies only based tasks performed regardless of the level of education required. On the other hand, ISCO-08 includes subsistence livelihoods, notably in the primary sectors.

Nevertheless, these could include informal subsistence workers in other sectors. In contrast, SOC only considers occupations that are performed with the intention of earning a profit by excluding, for example, occupations that are exclusive to volunteers.

Another difference is that ISCO is an international classification, intended to be a standard adapted by countries to reflect their local labor markets, and in turn may or may not include relevant occupations for all countries or retain statistical representativeness of each occupation. The SOC aims to represent current occupations in the U.S. labor market in order to compile statistical occupational information. In this respect, each occupation included in the classification must be measurable by the Bureau of Labor Statistics or the U.S. Census Bureau.

Despite their differences, both the ILO and the BLS in the United States have crosswalk tables that allow the codes of both classifications to be reconciled for international comparative analysis. Perhaps one of the most salient challenges among the differences between the two classification structures is attempting to identify occupations that are carried out in largely informal environments, as they are not readily comparable in SOC. A further distinction are the multiple overlaps encountered when moving from one classification system to the other as there are differences in the educational level associated with an occupation. One example is street vendors. The SOC category that best approximates street vendors is code 41-9091 (door-to-door sales workers, news and street vendors, and related workers). In the crosswalk tables, the code is associated with four ISCO codes, 5211 (stall and market salespersons), 5212 (street food salespersons), 5243 (door to door sales representatives), and 9520 (street vendors (excluding food)). Categories 5212 and 9520 correspond to different skill levels in ISCO. The explanatory notes justify this differentiation by pointing to the skills required for food handling among others. Furthermore, the fact that the number of listed occupations differs so much (436 in ISCO and 867 in SOC) underlines the problem of multiple overlaps. More details are provided below on the structure of these two classifications.

International Standard Classification of Occupations (ISCO-08).

This classification uses the concepts of skill level[4] and skill specialization as criteria for grouping similar occupations. Its structure integrates the concept of occupational "skill content," where differences in skill content arise when comparing major groups of occupations (see Table 2). The structure is also hierarchical, since high-level occupations require a higher level of education. It should be noted that this classification considers the required skill level to competently perform the tasks associated with entry-level jobs in each occupational group (International Labor Office (ILO) 2012).

Table 2. Matching major ISCO-08 groups with skill levels

Code	ISCO-08 Major groups	Skill Level			
		1	**2**	**3**	**4**
1	Managers			X	X
2	Professionals				X
3	Technicians and Associate Professional			X	
4 5 6 7 8	Clerical Support Workers Services and Sales Workers Skilled agricultural, forestry, and fishery workers Craft and Related Trades Workers Plant and Machine Operators and Assemblers		X		
9	Elementary occupations	X			
0	Armed forces occupations	X	X		X

Source: (International Labor Office (ILO) 2012). Skill levels correspond to the following International Classification of Educational Levels (ISCED-97) education levels: 1 - Primary level of education; 2 – Lower secondary level of education, Upper secondary level of education, Post-secondary non-tertiary education; 3 - First stage of tertiary education (short or medium duration); 4 - First stage of tertiary education, 1st degree (medium duration), Second stage of tertiary education (leading to an advanced research qualification).

[4] "Skill level" and "skill specialization" are the terms used in the official documentation in English.

Standard Occupational Classification (SOC-2018)

The SOC's classification principles define it as a task-based classification system covering all occupations in which paid work is performed.[5] "The SOC is a mono-hierarchical system, under which each occupation is found in only one place. In addition, the categories in the SOC are exclusive, exhaustive, and the higher levels are completely described by the lower levels of aggregation."(Emmel and Cosca 2010) In other words, workers who differ in their skill level, education, or experience but who perform the same tasks would be classified under the same occupation (Emmel and Cosca 2010). By the same token, occupations would not necessarily be classified based on the industry in which the worker works, so that a worker performing the same tasks in different industries might have different titles (e.g. salesperson or customer service associate), even when they are under the same occupational classification. In such cases, the occupational title indexes, which identify the different titles related to the same occupation, perhaps in different industries, are particularly important.

Additionally, classification principle number nine establishes that collection of occupational statistics in SOC is the responsibility of the U.S. Department of Labor Statistics and the U.S. Census Bureau. Thus, for an occupation to be included in the classification at a detailed level, the possibility of collecting statistical information by either of the two agencies must exist. SOC has 23 occupational groups at the most detailed level,[6] however Table 3 shows an alternative aggregation suggested by SOC for statistical purposes that is more in line with the ISCO level of aggregation.

Table 3. Alternative aggregation from SOC-2018 at an intermediate classification level

Intermediate Aggregation	Major Groups Included	Intermediate Aggregation Title
1	11 – 13	Management, Business, and Financial Occupations
2	15 – 19	Computer, Engineering, and Science Occupations
3	21 – 27	Education, Legal, Community Service, Arts, and Media Occupations
4	29	Healthcare Practitioners and Technical Occupations
5	31 – 39	Service Occupations
6	41	Sales and Related Occupations
7	43	Office and Administrative Support Occupations
8	45	Farming, fishing, and Forestry Occupations
9	47	Construction and Extraction Occupations
10	49	Installation, Maintenance, and Repair Occupations
11	51	Production Occupations
12	53	Transportation and Material Moving occupations
13	55	Military Specific Occupations

Source: (Bureau of Labor Statistics 2018)

Although occupational classification systems serve to provide comparable statistical information over time and between countries, there are limitations to their usefulness in generating information for decision-making in the labor market. In response, more detailed classifications have been developed, which can better inform job seekers or those seeking training opportunities. Below, we discuss how occupational ontologies complement and expand national occupational classifications to better deliver labor market information.

