SKILLED MANPOWER FORECASTING

DEFINITION AND METHODOLOGY

ASGHAR ADELZADEH*, CYNTHIA ALVILLAR* AND MADHU KANJI*

* Applied Development Research Solutions (ADRS)

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Acronyms

ADB	Asian Development Bank
APEC	Asia Pacific Economic Cooperation
BEA	Bureau of Economic Analysis
BERL	Business and Economic Research Limited
BIBB	Federal Institute for Vocational Education and Training
BLS	Bureau of Labour Statistics
BRICS	Brazil, Russia, India, China and South Africa
CEDEFOP	European Centre for the Development of Vocational Training
CE	Cambridge Econometrics
CEET	Centre for the Economics of Education and Training
CGE	Computable General Equilibrium
COPS	Canadian Occupation Projection System
ESCO	European Skills Competences and Occupations
ESDC	Employment and Social Development Canada
ETF	European Training Foundation
GDP	Gross Domestic Product
GWS	Institute of EconnEW zEAomic Structures Research
IAB	Institute for Employment Research
ICT	Information and Communication Technologies
IER	Institute for Employment Research
ILO	International Labour Office
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
ISIC	International Standard Industrial Classification
KEIS	Korea Employment Information Service
KldB 2010	Classification of Occupation (Germany)
LFS	Labour Force Survey
LDFS	Labour Demand Forecasting System
NA	National Accounts
NAICS	North American Industry Classification System
NAIRU	Nonaccelerating inflation rate of unemployment
NCVER	National Centre for Vocational Education Research
NIPA	National Income and Product Account
NOC	National Occupation Classification
NQF	National Qualifications Framework
NSDS	National Skill Development Strategy
NZIER	New Zealand Institute of Economic Research
OECD	Organisation for Economic Cooperation and Development
OSP	Occupational Skills Profile
QLFS	Quarterly Labour Force Survey
SEDS	Socio-economic Development Strategy
SENAI	National Service for Industrial Training
SUTS	Input-Output Supply and Use Tables
SOC	Standard Occupational Classification

SSK	Sector Skills Plan
STEM	Science, Technology Engineering and Mathematics
TVET	Technical Vocational Education and Training
UKCES	UK Commission for Employment and Skills
UNESCO	The United Nations Educational, Scientific and Cultural Organization
VET	Vocational Education and Training
WTO	World Trade Organization

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EXECUTIVE SUMMARY

There has been a recent resurgence of international interest in skills forecasting. This report aims to explore the definition of skill as it is used in developed and developing countries and to provide an overview of methods used for manpower skill forecasting.

The report begins with definition of skill in developing and developed countries. The definition of skills appears to be straightforward but as scholars attest there is no commonly accepted definition, much less a universal definition of skill. The first section explores the way in which skill is used in academic and vocational training, workplace settings, for planning purposes and across country specific characterization. As a matter of practical interest and existing research, the focus tends toward the intersection of work and the education and training systems that increasingly aim to support it.

The debate on manpower skill requirements has re-emerged in the last 20 years. The field includes diverse methods, tools, statistics and definitions and the literature on the topic is extensive. The main aim of manpower forecasting in any economy is to assist long term investment in the education and training sector. The scale of such investment can only be specified if skills needs are carefully identified. The problems of unemployment, changing technologies, skill requirements and knowledge obsolescence only heighten the need for good forward looking tools for skills demand and supply. Therefore, the historical interest in manpower forecasting can be traced to three sources: interest in linking educational expansion to human resource requirements of a growing economy; translation of targets for economic growth to targets for the demand for skills; and the need for skills forecasting in order to better plan vocational counseling and placement services. A common thread that runs through the different interests in manpower planning is that surpluses and shortages of skills/manpower must be controlled and minimized in all economies.

Criticisms of the original manpower requirement approach (MRA), which was the dominant approach in the 1960s, have led to the emergence of a number of new approaches over the last 50 years. In this report, we have classified the current approaches into three groups: quantitative, qualitative, and hybrid approaches. The quantitative approach is distinguished by its use of models and formal quantitative methods to produce projections of future skills needs. Practices that fall under qualitative approaches use ‘soft’ qualitative data alongside the ‘harder’ statistical information to anticipate future skills needs. They significantly rely on key experts and

stakeholders for skills anticipation. Finally, and increasingly, countries are combining quantitative and qualitative approaches for their skills forecasting needs.

The report sheds light on the overall distinction between these approaches and on the differences within and between the approaches in terms of the estimation methods for forecasting skilled manpower at the national level. The report also uses cross country experiences to highlight additional methodological and implementation issues in manpower skill forecasting.

Our review of the diverse approaches supports other reviews that 'best practice' in skill forecasting worldwide involves quantitative methods based on the use of large-scale, multi-sector macroeconomic models to produce a comprehensive overview of how structural economic and technological changes are affecting the demand for skills. To this, however, we have added two observations. First, since the same policy can have different effects in different models, having the appropriate model deeply matters for policy purposes. Therefore, within quantitative approaches we have distinguished between macroeconometric models that mainly have non-neoclassical theoretical orientation and their parameters are estimated using time series data, and those that are based on computable general equilibrium models, that are strictly based on the neoclassical economic theory and use calibration techniques for its parameters. Second, country experiences show that a 'good' approach to manpower forecasting complements the selected top-down quantitative approach with other more qualitative approaches.

The report includes 10 recommendations that are centered on key attributes of an effective long term approach to skills forecasting for India.

INTRODUCTION

The main focus of this report is on skills and manpower skills forecasting. The aims of this report are to explore the definition of skill as it is used in developed and developing countries (Part 1) and to provide an overview of estimation techniques used by various approaches to manpower skills forecasting (Part 2). The report also uses cross country experiences to highlight additional methodological and implementation issues in manpower skill forecasting (Part 3). The final part focuses on recommended key attributes of an effective long term approach to skills forecasting that can inform skilled forecasting in India.

PART 1

DEFINITIONS OF SKILL

1. INTRODUCTION

On its face, the definition of skills appears to be straightforward. Everyone who works, wants to work or hires people to work has a notion of skill in relation to the job they have, want to have or aim to fill. Yet, as scholars attest, there is no commonly accepted definition, much less a universal definition of skill. Moreover, different countries use a variety of definitions, often with subtle distinctions. This section explores the meaning and definition of skill in the many ways it is used in academic and vocational training, workplace settings, for planning purposes and across country specific characterization. Invariably, the focus will tend toward the intersection of work and the education and training that supports it.

The remainder of this section is organized into four parts. Following a general definition of skills in Section 1.2, we discuss the definition of skill in developed countries in Section 1.3, and in Section 1.4 explore the definition of skill as it is used in developing countries. The conclusion is presented in Section 1.5.