Occupational Ontologies

An ontology is defined as "a set of knowledge terms, including the vocabulary, the semantic interconnections and some simple rules of inference and logic, for some particular topic" (Hendler 2001). An ontology defines each element of a knowledge base and how they relate to each other. In the context of occupations, an ontology allows one taxonomy of occupations to be related to other taxonomies. For example, skill taxonomies or of qualifications associated to those occupations. Thus, when an occupation is identified, it is also possible to identify the skills and qualifications related to it. This offers the possibility of performing workforce management for individuals based on the required skills and not just based on job titles or duties. This is particularly important in a changing labor market, where tasks performed by workers can shift with technology adoption

[5] Includes work in family businesses where there is no direct compensation for family members, but excludes occupations that are performed exclusively by volunteers.
[6] For a detailed description of SOC, visit https://www.bls.gov/soc/2018/home.htm.

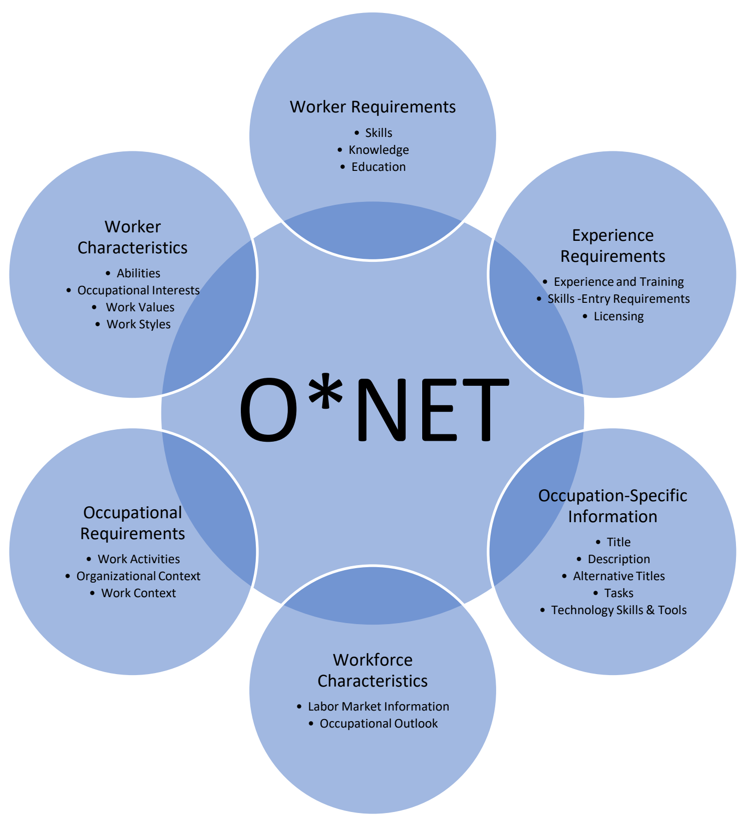
(African Development Bank Group et al. 2018). As a result, it becomes important to accurately measure, with a very high level of granularity, the scope of tasks, skills, and abilities related to an occupation. Ontologies enable such processes.

O*NET-SOC 2010

The Occupation Information Network (O*NET) is an information system maintained and updated by the U.S. Department of Labor. O*NET expands the taxonomy of the Standard Occupational Classification (SOC-2010) developed by the U.S. Bureau of Labor Statistics. For occupations in it, O*NET uses the same SOC structure, all the way up to the detailed occupation level (six digits) and adds two digits at the end of each SOC occupation. This is done to preserve or increase the level of detail in an occupational category. If the level is kept, the digits 00 are added on, whereas, if a SOC occupation is expanded, then the digits start at 01. The latest version of the O*NET taxonomy matches the SOC 2010 structure[7]. O*NET-SOC 2010 has 1110 occupational titles, of which 840 come directly from the SOC 2010 structure, 269 relate to the O*NET-SOC level, i.e., it expands the SOC level of detail, and 1 represents an exceptional case. O*NET-SOC 2010 has detailed information for 974 occupations (704 at SOC level and 270 at O*NET-SOC level), and 136 occupations for which there is only a title attached to the code.

O*NET captures detailed information about workers and their jobs for all U.S. occupations. By detailed information, I mean the information gathering processes carried out by workers, expert analysts, and occupational experts consistent with the O*NET content model. Illustration 1 depicts this O*NET content model with its six information domains.[8] There is data that is captured from the worker's perspective such as characteristics, requirements, and experience, and there is data that is captured from the job perspective such as occupational requirements, workforce characteristics, and occupation-specific information.

*Illustration 1. O*NET Content Model*



Source: https://www.onetcenter.org/content.html

Information regarding abilities and skills is collected through surveying occupational analysts, since they understand the abilities and skills constructs better than those performing the job (Reeder and Tsacoumis 2017b, 2017a). Illustration 2 depicts the collection process. Skills are defined as competencies developed through training or experience, while abilities are defined as relatively stable attributes for individuals'

[7] Since January 2018, the SOC 2018 version, which replaces SOC 2010, has been available. The O*NET-SOC taxonomy is expected to be updated accordingly.
[8] The six information domains are contained in four dimensions: Worker-oriented, Job-oriented, Cross Occupation and Occupation Specific.

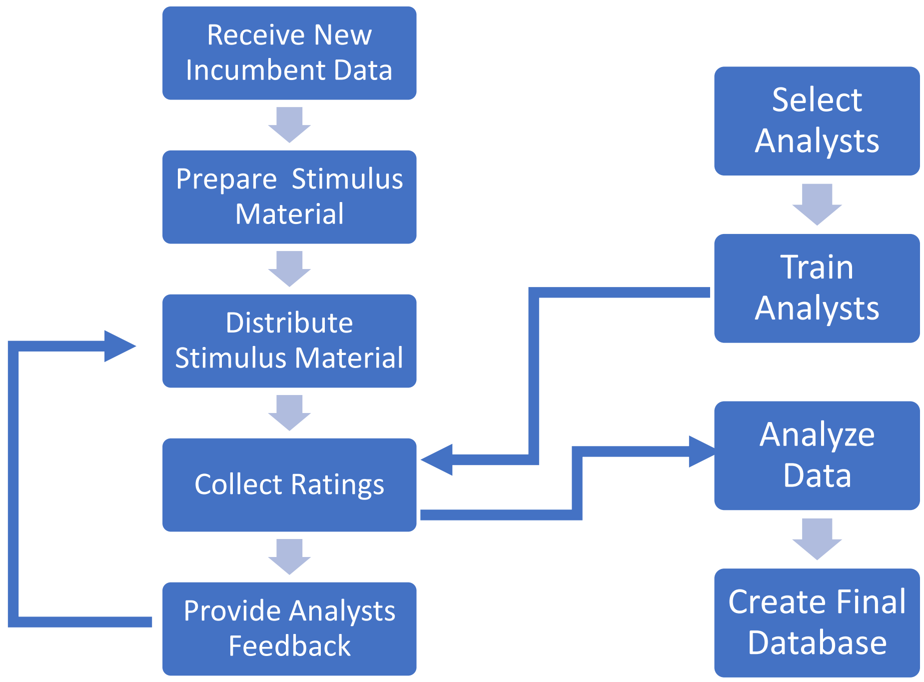
capacity to perform a particular set of tasks (Fleisher and Tsacoumis 2012a, 2012b). Abilities are grouped into four categories: cognitive, psychomotor, physical, and sensory. For their part, skills are grouped into seven categories: content, process, social, complex problem solving, technical, systems, and resource management. Table 4 describes these categories in more detail.

*Table 4. O*NET Abilities and Skills*

Abilities	**Definition**	**Examples**
Cognitive	Abilities that influence the acquisition and application of knowledge in problem solving.	Verbal, Idea Generation and Reasoning, quantitative, memory, perceptual, spatial, attentiveness.
Psychomotor	Abilities that influence the capacity to manipulate and control objects.	Fine manipulative, control movement, reaction time and speed.
Physical	Abilities that influence strength, endurance, flexibility, balance and coordination.	Physical strength, endurance, flexibility, balance, and coordination.
Sensory	Abilities that influence visual, auditory and speech perception.	Visual, auditory, and speech.
Skills	**Definition**	**Examples**
Content	Background structures needed to work with and acquire more specific skills in a variety of different domains.	Reading comprehension, active listening, writing, speaking, mathematics, science.
Process	Procedures that contribute to the more rapid acquisition of knowledge and skill across a variety of domains.	Critical thinking, active learning, learning strategies, monitoring.
Social	Developed capacities used to work with people to achieve goals.	Social perceptiveness, coordination, persuasion, negotiation, instructing, service orientation.
Complex Problem Solving	Developed capacities used to solve novel, ill-defined problems in complex, real-world settings.	Complex Problem Solving- Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
Technical	Developed capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems.	Operations analysis, technology design, equipment selection, installation, programming, operation monitoring, operation and control, equipment maintenance, troubleshooting, repairing, quality control analysis.
Systems	Developed capacities used to understand, monitor, and improve sociotechnical systems.	Judgment and decision making, systems analysis, systems evaluation.
Resource Management	Developed capacities used to allocate resources efficiently.	Time management, Management of financial resources, Management of material resources, Management of personnel resources.

Source: (Fleisher and Tsacoumis 2012b, 2012a)

*Illustration 2. Information gathering skills and abilities process in O*NET*



Eight occupational analysts complete the surveys for each of the 52 skills and 35 abilities in the O*NET content model for each occupation. Each round (The 18th was completed in December 2017) evaluates about 100 occupations per year. As such, considering that the 2017 version of O*NET has 974 occupations, this strategy is mainly limited in that each occupation is revisited every 9 years.