2. GENERAL DEFINITION OF SKILLS

Scholars have said that "[t]he problematic nature of 'skill' is a recurrent theme in skills research. There is a lack of commonly accepted definition of skill, differences in the constructs used in the range of available tools, varied methods of measurements and lack of any common standards."[1] The seminal definition of skills in the OECD Skills Strategy sees "skills (or competencies) as the bundle of knowledge, attributes and capacities that can be learned, that enable individuals to successfully and consistently perform an activity or task, and that can be built upon and extended through learning. This definition includes the full range of cognitive (e.g. literacy,

[1] (cited in Balgobin *et al.*, 2004; Betz and Rottinghaus, 2006; Borghans *et al.*, 2001; Clayton *et al.*, 2003; Dostal, 2003).

numeracy), technical (e.g. sector or occupation specific) and socio-emotional (e.g. teamwork, communication) skills.[2]

In the most general sense, skill is the possession of knowledge (facts, principles, theories and practices) and ability that can be applied to the completion of a task or problem solving. Many but not all skills result from the assimilation of information through learning. Competence, on the other hand, is described as the "proven ability to use knowledge, skills and personal, social and/or methodological abilities in work or study situations, and in professional and personal development."[3] (ESCO Service Platform data model, INSERT YEAR: 6)

In the absence of a universally agreed upon definition about skills, one can infer the definition of skills from the way in which skill is utilized in practical terms. Experts and practitioners have spent a good deal of time examining what skills are needed in the world of work. While agreeing that there is "by no means consensus on terminology, definitions, or measurements of these skills," Stasz distills four skill areas from the literature: 1) Cognitive or academic skills that are generally learned; 2) Generic skills that are defined by work contexts; 3) Technical skills: and 4) Soft skills.[4] (Stasz, 2001:386) Thus, if a skilled worker is generally defined as any worker who has special skill, training or knowledge to do their job, or specialized knowledge, training and experience to carry out more complex physical or mental tasks beyond than routine job functions, then skill in the most general sense is the training, knowledge or experience possessed by the worker.

Along this line of reasoning, skills fit into two broad categories. The first category represents the knowledge based or technical skills that have been acquired in the specific areas of study. Skilled workers may acquire their skills from a post-secondary institution or on the job. The second category refers to the basic employability skills such as the ability to work in teams and communicate effectively, which is a requirement for graduate level jobs across most sectors. (Damico, 2010:66)

The Human Capital Report 2016[5] of the World Economic Forum developed a Human Capital Index to quantify how 130 countries develop and deploy their human capital potential. The index is a tool that captures the complex relationship between education, employment and workplace dynamics. Leading the index are high income countries Finland (1), Norway (2) and Switzerland (3), which all have high educational attainment and large shares of their workers in high-skilled occupations. New Zealand (6) outranks Canada (9), while Australia (14) is followed by the United Kingdom (19), the US (24) and the Rep. of Korea (32). At the lower end of the spectrum are China (71), South Africa (88), Vietnam (68) and India (105). (2016:5).

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[2] (OECD (2012:12, Box 1.1), Better Skills, Better Jobs, Better Lives: A Strategic Approach to Skills Policies, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264177338-en

[3] European Union, ESCO Service Platform Data model, ADD YEAR, Luxembourg.

[4] Stasz, Oxford Economic Papers 3 (2001), 385-405, (2001: 386)

[5] World Economic Forum, Human Capital Report 2016, Geneva, 2016

The Human Capital Report also provides insight on the broad nature of skills. It asserts that although economies of the future are becoming more knowledge-based and technology-driven, demands of the 21st century require creativity, collaboration and other non-cognitive skills, along with competence in technology (2016:17). It is also recognized that as necessary as the STEM fields of core science, technology, engineering, mathematics and computer programming are, broader non-cognitive skills are also needed.

Developed countries and developing countries alike have seen the shifts in the nature of work and global competition. Unlike the past, when local production featured routine processes, and mass production emphasized discipline to the assembly line, demands on business and workers are now dictated by world class standards that must be met to remain competitive.

3. DEFINING SKILL IN DEVELOPED COUNTRIES

In developed countries that exhibit advanced technology, the breadth of general skills is expanded to include those that are required in technologically-rich employment settings. Jobs dependent or related to science, technology, engineering and mathematics (known collectively as STEM) are increasingly demanding skills and training to match the needs of these jobs.

In addition to excellent technical education, STEM-related fields require workers to have thinking skills that "help the workers to problem solve, to develop innovative, cost-effective solutions and to understand how different parts or systems interact with each other. Communication skills such as technical writing, public speaking and interpersonal communication are also very important." (Vilorio, 2014:9,10)[6]

Indeed, one of the best places to uncover the practical definition of skills is at the intersection of business needs and worker capabilities mediated through government agencies responsible for education and the labor market. In the **United States**, Secretary of Labor Lynn Martin launched a bold initiative entitled The Secretary's Commission on Achieving Necessary Skills (SCANS) to strengthen the link between business needs and schooling that provides functional student education and know-how.

In a SCANS document entitled "Identifying and Describing the Skills Required by Work",[7] skills were described as three types: <u>functional skills</u>, which reflect what people in a wide range of jobs actually do at work; <u>enabling skills</u> which underlie the performance of functional skills; and

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[6] Vilorio, Stem 101: Intro to tomorrow's jobs, Occupational Outlook Quarterly, Bureau of Labor Statistics, Spring 2014. Retrievable at https://www.bls.gov/careeroutlook/2014/spring/art01.pdf

[7] SCANS, Identifying and Describing the Skills Required by Work, September 14, 1990, Washington, D.C., https://wdr.doleta.gov/scans/idsrw/idsrw.pdf

workplace scenarios, which describe skills in the context of real work activities." (SCANS, 1990:11-13).

In their subsequent and pivotal document, SCANS set out skills that are needed in the world of work, with special interest in high performance skills that are required to succeed in the high performance workplace. The 1991 report entitled "What Work Requires of Schools: A SCANS report for America 2000"[8] identified fundamental skills as the essential three-part "solid foundation" required in the workplace. Secretary Martin noted that five competencies "in conjunction with a three-part foundation of skills and personal qualities lie at the heart of job performance today." (SCANS, 1991:ii)

First in the three-part foundation is basic literacy and computational skills consisting of reading, writing, the ability to perform arithmetic and mathematical operations, listening and speaking skills. Second are thinking skills, i.e., the ability to put knowledge to work through the use of creativity, decision-making, problem solving, visualization, reasoning and the ability to learn. The third part was identified as "personal qualities that make workers dedicated and trustworthy" which are present when workers display responsibility, self-esteem, sociability, self-management, integrity and honesty. (SCANS, 1991:13,14) Taken as a whole, these skills capture the cognitive, non-cognitive, technical, and soft skills. Upon these foundational skills, SCANS also identified skills that comprise workplace competencies. Such competencies include resources: knowing how to identify, organize, plan and allocate resources; interpersonal skills: the ability to work with others through interpersonal skills; information: the ability to acquire and use information; systems: understanding of systems and their complex inter-relationships; and technology: the ability to work with a variety of technologies. (SCANS, 1991:10)

Appreciation and demand for technologically-based skills is echoed in the **United Kingdom** in its drive to match employer need in its economic imperative to remain globally competitive. Indeed, the independent panel, convened under the direction of Lord Sainsbury and on behalf of the Departments of Education and Business, Innovation and Skills; the Prime Minister's Office; and HM Treasury, stated: "Our vision is of a thriving economy made up of businesses able to compete internationally and respond to rapid technological change."[9] (Sainsbury, 2016:12) Moreover, it ascribed to employers and industry a central role in defining its needs, setting standards, and defining "the skills, knowledge and behaviours required for skilled employment." (Ibid. 2016:12 Box).