The process is summarized in the Illustration 2. First, analysts are selected based on the following criteria: Have at least two years of professional experience; have two years of postgraduate education in Industrial/Organizational Psychology, Vocational Psychology, Human Resources or Industrial Relations; have completed courses in both employment analysis and research methods. They then receive an eight-hour training in which the evaluation process is outlined in detail and practice how to conduct assessments. A total of 16 analysts are randomly separated into two groups. The information gathering operation is structured so that each analyst evaluates a group of five occupations per week until her load is exhausted, so that each occupation is evaluated by eight analysts. The first two sets of occupations are evaluated by both teams of specialists in order to check the reliability of ten occupations' ratings.

In parallel to the selection process, an illustrative package is prepared to support each analyst's evaluation process. This package includes information about the title, definition, level of education, experience, and training needed to perform the job, the occupational tasks and their importance, the general activities relevant to the occupation, and the workplace context relevant to the occupation. All this information is compiled from worker data for each occupation that O*NET collects. To this end, the views of those who work in each occupation are important. While analysts are best placed to evaluate each occupations' skills content, workers provide important information that provides context and is essential for the analyst's understanding.

In addition to the database of detailed information on each occupation coming from interviews with both experts and workers in each occupation, O*NET has several web-based applications to assist in job searches and provide useful career advice. In the following section, I describe in detail the O*NET taxonomy, known as O*NET-SOC 2010.

To accommodate changes in the labor market, O*NET also maintains a list of new and emerging (N&E) occupations. While these occupations do not come from SOC, they can be incorporated into the SOC-O*NET taxonomy. O*NET employs the Bureau of Labor Statistics definitions to determine the fastest growing occupations. In addition, the information is used by the President's High Growth Job Training Initiative to identify high-growth industries. In these industries, new and emerging occupations are sought. During the 2009 taxonomy review, 153 N&E occupations were incorporated. 52 were breakdowns from the SOC classification, and the remaining 101 were included as part of the residual SOC category, "All other."

*Table 5. Steps to incorporate new and emerging (N&E) occupations into O*NET*

Step	Process	Notes
1	Develop list of potential N&E occupations in in-demand industry clusters.	Web search on relevant industry, professional, and educational association sites. Additional job search sites (Monster, CareerBuilder, among others). Consult government agencies such as the Department of Labor and the Employment and Training Administration for potential candidates to N&E occupations.
2	Department of Labor (DOL) and Employment and Training Administration (ETA) review and approve proposals for N&E occupations prepared by the O*NET team.	
3	Develop task lists for approved N&E occupations.	
4	Finalize occupation profiles.	Includes essential task identification, alternative degrees, and excluded occupations.
5	Create occupation profiles and submit to DOL/ETA for approval.	Includes SOC-O*NET code, title, and description.
6	Initiate data collection.	Occupations are assigned to occupational entities or experts for collection.
7	Refine criteria and methodology (continuous).	As a result of documenting the process, improvements to the identification criteria and methodology for creating codes, tasks, and descriptions for N&E occupations are suggested.

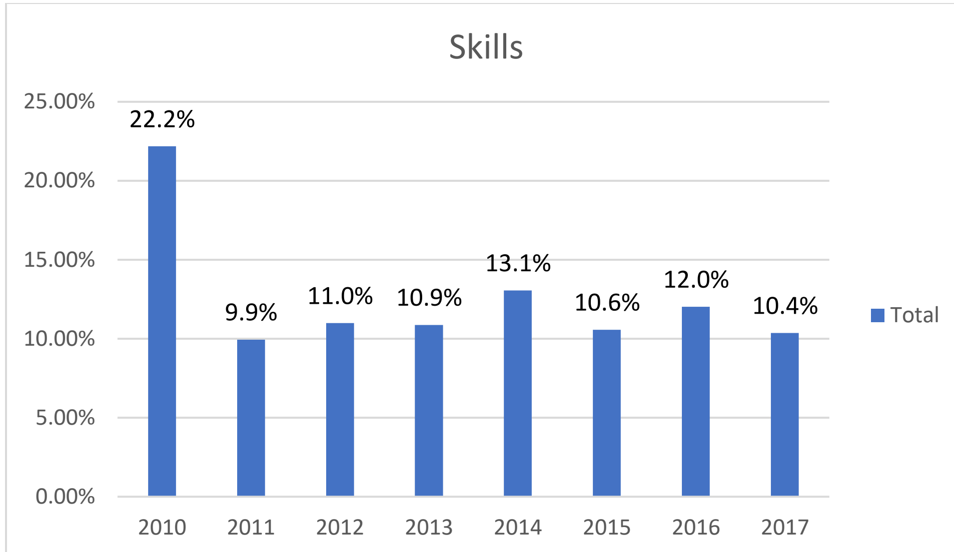
Source: (The National Center for O*NET Development 2006, 2009)

O*NET's occupational taxonomy (SOC) was updated in 2000, 2010, and 2018. Each occupation's content has a permanent calendar of updates. Illustration 3 shows the share of occupations updated per year in terms of the skills required to perform the occupation. On average, 100 occupations were updated annually between 2011 and 2017, suggesting that a complete update of the database could take a decade.[9]

[9] The Illustration 4 in the

Appendix shows a similar pattern for tasks and skills.

*Illustration 3. Percentage of updated occupations by year. O*NET*



Source: O*NET Resource Center

ESCO

In July 2017, the first version of the European multilingual classification of skills, competencies, qualifications, and occupations, ESCO, was launched. ESCO aims to meet multiple objectives among which are:

- Improve communication between the training sector and the European labor market;
- Support labor mobility in Europe, make data transparent and readily available to different stakeholders, such as public employment services, educational institutions, and statistical agencies;
- Facilitate the sharing of information between employers, education providers, and job seekers regardless of language;

To do this, it is structured around three pillars: 1) occupations, 2) skills, knowledge, and abilities, and 3) qualifications. The occupations pillar is based on the international ISCO-08 classification, but the level of detail is much higher; while ISCO has 426 occupations at its most detailed level, ESCO has about 3,000 detailed occupations. In any case, it is always possible to aggregate occupations at levels comparable to ISCO-08, thus allowing for international comparison. The skills, knowledge, and abilities pillar contain a comprehensive list of relevant European labor market skills. The v1 version of ESCO has 13,485 objects in this pillar between skills, knowledge, and abilities. The ESCO qualifications pillar collects information from two sources: (1) The qualifications databases of member countries and (2) the qualifications provided directly to ESCO by those conferring these qualifications.

One characteristic of ESCO is that it is published as linked open data. These are structured data publication methods that can be interconnected. It employs network information storage technology, meant to be read by computers, not necessarily by humans (Wikipedia n.d.). The universe of linked data forms what is known as the Semantic Web or Data Web (W3C n.d.). The main advantage of publishing in this format is that information can be used (or *reused* in information systems language) between applications, organizations, and communities (European Commission 2017). Thus, those who develop end-user applications can use ESCO as a starting point in the provision of services such as search and matching, career guidance, and self-assessment (European Commission 2017).

Box 1 summarizes the ESCO construction process and is meant as an approximation to understanding the complexities associated with developing such a tool. The key message is that building an ontology is a complex process and requires adequate institutions both politically and technically. Nevertheless, the benefits are clear. Such ontologies are public goods that enable the development of information systems around them to, in more detail, inform decision-makers in the labor market. In addition, information is relevant at the local level, which is a valuable tool for informing and designing public policy. A multilingual regional ontology such as ESCO allows for better labor market coordination in different countries by enabling a comparison of occupations and the skills needed to perform them.

Box 1. The ESCO construction process

The ESCO's development was spearheaded by the European Commission with technical support from the European Centre for the Development of Vocational Training (Cedefop).

The institutional framework consisted of five members:

1. The ESCO Maintenance Committee. Provided guidance on the conceptual and technical development of ESCO. Operated for two terms 2011-2013 and 2014-2017.
2. The ESCO Board of Directors. Made up of high-level experts who provided strategic direction to the commission on its communication strategy and strategic framework. Members were selected based on their personal experience without regard to geographical location. Operated for two terms 2011-2013 and 2014-2016.
3. Member States Working Group. Established in 2015 with member states representatives. Each country nominated two national experts in employment, education, and training. Observers such as representatives of the European Economic Area as well as candidate countries were welcomed. Supported the commission in implementing and developing ESCO and EURES regulatory compliance.
4. Sectoral Reference Groups. Composed of experts in specific economic sectors such as social actors, employment services, employers, professional associations, vocational skills councils, technical and educational institutes, and statistics agencies. Provided support for the development of ESCO version 1 between 2011 and 2015.
5. Cross-sector Reference Groups. Experts with knowledge of the relationship between education, training, and the labor market. Provided support for the cross-cutting competencies and skills, coherence between the skills pillar and the qualifications pillar. Worked between 2011 and 2015.
6. Other stakeholders were consulted online and provided feedback on occupational profiles between 2015 and 2016.

A five-phase process was used to construct the classification content:

1. Collecting the occupations : A list of occupations was chosen based on desk research and source reviews such as: existing sectoral and national classifications, observatory and skills guidance publications, occupational and qualification standards, regulations, scientific articles, job descriptors, and vacancy descriptors.
2. Refining the list of occupations : The list was subsequently winnowed by grouping similar terms. An initial list of preferred and non-preferred occupational terms was made at this stage.
3. Development of sectoral breakdown: The list of terms was compiled on the basis of the ISCO and NACE classifications (Statistical Classification of Economic Activities in the European Community).
4. Development of the occupational profiles: A complete description of occupations was developed, including knowledge, skills, and abilities.
5. Coverage validation: Correlation review with existing classifications. Review of labor market realities against vacancies in the European labor market using pilot tests.

Source: (European Commission 2017)

In ESCO, the first four occupational taxonomy levels correspond exactly to the ISCO-08 classification, while levels 5 and up are ESCO-specific. There are obvious advantages in being able to aggregate each occupation listed in ESCO at the most disaggregate ISCO level, therefore ensuring cross-country comparison. On the other hand, specificity at the local level is not sacrificed, since each occupation is broken down into relevant categories for which there is detailed information on qualifications, skills, and abilities, according to the needs of each country.

In each occupation description, ESCO defines two types of competencies for each occupation: essential and optional. The first refers to the competencies that are generally relevant to an occupation, regardless of context, employer, or country. While the latter are those that do depend on the context, employer, or country. These are considered of vital importance for job matching in the labor market as they reflect the variety of jobs within the same occupation (European Commission 2017).