The resulting Post-16 Skills Plan identified a comprehensive strategy and implementation mechanism to provide a technical learning option to students with solid foundations in core academic subjects up to 16 years (or older if their education has been delayed) to complement existing academic options.

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[8] SCANS, What Work Requires of Schools: A SCANS Report for America 2000, US Department of Labor, June 1991. Available at https://wdr.doleta.gov/scans/whatwork/whatwork.pdf

[9] Sainsbury, Department for Business Innovation and Skills, Post-16 Skills Plan, London, July 2016.

Thanks in part to the seminal work on contextual learning by Stasz and others (anticipating the work of the panel), many of the skills plans and strategic thinking on economic imperatives for global competitiveness include a broader view of skills derived in context. The broader perspective of non-formal education and training can be seen in strategic efforts to expand technical training and non-formal training alongside academic options. Indeed, there is growing recognition that the development of skills from experiential learning occurs with or without formal academic based training. As SCANS aptly points out, "Individuals learn best when they are taught in a context of application—in a functional context." (SCANS (1990:1)

Elevating focus on the technical option in the Skills Plan helped identify the practical skills and technical knowledge valued by industry. For example, the panel identified core knowledge and skill base to include sufficient literacy to be able to write clear and legible English and sufficient mathematical understanding to spot errors, make quick estimations, and employ basic mathematical concepts such as sequences, probability and statistics. (Sainsbury, 2016:16) Generic workplace skills include communication, working in a team and solving problems.

Importantly, in addition to cognitive skills, knowledge and behaviors required of workers, the Skills Plan is cognizant that skills must be continually updated to efficiently intersect with the rapid rate of technological innovations. To that end, digital skills are added to literacy and numeracy, in the set of transferable skills that the current workforce must possess because "everyone needs an essential set of digital skills to succeed in the modern workplace." (Sainsbury, 2016:24).[10] For important insight into digital skills, the Sainsbury panel relied on extensive work undertaken on digital skills in the modern economy and on ways to overcome deficiencies in the existing workforce, such as the 2016 DCMS Digital Skills Report[11] and the work of Ala-Mutka.[12]

> "The definition of digital skills has "broadened" over time. The first definitions of computer or ICT[13] literacy focused on technical, operational and procedural knowledge about computer use, while later definitions covered cognitive, attitudinal, social and emotional skills…
>
> "Computer literacy is the narrowest digital concept, emphasizing the technical use of computers and software, while internet literacy adds the considerations and ability to function successfully in networked media environments. Digital literacy is the broadest concept, and it includes the main aspects of the other concepts. According to Ala-Mutka, digital literacy includes a continuum of

[10] Ibid.
https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/536043/Post-16_Skills_Plan.pdf Retrieved last on April 14, 2018.
[11] DCMS Digital Skills Report, January 2016 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/492889/DCMSDigitalSkillsReportJan2016.pdf Last accessed April 14, 2018.
[12] ALA-MUTKA, K. 2011. Mapping Digital Competence: Towards a Conceptual Understanding. Institute for Prospective Technological Studies. Published October. Available: http://ipts.jrc.ec.europa.eu/publications/pub.cfm?id=4699.
[13] Information and Communication Technologies

skills ranging from basic, operational skills to higher order cognitive, social and attitudinal skills and abilities." (DCMS, 2016:17)

The panel also relied on an assessment of existing digital skills definitions which resulted in the identification of three broad categories of digital skills requirements.

1. Basic digital literacy skills are the skills needed to carry out basic functions such as using digital applications to communicate and carry out basic internet searches. Cyber security sits under this category.
2. Intermediate digital skills for the general workforce include basic skills plus the workplace required skills needed such as those generally linked to the use of applications developed by IT specialists and information processing.
3. Advanced digital skills for ICT professions (digitally innovative and creative individuals, organisations and businesses) include basic and intermediate skills plus skills needed to work across the diverse IT sector. They include digital skills linked to the development of new digital technologies, and new products and services. (DCMS, 2016:23).[14]

For Europe more generally, the OECD also identifies digital skills as critical aspect of the definition for skills and imperative for taking advantage of particular growth opportunities. Importantly, however, the OECD, Development Economics and UKforCE definitions make clear distinctions between the skills needed by different user groups. (DCMS, 2016:23.)[15]

The 2006 European Parliament proposed recommendations on key competencies[16], acknowledged digital competence (among other forward-thinking skills) as one of the eight key competencies for lifelong learning by the EU. The eight key competencies set out by the Reference Framework "which all individuals need for personal fulfillment and development, active citizenship, social inclusion and employment," are:

1. Communication in the mother tongue
2. Communication in foreign languages
3. Mathematical competence and basic competences in science and technology
4. Digital competence
5. Learning to learn
6. Social and civic competences
7. Sense of initiative and entrepreneurship; and
8. Cultural awareness and expression

They go on to note that "critical thinking, creativity, initiative, problem solving, risk assessment, decision taking, and constructive management of feelings play a role in all eight key

[14] Ibid.

[15] See also, OECD 2005. NEW PERSPECTIVES ON ICT SKILLS AND EMPLOYMENT OECD. Published April 22. Available: http://www.oecd.org/internet/ieconomy/34769393.pdf

[16] Recommendation of the European Parliament and of the Council of 18 December 2006 on key competences for lifelong learning (2006/962/EC), Official Journal of the European Union, Retrieved last on April 20 2018, at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2006:394:0010:0018:en:PDF

competencies."[17] It is also noteworthy that the list of competencies includes "communication in foreign languages" defined as a skill that "requires mediation and intercultural understanding" while simultaneously recognizing that skills are defined by societal and cultural realities, and by local values. Indeed, the authors further note that how these definitions of competencies are applied "are a matter for individual Member States in accordance with their specific needs and circumstances." [18]

Within the context of OECD membership, the case of **Ireland** provides another example of the rise in the requirements and technical skills and the concomitant shift toward increasingly broader definition of generic skills. The Expert Group on Future Skills Needs (EGFSN) was charged with research upon which to create the National Skills Strategy. Among other things, they noted that, "[e]mployees in all jobs will be increasingly required to acquire a range of generic and transferable skills including people-related and conceptual/thinking skills." Flexibility, continuous learning and individual initiative and judgment will also be required. (2007:10)[19]

The EGFSN identified the following features of the generic skills portfolio.