In the absence of ontologies of their own in Latin America and the Caribbean, international ontologies have great appeal when it comes to studying in-depth occupational behavior. That being the case, it is possible to extrapolate detailed information available in O*NET or ESCO to better understand what characterizes occupations in the Latin American context. In the following section, we will look at how some studies have been carried out and what the results have been.

Using task and ability catalogs to analyze labor markets in Latin America

In this section, we discuss the articles that used O*NET information and that of other similar classifications to analyze skills or education requirements for occupations in Latin America. The underlying assumption is that the characteristics of occupations in the countries studied are similar to those in the United States. Since that is not the case across the board, as will be discussed below, the results should be interpreted prudently as they may contain difficult-to-identify discrepancies. For example, technology used to carry out the same duties can vary county to country in the region as opposed to the United States and Europe. As a result, the skills needed for the same occupation can differ. It is only when precise measurements are used to analyze job duties in local markets that such discrepancies are minimized. As such, the efforts made to produce this type of information in the region are important.

Arias Ortiz and Ñopo (2015) use the information reported by workers in the O*NET database of occupations to determine the degree of labor mismatch. The authors take the education level for an occupation in Mexico and compare it with the education level required for that occupation in O*NET. They find more evidence that workers have lower levels of education than required for the occupation, rather than higher levels of education than required when using O*NET data. When they use an alternative method that compares the educational level of individuals relative to the type of occupation, their results are reversed.

Arias Ortiz, Bornacelly, and Elacqua (2017) use Brazilian management data to identify the content of tasks performed in each occupation based on the O*NET database classification. The authors follow Autor, Levy, and Murnane (2003) in categorizing the occupations based on the content of tasks performed such as: Non-routine (analytical or interactive), cognitive routine, manual routine, non-routine manual, and social. They find evidence of significant employment growth in low-pay jobs, a drop, in average-pay jobs, and a slight rise in high-pay jobs, which is consistent with the labor market polarization hypothesis. When separating by age groups, they find that the growth in the share of low-paying occupations is attributed to older individuals (35-64 years), while increases in higher-paying occupation employment are explained by younger generations. They find that the demand for employment in jobs requiring routine, manual, and cognitive tasks increased significantly for the lowest quintile of the income distribution, while for the top quintile, the demand for non-routine cognitive tasks were the fastest growing.

Apella y Zunino (2017) combine household surveys for Argentina and Uruguay for the period 1995-2015 with the O*NET occupation task content to study the effects of technological change on labor markets in both countries. They find increases in the relative importance of non-routine cognitive tasks and a reduction in manual tasks. Unlike developed countries, they find that employment in routine cognitive tasks has increased. The authors suggest that the most important element in accounting for changes in job profiles in Argentina and Uruguay is the movement of workers between occupations, made easier by increases in educational achievement. This implies that cross-cutting skills are important for ensuring workers' employment. The authors consider the importance of the type of tasks performed over the probability of being unemployed and over income. They find that when routine manual activities are important in prior employment, the likelihood of being unemployed increases. Conversely, they find that non-routine manual tasks reduce this likelihood and the correlation is stronger in Argentina. In terms of wages, they find that the return from non-routine cognitive tasks is significant and positive, while non-routine manual tasks are negative. The authors suggest that these trends could end in polarization as the demand for low-paying manual jobs and jobs with high-paying cognitive tasks increases.

In contrast to using O*NET, other authors have used adult skills surveys in the region. Dicarlo et al. (2016) compare the content of tasks in developing countries with the content of tasks in the United States, using STEP surveys and the Princeton Data Improvement Initiative (PDII). They find a high correlation in analytical tasks, while correlations with interpersonal and routine tasks are lower. They suggest that using the content of U.S. task in developing countries can lead to erroneous predictions due to differences in the way occupations are performed. On the other hand, Messina, Oviedo, y Pica (2016) find the same result when using surveys from Bolivia, Colombia, and El Salvador. Dicarlo et al. (2016) suggest that there may be convergence in skill content by finding a positive relationship between skill correlation and countries' income level. Messina, Oviedo, y Pica (2016) find evidence of employment polarization in Chile but not in Mexico, and find no evidence of income polarization.

The above studies have a common interest in determining whether the trends documented in the United States regarding the impacts of technology on employment and wage polarization are also seen in the region. To this end, given the lack of information on the content of tasks, skills, and competencies in the region, the authors use the information available for the United States. Collectively, the results are mixed and suggest the need for country-specific information when conducting studies on income polarization or the effects of automation in the region.

In line with the aforementioned evidence, Chaparro and Franco (2018) surveyed human resources professionals in Colombia using a survey comparable to that used by O*NET in the United States when collecting information on skills and abilities. In short, the authors used the O*NET methodology to gather information from the Colombian market. Their preliminary results for 13 occupations in the civil engineering industry confirm that there are significant differences in ability intensity reported by occupational analysts. In Colombia, physical ability requirements would be higher in almost all occupations when compared to those reported in O*NET. For less-skilled occupations, there appears to be greater demand for social and cognitive abilities in the United States than in Colombia. Such findings reinforce the idea of having mechanisms to measure ability content in each of the region's countries in order to understand the dynamics that technology incorporation can have in the labor market.

Using computer science to maximize the value of occupational classifications and taxonomies.

In this section, we discuss how advances in search algorithms and the use of artificial intelligence have overcome many of the limitations in using taxonomies to help people find work. The limitations refer to the fact that job titles do not always coincide with occupational classifications. This makes it difficult to match a job requirement with a potential candidate. Thus, the discussion will focus on the functionality of occupation classifications, the job search of individuals either using government employment resources or online job search engines.

Modern employment matching processes require that both the information contained in a resume and a job posting be entered into an information system. Generally, algorithms are used to read information, known as natural language processing (NLP) (Kiser 2016). NLP is a branch of computer science that deals with the interaction between humans and computers, so that the latter understand language used by humans (Kiser 2016).[10] Using machine learning, computers learn language rules using a set of samples ranging from sentences to whole books (Kiser 2016).

Having information on applicants and job openings within the information system is only the first step. To be able to interpret the information, requires a knowledge base rich enough to be able to classify the data. As such, occupational taxonomies and classifications, coupled with taxonomies for tasks, competencies, qualifications, and other inherent occupational information are what allows the different elements of resumes to be connected to the items required in a job post (Dusi et al. 2017).

Search technologies have advanced from keyword search to cognitive search (Dusi et al. 2017). Early search methods consisted of algorithms, similar to those used by web browsers, where one or more keywords were entered with applicant information and then matched with job post information. For instance, the name of the occupation. The main drawback is that when words are misspelled, returned results make no sense or no results are found. Worse yet, the inability to recognize that *doctor* and *doctora* (male and female form of "doctor" in Spanish) mean the same occupation often resulted in incomplete or biased searches (Morris 2013). Therefore, keyword searches require a very precise understanding of what is being searched for in order to produce accurate results.

Semantic searches expand keyword searches, including keywords that have the same or similar meaning as the original keywords. So, it is possible to set the algorithm to understand that doctor means the same as physician. Likewise, it would be able to understand that surgeon may also be a valid result. Taxonomies or occupational classifications have always been at the center of labor market search and matching processes (Dusi et al. 2017). Such information gives rise to contextual searches when combined with machine learning. A contextual search algorithm can use taxonomies and ontologies to return job results with similar skills or abilities, since the knowledge base relies on relationships between each piece of larger knowledge blocks (e.g. occupations, skills, tasks, abilities, qualifications, etc.). Similarly, given a job seeker's context, such as geographical location, age group, and educational level, different results could be returned for the same skill. In other words, it can contextualize the search with an individual's particular characteristics (Dusi et al. 2017).

Finally, cognitive search takes all the previous elements and uses artificial intelligence[11] to produce results better tailored to the individual. It can indicate qualifications that the individual should have given experience, that the person can then substantiate. It may give different results for someone who has just entered the labor market, relative to someone who has been unemployed for a long time (Dusi et al. 2017). A major

[10] Its applications include summarizing text blocks, creating chat bots, generating automatic tags, opinion mining, reducing words to their root, among others.
[11] "Artificial intelligence is a technology that includes a wide range of disciplines that seek to design computer systems or intelligent machines that can mimic human cognitive functions such as thinking, reasoning, understanding or assimilating and processing information."(Analysys Mason, 2017)

difference with previous systems is a richer and more personalized interaction between the individual and the system, as well as the ability to learn from previous interactions.

The private sector and the use of occupational ontologies

While open ontologies such as O*NET and ESCO provide valuable insight on how labor markets work, it should be noted that these ontologies must balance two objectives: Ensure comparability over time and provide the most in-depth information on the current labor market. The former is accomplished through consistency in the occupational classification employed by the ontology and the latter through to update schedule for the ontology content. As we have demonstrated, providing up-to-date information about all current occupations in labor markets is a challenge for O*NET. Therefore, companies specialized in providing labor market information such as Google or LinkedIn have developed their own ontologies using O*NET as a starting point. Their main motivation is to enter the job search services market.

In June 2017, Google Inc. launched *Google for Jobs* in the United States, which allows individuals to start their job search process from the Google Chrome browser. On January 30, 2018, it spread to five Latin American countries: Argentina, Brazil, Chile, Colombia, and Mexico. At its core, this tool takes advantage of Google's cloud technology, Google Cloud, and its machine learning applications to deliver to the user a list of openings that the tool compiles from job portals and private companies. The search process takes advantage of Google's proprietary ontology based on O*NET and expands it to 250,000 specific occupations. In addition, it includes an ontology of 50 thousand skills ranging from hard to soft.

As for LinkedIn, the platform continuously develops its ontology, which includes occupations, skills, and other items in its knowledge base. LinkedIn uses machine learning to classify user entries on its platform. It also learns from users' response to suggestions made by the system. For a company like LinkedIn, it is necessary to constantly update the items that make up its knowledge base. In this respect, ontologies such as ESCO and O*NET fall short when faced with the needs of this type of organization, even though they are the backbone on which these companies developed their own taxonomies.