1. Basic or fundamental skills including literacy, numeracy and IT literacy.
2. People-related skills including communication, interpersonal, teamwork, and customer-service skills.
3. Conceptual/thinking skills including collecting and organizing information, problem-solving, planning and organizing, learning to learn skills, innovation and creativity skills, systematic thinking. (2007:34)

The EGFSN also note, however, that skill and qualification requirements for jobs at all levels are rising, leading to an increasing emphasis on generic skills. (2007:45)

Like other parts of Europe, the Expert Group points out that in Ireland, it would appear that virtually all sectors of industry are becoming more knowledge-intensive. This involves a change in the types of skills required, with a rise in the importance of generic skills, including the ability of individuals to work more autonomously; be self-managing, work as part of flexible teams, adapt to change, solve complex problems, think creatively and engage with innovation as a continuous process. (2007:48)

Indeed, a key contribution by the Expert Group is their acknowledgement and insight regarding the expanding scope of the generic skills portfolio. Generic skills (also commonly referred to as 'horizontal', 'basic', 'soft', 'key', 'transferable', 'employability' (2007:49)) are broadly a combination of skills and personal attributes which are essential to be effective in the modern

[17] Ibid. 2006:14

[18] Ibid. in footnote 2.

[19] EGFSN, Tomorrow's Skills Towards a National Skills Strategy, 5th Report, 2007.

workplace. The Expert Group examination of the shifts in the nature of the workplace and the redefining of some skills once seen as 'specialist' but are now 'basic' highlight the growing relative importance of generic skills and the continual adaptation required of them.

4. DEFINING SKILL IN DEVELOPING COUNTRIES

Developing countries, like their high income counterparts, have long sought to strengthen the links between skill improvement and positive economic outcomes. The conceptualization and implementation of comprehensive skills development programs typically build on the provision of basic foundational skills and combine secondary schooling with technical vocational training in conjunction with options for advanced academic training and on-the-job training. These concerted efforts aim to match academic and non-academic education and training to the demands of industry.

Not surprisingly, the profiles of skilled workers are strikingly similar to those found in the high-income countries including, for example, basic competencies along with technical and soft skills. For a host of reasons, including the evolving digital age, countries globally have begun to rethink their skills development, paying particular attention to technical and soft skills.

Observations across **APEC countries** have revealed that highly skilled workers are required to have specific knowledge and technical skills as well as soft skills. The relevant soft skills include entrepreneurial and creative spirit, teamwork and communication skills (APEC 2014:14). Core values include self-reliance, ability to multi-task, to be goal and achievement oriented, entrepreneurial, have tenacity and to be users of gadgets and technology. This skilled labor force should be willing to take risks, complete tasks speedily, thrive through networking and believe in collaborating and cooperating. (APEC, 2014: 6).

This view aligns with the World Bank (2016) assessment that "workers in the digital age require higher-order cognitive, socioemotional, and technical skills." These three skills needed in a modern economy are further explained as: Cognitive skills include literacy, numeracy, and cognitive skills; problem-solving ability; verbal ability, memory, and mental speed. Social and behavioural include socioemotional skills and personality; openness to experience, conscientiousness, extraversion, and emotional stability; self regulation, mindset and interpersonal skills. Technical Skills: knowledge of methods and tools; general technical skills from schooling and training; occupation-specific skills." (APEC 2016:7)[20]

Soft skills reflect a worker's personality, predisposition, attitude and mindset. For developing countries, the detail and breadth ascribed to technical skills, and soft skills in particular,

[20] World Bank 2016, cited in APEC Regional Trends Analysis: Rethinking Skills Development in the Digital Age, APEC Policy Support Unit, November 2016, p.7 Available from: https://www.apec.org/Publications/2016/11/APEC-Regional-Trends-Analysis-Rethinking-Skills-Development-in-the-Digital-Age

evidence interest in reaping potential economic benefit that has heretofore remained a latent, if not relegated, feature of worker capacity. Importantly, a review of the literature shows that though recognized competencies, and are incorporated into many levels of policy, they are characteristically defined by local conditions and values.[21]

Moreover, many countries have taken the steps to promote soft skills while students are still in school through, for example, the adoption of 21st century competencies. Like their high-income counterparts, the developing world is acutely aware of the value of technical skills and soft skills, even if concomitant implementation processes are uneven. APEC member countries identified four overarching competencies that could fulfill the need "to go beyond the teaching/learning approach which is solely based on knowledge acquisition." They listed: 1) Lifelong learning: a general acknowledgement of the changing nature of our times and as a consequence, the need for continuous skill development through a lifetime. 2) Problem solving: to prepare students to react to diverse and concrete situations with implications for skills such as creativity, initiative, critical thinking, and decision making. 3) Self-management: the development of students as independent and self-directive with development of critical, reflective, and independent thinking. 4) Teamwork: concurrent with autonomous thinking and learning is the need to develop capacities for team work that require communication, confidence, information sharing, tolerance, and democratic attitudes.[22]

Singapore exemplifies countries that place soft skills at the heart of skills development programs.[23] It adopted the 21st Century Competencies Framework as a major policy initiative. The Singapore Ministry of Education (MOE) identified competencies as the foundation upon which future skilled workers are to develop. The competencies, based on a set of core values, radiate outward to include social and emotional competencies and their "emerging" 21st century competencies.[24] The prominence of soft skills is evident in their inclusion in the descriptions of each competency.

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[21] There is also a lot of cross-pollination such as Jamaica's core competencies that correspond to those from Australia, and as we see below, Korea's "approach and structure are very similar to Australian employability skills." Cited in Jin, M. (2014). Transferable skills education in Technical and Vocational Education and Training (TVET) in the Republic of Korea, TVET@Asia, issue 3, 1-17. Retrievable from: http://www.tvet-online.asia/issue/3/jin_tvet3.pdf

[22] Higher Education Learning Profile and Social Development in the Asia-Pacific, APEC Human Resources Development Working Group, APEC, August 2012 (2012:8)) (https://www.apec.org/Publications/2012/08/Higher-Education-Learning-Profile-and-Social-Development-in-the-Asia-Pacific

[23] World Economic Forum (2016), The Global Information Technology Report 2016.

[24] Data Science and Analytics Skills Shortage: Equipping the APEC Workforce with the Competencies Demanded by Employers, APEC, November 2017. https://www.apec.org/Publications/2017/11/Data-Science-and-Analytics-Skills-Shortage).

The core values at the center, and upon which all the other competencies are built, define a person's character, shape beliefs, attitudes and actions of a person. Respect, responsibility, resilience, and integrity are prized as outcomes of these core values. Social and emotional competencies are characterized by self awareness, self-management, responsible decision-making, social awareness, relationship management. They underpin the ability to recognize and manage emotions, care and concern for others, responsible decision-making, establish positive relationships, and effective handling of challenging situations. Lastly, emerging 21st century competencies: civic literacy, global awareness and cross-cultural skills; critical and inventive thinking; communication, collaboration and information skills.[25]

Soft skills are integrated into all levels of its skills framework. For example, as part of its national skills framework, Singapore also provides key information on existing and emerging skills required for job roles and specific occupations, among other things, on its SkillsFuture portal.[26] "The Skills Framework is a SkillsFuture initiative developed for the Singapore workforce to promote skills mastery and lifelong learning." Jointly developed by government, employers, industry associations, education and training providers, it provides, among other things, "useful information on existing and emerging skills." Each job has its own unique set of technical skills and competencies, which include soft skills. For example, in the field of ICT, the top 5 competencies listed as critical generic skills are: communications, creative thinking, problem solving, sense making, and teamwork.[27]

The **Philippines** has also long recognized that education and training plays a central role in national development. Its early educational reforms, undertaken to respond to the growing demands of the labor market, predate efforts in the US with SCANS and Australia's Mayer study.[28] The development of the Philippines Qualification Framework (PQF) "describes the levels of educational qualifications and sets the standards for qualifications outcomes" established a national quality-assured system (PDF, 2017:18) and led to the growth of competency-based TVET framework under the Technical Education and Skills Development Authority (TESDA).