Far from being an exhaustive list, the examples of Google and LinkedIn show how the use of computer science and massive data can be used to complement the more traditional occupational catalogs such as O*NET, ESCO, or ISCO and provide near real-time information on labor markets. Yet there seems to be a trade-off. On the one hand, how representative of national economies is the information used by the platforms. On the other, how up-to-date and relevant is the information on labor market trends. To this end, a public-private partnership that seeks to fill the gap in the specificity of skills demanded and offered in local markets in the United States is the Open Skills Project of Data at Work. This University of Chicago-led initiative, and includes other public and private institutions, aims to promote the creation, use and, dissemination of open workforce data, using massive open data and computational algorithms.

Opportunities and challenges for the region

In this paper, I have discussed what occupation catalogs are and how they can be used to inform public policy on labor markets. Catalogs play a valuable role in providing a standardized language for the activities that people perform in the labor market. They allow for the construction of statistical employment and wage information, guiding job seekers through information on job opportunities and vacancy requirements; and assisting those who wish to be trained for entry into the labor market or make a career change. Compiling and updating catalogs is a monumental undertaking from the point of view of institutional coordination and requires specialized knowledge on the part of the stakeholders involved. Therefore, processes can be lengthy, and it is common for updates to take decades. The advantage of maintaining a classification framework for such a long time lies in the comparability of statistical information over time. The disadvantage in such a dynamic labor market is that the information is potentially no longer relevant. The latter will depend on how much the content of tasks, skills, and abilities change within each occupation. On this point, there is fairly little information even when O*NET has been used. As such, generating information about changes in occupation characteristics over time is an opportunity.[12] First of all, it helps to improve the relevance of labor market information in the region, and secondly, it provides information on how often such information should be updated.

Table 6 in the Appendix shows that in Latin America and the Caribbean the classification systems used by the countries are based on ISCO-08, which reflects statistical institutions' interest in generating internationally comparable information. As for international approaches, ESCO, the European ontology, has great potential for Latin American countries, perhaps surpassing O*NET in terms of its structure. First, occupation codes

[12] See Amaral et al. (2018) for a proposal to identify changes in demand for skills based on changes in demand for occupations. The authors argue that changes in demand for skills can be broken down into an effect ranging from one that captures changes in demand for skills explained by changes in demand for occupations to one that captures changes in demand for skills resulting from changes in the importance of skills within each occupation.

are comparable with ISCO-08 and most countries already use it or have slightly adapted it. Second, it is linked to the skills and qualifications content of European occupations and can serve as a starting point in the construction of qualifications frameworks for the region. Third, it is available in all the languages of the countries in the region. Lastly, it is open-source and can be directly linked to national classifications through APIs. The main limitation is that it is of recent creation, while O*NET has been in place for years. For this reason, O*NET can shed light on how updates should be carried out and on good practices for collecting the information that nourishes the ontology thereof. There appears to be an opportunity to design more context-appropriate policies as local systems are built for gathering and updating the content of skills, abilities and tasks in the occupations of the countries of the region. The experience of Chaparro and Franco (2018) could serve as a starting point for the adaptation of appropriate methodologies in the region.

The ESCO experience allows us to see how similar processes could be developed for Latin America and the Caribbean. Accordingly, it would be worthwhile to investigate pilots for building a regional classification that countries could adopt if they so wished, but that would guarantee consistency with each of the systems in order to generate comparable regional statistics on the tasks, skills, abilities, and statistics from regional markets in the region. At the outset, the proposal should take advantage of computer science tools to generate its own taxonomy to be updated with information from: household surveys, public and private job sites, as well as private organizations such as Google and LinkedIn. The experiences of public and private alliances such as Data at Work in the construction of open and shared information with local relevance would also be worth considering.

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Appendix

Table 6. Occupational classification used in Latin America

Country	Survey	Year	Occupational Classification	International Reference
Argentina	EPHP	2000-2001	National Occupational Classification (INDEC) - 1991	Proprietary classifier corresponding to ISCO-08
		2002	National Occupational Classification (INDEC) - 2001	
	EPHC	2003-2015	National Occupational Classification (INDEC) - 2001	
Bolivia	ENH	2000-2015	Occupational Classification of Bolivia (COB) - 1998	ISCO-88
Chile	CASEN	2000-2015	International Standard Classification of Occupations (ILO) - 1988	ISCO-88
Colombia	ECH	2001-2005	National Occupational Classification	ISCO-88
	GEIH	2006-2015	National Occupational Classification	
Costa Rica	EHPM	2000-2009	Occupational Classification of Costa Rica - 2000	
	ENAHO	2010-2015	Occupational Classification of Costa Rica - 2000	
Ecuador	ENEMDU	2000-2015	International Standard Classification of Occupations (ILO) adjusted for Ecuador - 1988	ISCO-88
Mexico	ENIGH	2000-2010	Mexican Occupational Classification - CMO	ISCO-88
		2012-2014	National Occupational Classification System - SINCO	ISCO-08
Paraguay	EPH	2002-2015	Paraguayan Occupational Classification - CPO	ISCO-88
Uruguay	ECH	2000-2004	National Standard Occupational Classification - CNUO 1995	ISCO-88
		2005-2015	International Standard Occupational Classification (ILO) adapted for Uruguay - 1988	

Source: Statistical institutions from each country Compiled by: Alvaro Altamirano and Ivan Bornacelly, IDB consultants.

*Illustration 4. Percentage of occupations updated by year. O*NET*