[25] Ministry of Education, Singapore, https://www.moe.gov.sg/education/education-system/21st-century-competencies and Li, Liew Wei, Presentation at OECD-CCE-MOE "Educating for Innovation" Workshop 15 January 2013, Ministry of Education, Singapore, Retrieved from http://www.oecd.org/education/ceri/02%20Wei%20Li%20Liew_Singapore.pdf
[26] (http://www.skillsfuture.sg/skills-framework
[27] Skills Framework for Infocomm Technology, A guide to Occupations and Skills, Singapore, November 2017. Retrieved from www.skillsfuture.sg/-/media/...Infocomm-Technology/FINALFA_ICT_lowres.pdf
[28] Brewer, et al, ILO 2015:82, retrieved at http://ilo.org/wcmsp5/groups/public/---ed_emp/---ifp_skills/documents/publication/wcms_470726.pdf

TESDA identifies nine basic competencies that integrate 21st century skills consisting of: collaboration, communication, critical thinking, entrepreneurship, environment literacy, information technology, learning and innovation, life-long learning, and occupational health.

As TESDA explains, "these characteristics are essential if a nation's workforce is to be globally competitive and flexible. Moreover, these positive attributes are deemed to facilitate greater mobility across occupations or locations." (TESDA 2011:19)[29]

Along with detail for each, TESDA defines the competencies as "non-technical skill (knowledge, skills and attitudes) that everybody will need in order to perform satisfactorily at work and in society and are considered portable and transferable irrespective of jobs and industrial settings." For example, the basic competencies of "collaboration and teamwork" are described as: knowledge, skills and attitudes required when working with others and teams, leading, developing and managing teams. This is a basic competency that is a "non-technical skill (knowledge, skills and attitudes) that everybody will need in order to perform satisfactorily at work and in society and are considered portable and transferable irrespective of jobs and industrial settings."[30] Similarly, Information technology is described as the knowledge, skills and attitudes (*emphasis added*) required when accessing, presenting, using, managing/evaluating and developing information systems and processes.[31]

Despite recent findings by the World Bank that Philippine firms report difficulty "finding workers with an adequate work ethic or appropriate interpersonal and communication skills" the country's educational system, vocational system, government and employers continue to value such skills as vital to national development. (Acosta, et al., 2017)[32]

In **Korea**, which has historically placed education and training at the center of its industrialization process, its National Competency Standards (NCS) has emerged alongside its national qualification framework.[33] The Korean NCS, comparable to the UK and Australian

[29] Technical Education and Skills Development Authority, Investing in the 21st Century Skilled Filipino Workforce, The National Technical Education and Skills Development Plan, September 2011. Retrieved http://tesda.gov.ph/uploads/File/LMIR2011/july2012/NTESDP%20Final%20asofSept12.pdf

[30] http://www.tesda.gov.ph/Uploads/File/21st%20Century/Collaboration.pdf

[31] http://www.tesda.gov.ph/Uploads/File/21st%20Century/Information%20Technology.pdf

[32] http://documents.worldbank.org/curated/en/333521498727263689/pdf/ACS22716-REVISED-PUBLIC-Philippines-STEP-Book-2017.pdf

[33] Globally, national competency standards tend to emerge alongside national qualification frameworks such as Australia's Training Package and Scotland's Vocational Qualifications. Comparatively, the Qualifications Framework of the United Arab Emirates (UAE) contains key competencies required "for effective participation in the workplace, in learning and in daily life." Known as "CoreLife Skills," the set of generic skills are considered essential to all UAE workers, and along with literacy and numeracy, include: 1) Information: collecting, analyzing and applying information in a given context; 2) Communication: communicating information, concepts and ideas; 3) Organizing self: the entrepreneurial spirit, creativity, and discovery, and the ability to self-organization, and the organization of events and activities; 4)

frameworks and Australian employability skills (Jin 2014), is an example of government-led efforts to identify and standardize competencies that are required for successful job performance.

Jointly implemented by the Ministry of Education and the Ministry of Employment and Labor, the NCS aims to match the qualification system and training to the demands of industry. In Korean parlance, these "transferable skills" are defined as the essential skills required for successful job performance, regardless of the type of occupation or position. They include cognitive, technical and soft skills: 1) Communication skills: document literacy, documentation skills, listening skills, language skills, basic language skills. 2) Resource Management Capabilities: The ability to manage time, resources, budget management skills, ability to manage financial resources, human resources management skills. 3) Problem-Solving Skills: thinking, problem solving capability. 4) Information Capacity: computer literacy, information processing capabilities. 5) Ability to understand organizational structures: global competence, ability to understand organizational system, management ability to understand, ability to understand business. 6) Numeracy: basic math skills, basic statistical skills, analytical skills, chart, charting capabilities. 7) Self-development Capability: self-awareness, self-management skills, career development skills. 8) Interpersonal Skills: teamwork skills, leadership skills, conflict management skills, negotiation skills, customer service skills. 9) Technical Skills: technology literacy, technology selection skills, applicable technical skills. 10) Professional ethics: work ethics, ethical community.[34]

Korea also identifies essential cognitive, technical and soft skills specifically for college students, which are similarly aimed at responding to the demands of the business sector. They include: 1) Communication: listening comprehension; discussion and moderation; reading; writing; speaking. 2) Resources-Information-Technology Processing and Application: resources processing and application; information processing and application; technology processing and application. 3) Interpersonal & Cooperative Skills: working in diverse environments, teamwork; leadership; systematic thinking. 4) Global Competency: attitudes to diverse cultures; understanding diversity; understanding globalization. 5) Higher Order Thinking (HOT): analytical thinking; inferential thinking; evaluative thinking; alternative thinking. 6) Self-management: self-

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Working with others: working with others in teams, including leadership; 5) Mathematical/problem solving: solving problems including using mathematical ideas and techniques; 6) Technology (ICT): Applying information and communication technologies; 7) Societal: Participating in social and civil life including ethical practice.
Retrieved from: https://www.nqa.gov.ae/EN/Pages/QFEmirates/CoreLifeSkills.aspx

[34] www.ncs.go.kr. 2013, cited in Jin, M. (2014). Transferable skills education in Technical and Vocational Education and Training (TVET) in the Republic of Korea. In: TVET@Asia, issue 3, 1-17. Retreivable online from: http://www.tvet-online.asia/issue/3/jin_tvet3.pdf

directed learning; goal-oriented planning and organization; personal, social, and civic responsibility; emotional self-control.[35]

The Korean skills development strategy has always been fundamental to its Five-Year Economic Development Plans. While the government-led skills development system, designed “to assure industry the supply of a skilled workforce,” (Ra, Y and Shim, KW 2009:2) it has also been recognized as one of the key drivers of Korea becoming one of the most diversified and technologically advanced economies in the world.

5. CONCLUSION

Countries, albeit at different levels of development, aim to achieve a state of full employment and to have their labor demands properly and efficiently match their labor supply. The set of skills needed to improve economic prosperity and to build social cohesion are influenced as much by a country’s demand and supply of labor as by the quality of available jobs and the socioeconomic and demographics of its labor force. The overlay of digital and technological forces shaping the economy is also redefining the future of work and its requisite skills.

What is clear is that basic skills in literacy and numeracy remain vital but increasingly technical skills and non-cognitive skills such as individual behavior, attitude and mindset are becoming as important as technical know-how.

Indeed, as the preceding section demonstrates, the definition of skill is not a simple task. The examples presented were provided in part to show that the way in which skill is conceptualized has an impact and influence on how and where skills are imparted, leaving aside how and even whether skills can be measured. Given the imperative of policymaking and “high-stakes accounting” one branch of the literature is replete with examples of definitions of skills that are the consequence of investing in human capital while another, especially where soft skills are concerned, are job specific or at the very least go to the contextual aspects of the job.

PART 2

[35] Jin, M. et.al. (2013). The Implementation of Korea Collegiate Essential Skills Assessment Test (K-CESA)

REVIEW OF SKILLS FORECASTING TECHNIQUES

1. INTRODUCTION

The main aim of manpower forecasting in any economy is to assist long term investment in the education sector. The scale of such investment can only be stipulated if skills needs are carefully identified (Agapiou, 1996). The problems of unemployment, changing technologies, skill requirements and knowledge obsolescence only heighten the need for good forward looking tools for skills demand and supply. Therefore, according to Ahamad and Blaug (1973), the historical interest in manpower forecasting can be traced to three sources: interests in linking educational expansion to human resource requirements of a growing economy; translation of targets for economic growth to targets for demand for skills; and the need for skills forecasting in order to better plan vocational counseling and placement services. Finally, the common thread running through the different interests in manpower planning is that surpluses and shortages of skills/manpower need to be controlled and minimized in all economies (Prasirtsuk, 1993).

The experience with manpower forecasting and the literature on various approaches are extensive going back to 1920s in the old Soviet Union. It includes various techniques used to forecast occupations and skills at national, regional, industrial, and firm levels. The focus of this report is on the national forecasting approaches. It provides an overview, followed by short summaries of country experiences, with manpower forecasting. Our choice of countries was constrained by the availability of detailed information about the specifics of methodologies used, since many of the experiences have not been fully or properly documented in terms of technique details.

2. ESTIMATION METHODS OF SKILLED MANPOWER

The literature on manpower forecasting approaches is extensive.[36] The main estimation methods used for forecasting skilled manpower can be grouped into three categories:

[36] The reviews of literature on manpower techniques include Bryant *et al.* 1973, Debeauvais and Pscharopoulos 1985, Smith and Bartholomew 1988, Cambell 1997, Hopkins 2002, Wong *et al.* 2004, Spalletti 2008, El Achkar (2010), Bakule et al. (2016), Siekmann and Fowler (2017).

quantitative, qualitative, and mix approaches. The quantitative approach is distinguished by its use of models and formal quantitative methods to produce projections of future skills needs. Practices that fall under qualitative approaches use ‘soft’ qualitative data alongside the ‘harder’ statistical information to anticipate future skills needs. They significantly rely on key experts and stakeholders for skills anticipation. Finally, and increasingly, countries are combining quantitative and qualitative approaches for their skills forecasting needs. The rest of this section provides an overview of the three broad category of approaches.

2.1. QUANTITATIVE APPROACHES

Quantitative approaches to skills forecasting use a wide range of empirical methods to produce actionable intelligence about future skills needs. They offer a consistent and detailed picture of future developments by sector, occupation, qualification or skills. They show how future outcomes can be generated to guide current decision-making. This allows policy-makers to understand mid- to long-term developments and to react towards expected imbalances. (Bakule et al., 2016).

As a dominant approach within the universe of quantitative approaches, the use of empirical models for skills forecasting and planning has particularly been expanding because of increasing availability of data. Empirical models are also being used, broadly speaking, because economic models are increasingly found to be useful to: (a) outline and analyze in a consistent manner future developments under current policies; (b) provide insight into the likely effects of policy options or policy variants; (c) show the sensitivity of forecasts or policy effects due to certain parameters or model specifications; (d) calculate uncertainty variants that show how the projections will change in response to different developments in the exogenous variables that drive the model: and (e) to analyze what happened in the past and what might have happened in the past under different circumstances.

However, quantitative models also have some disadvantages such as: technical limitations; being built on past patterns of behavior; substantial requirements of data and investments of time and resources; and being expensive to maintain.

For this review, quantitative approaches to manpower forecasting are grouped into three categories: the time series extrapolation approach, bottom up approach and top-down approach. Each approach is discussed along with their key methodological differences.

Table 1: Approaches to Skills Forecasting

APPROACH			COUNTRY
QUANTITATIVE APPROACHES (Use formal, quantitative, or models to anticipate future skills needs)	**Time Series Extrapolation Approach** (Using past trends to extrapolate the trend into the future)		Hong Kong
	Bottom-up Coefficient Approach (Estimate economy-wide needs by estimating and then adding up project level requirements using labor multipliers)		South Africa (SIPs)
	Top-Down Approaches	**Traditional Approach** (Use simple relationship between output, productivity and employment for the employment projection of MP forecasting)	Greece, Italy, Portugal, Spain, Turkey, US, UK, France, Germany, Hungry, Poland, Old USSR, India, Ivory Coast, Tanzania, Egypt, Sweden, Thailand, Nigeria
		Econometric Approach (Use a macro-econometric model for the employment projection of MP forecasting)	US, UK, EU, South Africa, Vietnam, Netherlands, Germany
		CGE Approach (Use a CGE model for the employment projection of MP forecasting)	Australia, New Zealand, Vietnam
QUALITATIVE APPROACHES (Use 'soft' qualitative data alongside the 'harder' statistical information to anticipate future skills needs)	**Labor Market Information & Signaling Approaches** (Use labor market information and signals to guide schooling and training decisions and to assess how well the labor markets are function)		Canada, Australia
	Foresight Approaches (Use Delphi method, expert panel, scenarios, literature and statistics review, brainstorming and SWOT analyses for skills anticipation) (uses inputs from key experts and stakeholders for skills anticipation)		Brazil, Germany, Finland, Japan, Korea, EU, Russia, Australia, UK, US
HYBRID (MIX) APPROACHES (Use a combination of quantitative and qualitative approaches to establish future manpower requirements)			Canada, Hong Kong, South Africa (SIPs)

2.1.1. TIME SERIES EXTRAPOLATION APPROACH

The time series approach uses past trends in manpower related indicators to make projections into the future. It extrapolates the trend into the future by examining the relationship exclusively between the past performance of an indicator and time (Bezdek 1975). The approach uses varied methods ranging from a simple deterministic model (e.g., linear extrapolation) to more complex stochastic models (e.g., Box-Jenkins models).

Historically, this approach has been used in some of the work on manpower forecasting undertaken in Australia, Hong Kong, the Netherlands, the UK, the US, Finland, and Poland. In Part 3 on country experiences, a summary of Hong Kong's recent use of this approach for its Report on Manpower Projection to 2022 is presented.

Some advantages of the time series extrapolation approach are that it is relatively simple and inexpensive, fairly accurate, relatively less influenced by personal bias, and allows focusing on the data's underlying features and patterns. At the same time, however, the approach suffers from several important weaknesses. The approach is mainly suitable for producing short term forecasts; it assumes that the future is a continuation of the past; and it does not provide insight into economic, demographic, and other possible factors that drive the projections (Wong *et al.* 2004).

2.1.2. BOTTOM-UP COEFFICIENT APPROACH

This approach to manpower forecasting is based on reasoning that people (supervisors and managers) at the bottom, i.e., at the project level where the action is, are most knowledgeable about employment, occupation and skill requirements. Moreover, it is based on the premise that the labor requirement per unit of expenditure of all projects that fall under a project type is the same, i.e., similar projects have similar demand patterns. Therefore, based on information collected from different project sites about daily labor deployment and the project expenditure, it is possible to estimate labor multipliers (man-day per one million dollar spent on the project) associated with various types of projects (e.g., public utilities, railway works, public works). Future estimates of labor demand by occupation can then be generated by multiplying the expected expenditure on all future projects related to a project type by the corresponding labor multiplier. By adding up the estimated labor demands for all project types, the total future demand for labor by occupation is estimated (Wong *et al*., p. 45).

The approach includes using the same sources to establish estimates of possible future labor shortages by occupation. Projections of required manpower and shortages by occupation are expected to inform education and training authorities and programs. The estimation and use of fixed coefficients (i.e., multipliers) for various categories of works (e.g., housing, roads, and rails) are expected to implicitly take account of their differences in technology and thus labor productivity.

The forecast accuracy of this approach heavily relies on updated coefficients. However, the approach has a number of drawbacks that include being very demanding in terms of collecting past employment information and details of future projects, including planned expenditure. The coefficients that the approach relies on require significant investment of time and expense to update regularly. Finally, the approach solely depends on past data, which significantly diminishes its ability to take account of changing environments related to the impact of technology, policies, etc. (Wong *et al*. 2004).

This approach was recently applied in South Africa. The approach was used to assess skill needs of the Strategic Infrastructure Projects (SIPs). Eight steps were followed to identify the occupations in demand for the SIPs. These steps represent the process through which this approach starts from the bottom (project level) and works up to manpower needs by occupation and skills, as follows:

First, projects in the 18 SIPs were categorized by sector and sub-sector. Second, expert project managers in each sub-sector were asked to identify the size of a typical project in that sub-sector, which, depending on the project, was expressed in financial, physical, or other measurement units. Project managers were also asked to estimate the time it would take to implement a typical project and to outline the required occupational skill sets. Third, all relevant data about various projects in each SIP was collected (e.g., scope, size, budget, time line, etc.). Fourth, the initial steps helped indentify 64 prototypes across the 18 SIPs. They ranged across the sectors of agriculture, building, services infrastructure, manufacturing, health, mining, energy, and education. The relevant prototype was chosen for each project by assessing the skills needs of the project and matching it with a prototype. Fifth, prototypes were customized. This was done by adjusting the skills prototype to the actual project by a scaling factor. A manpower multiplier was used to translate specific prototype skills requirement to project specific skills needs, which gave an indication of individual skills demand per project or, when amalgamated, for a sector. The estimated skill needs for each project across a timeline were combined and a picture of the total demand for different occupations was estimated for all SIPs. It was found that 249 occupations, totaling some 205,329 workers were required at the peak of the current known development. The sixth and seventh steps were devoted to estimating scarcity. The originators of the base prototypes were asked to identify which occupations are difficult to fill using a four point system: adequate supply, shortage, significant shortage, and critical shortage. This enabled estimating skills positions that were difficult to fill and gave an early warning on critical areas that needed training or alternative sourcing of skills. Lastly, in the eighth step, the occupations that were identified as difficult to fill at prototype level were used to generate the scarce skills list. The initial scarce list included 58 occupations.

To ensure delivery of priority skills for the SIPs, the collected information and the estimation process was extended to also estimate skills needs at national level to ensure that those trained for SIPs would not end up working for other purposes. However, for the skill needs at national level, the team that worked on the project used projections from the Linked Macro-Education

Model of South Africa (LM-EM), which is a top-down econometric model and will be discussed in Part 3.

2.1.3. TOP DOWN APPROACHES

Both time series and bottom-up approaches overlook the importance of macroeconomic dynamics for manpower forecasting. Conversely, the starting point of the top-down forecasting approach is the view that a country's future manpower requirements are directly linked to future macroeconomic performance. More specifically, in the top-down approach, the dynamic relationship between employment, as the central input into manpower estimation, and the rest of the economy, plays a central role in forecasting manpower demand. This approach, which has evolved over time, remains the dominant approach to manpower forecasting. Our summary of techniques used in the top-down approach begins with the original Manpower Requirement Approach (MRA), which captures the central tenets of the approach.[37] Subsequent models in this category are grouped based on the orientation of their underlying macroeconomic framework. One group is defined based on using empirical Computable General Equilibrium models of the economy, which strictly use neoclassical economic theory to capture the working of the economy and produce projections of employment. The second group is characterized by using macroeconometric models of economies, which mainly use non-neoclassical economic theories (e.g., Keynesian, heterodox) to represent macroeconomic dynamics and to generate employment projections.

Beyond the differences in the macroeconomic foundation of top-down approaches, international experiences with using the approach to forecast demand and supply of skills include taking a number of additional steps to (a) translate demand for employment to demand for skills, (b) forecast supply of skills, and (c) produce projections of balances and imbalances in the demand and supply of skills. The steps that are involved in completing the above stages of forecasting skills demand and supply are mostly similar among the three top-down approaches. However, given country differences in data availability, preferences of modeling teams, and other factors, empirical methodologies that are deployed to deliver these steps are not uniform.

In the top-down approach, following the first step of using economic modeling techniques to produce likely forecasts of industry employment, nine additional steps are usually taken to translate the employment forecasts to likely future demand and supply of skills:

- Estimating future employment by occupation
- Estimating expansion demand by occupation
- Estimating future employment and expansion demand by educational qualification

[37] According to Debeauvais and Psacharopoulos (1985, p.13), "[A]lthough a variety of methodologies have been used to derive manpower forecasts in different countries, the dominant model is what is known in the literature as the 'manpower-requirements' one."

- Estimating future replacement or separation demand by occupation and by qualification
- Estimating future job openings by occupation and by qualification
- Estimating future size of labor force by occupation and by qualification
- Estimating job seekers by occupation and by qualification
- Comparing estimates of labor demand (stage 1) with estimates of labor supply (stage 2) to estimate imbalances by occupation and by qualification
- Determine future outlook for skills demand, supply, (im)balances, and mismatches by occupational and qualification

The range of methodologies that is currently used to estimate each of the above steps is discussed later as part of country experiences with skills forecasting.

2.1.3.1. TOP-DOWN ORIGINAL APPROACH

Historically, the approaches to skills planning have been influenced by the Manpower Requirements Approach (MRA), which received prominence in the OECD's Mediterranean Regional Project (MRP) in the 1960s. The aim of the initiative was to understand the changing economic structures in six Mediterranean countries: Greece, Italy, Portugal, Spain, Turkey and Yugoslavia. It involved producing detailed educational requirements that would stimulate desired growth through the optimum planning of education output. The three major steps in manpower forecasting include: (a) forecasting the demand for educated manpower; (b) forecasting the supply of educated manpower; and (c) balancing supply and demand. Following Debeauvais and Psacharopoulos (1985), in the MRA each step can be elaborated as follow.

<u>THE DEMAND SIDE</u>: The MRA approach includes five steps to assess the number of workers by educational level over time:

1. Estimating the future level of GDP or Output (X) or the economic growth rate between base and the target year.
2. Estimating structural transformation of economy or the distribution of GNP by economic sector (X_i/X), between base and target year.
3. Estimating labor productivity by economic sector for the target year, or its inverse (L_i/X_i), and its change between base and target year.
4. Estimating the occupational structure of the labor force within economic sector (L_{ij}/L_i) for the target year.
5. Estimating educational structure of the labor force in given occupations within economic sectors (L_{ijk}/L_{ij}) for the target year.

   Where i= economic sector; *j*= occupation; *k*= educational level; *a*= age; *s* = sex

The above five steps provide the necessary input for the demand function for educated labor:

$$L_{ijk}^{D} = f(X, \frac{X_i}{X}, \frac{L_i}{X_i}, \frac{L_{ij}}{L_i}, \frac{L_{ijk}}{L_{ij}})$$

THE SUPPLY SIDE: In MRA approach, the equation for the estimation of the supply of educated labor force is derived using four basic steps:

1. Estimating the population $P_{a,s,k}$ by age, sex, educational level. These projections take place according to any standard demographic model or, at the crudest, they are simple time extrapolations.
2. Assessing the number of graduates and drop outs, by age, sex, educational level, $E_{a,s,k}$. This takes place according to the standard social-demand model, namely school-level-specific transition probabilities are applied to the base population cohorts and these are followed through time until the students leave the educational system.
3. Finding labor force participants Ls, by applying age, sex , educational level specific participation rates to the graduates, $I_{a,s,k}$, generated in the previous step.
4. Estimating occupational supply based on labor supply by education level with an education to occupation matrix $M_{k,j}$.

Therefore, the supply function is specified as:

$$L_{j,k}^{S} = f(P_{a,s,k}, E_{a,s,k}, I_{a,s,k}, M_{k,j})$$

BALANCING LABOR DEMAND AND SUPPLY: The difference between the projections of labor demand and labor supply by occupation (D_j-S_j, or L^D_j-L^S_j) and by education (D_k-S_k, or L^D_k-L^S_k) provides foresight of possible imbalances in the demand and supply of particular occupation or education labor force. The adjustment mechanism will then take the form of revising one or more of the key assumptions (inputs) in the demand and supply functions. For example, "too much optimism on labor productivity could reduce the demand for labor while too much on labor force participation rates could increase the supply of labor. If reconciliation is not possible then this has significant implications for policy action to narrow the gap between educated labor supply and its demand." (Hopkins, 4).

CRITISIMS OF MRA: Many criticisms have been leveled against the MRA over the years. Following is Hopkins' (2002) characterization of the main criticisms by Psacharopoulos (1991), Blaug (1970) and Ahamad and Blaug (1973) that were founded on the experience of eight manpower studies in the United States, Canada, France, UK, Sweden, Thailand, Nigeria and India:

1. Significant forecast error related to the projections of employment by occupation.

2. The main reasons for the errors were the fixed-coefficient used in the demand equation and the assumed labor productivity growth.
3. Exacerbation of errors with longer forecast period.
4. No link between manpower forecasts and education policy decisions.
5. Occasionally lent support to what turned out to be a wrong decision, thus undercutting the argument that forecasting always improves policy decision. (Hopkins, 2002)

Historically, these and other criticisms of MRA[38] provided fertile ground for new approaches to emerge. The new approaches include those that fundamentally disagreed with using economic modeling techniques for manpower forecasting and planning (e.g., rate of return approach, labor market information systems, key informants, labor market signaling). Others continued to adhere to the top-bottom core principle, but improved how the working of the macroeconomy is represented in the approach. The rest of this section is dedicated to the latter group of models. Section 2.2 will provide a review of alternative approaches to the top-down models.

2.1.3.2. TOP-DOWN ECONOMETRIC APPROACH

Criticisms of the MRA (i.e., the original top-down model) directly or indirectly relate to the quality of its employment projections, where the approach relies on a simple relationship between output, labor productivity and employment. Later generations of top-down models of manpower forecasting have tried to remedy the MRA shortcomings by strengthening the analytical foundation of the approach, which is achieved through the use of macroeconomic modeling techniques to generate projections of growth and employment.

This extension of the top-down original approach exposed manpower forecasting to various approaches to macroeconomic modeling and to strands of thought in theories of employment and unemployment. Therefore, as suggested earlier, more recent international experiences with the top-down approach to manpower forecasting can be divided into those that are founded on macroeconometric models that mainly have non-neoclassical theoretical orientation, and those that use computable general equilibrium models that are strictly based on the neoclassical economic theory.

Since the two economic modeling traditions significantly differ in how they explain the workings of a market economy, especially the labor market, and how their macroeconomic models are built empirically, the employment projections of each model (which are used to estimate occupational and qualification demands) differ significantly. Therefore, for manpower forecasting, the choice of macroeconomic model to underpin the use of a top-down approach

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[38] For example, according to Youdi and Hinchliffe (1985) an important assumption in the MRP-type forecasting approach is that the elasticity of substitution between different types of labor is either equal or close to zero, which is incorrect in real world where the elasticity of substitution vary according to the degree of substitutability of various types of jobs.

has important implications for the growth and employment projections that will be used for skills forecasting.

The top-down econometric approach uses modeling specification and estimation processes to establish the model's theoretical and empirical foundations. Modeling specification is used to state the perceived nature of relations between variables in the economy (informed by theoretical literature), providing a theoretical foundation of the model. The estimation process utilizes historical time series data and econometric techniques to establish the explicit forms of the model's behavioral equations and parameters. The two processes are expected to yield a model that consists of theoretically acceptable relationships and statistically significant values for the parameters of the model equations.

For historical and practical reasons, macroeconometric models have predominantly non-neocloassical theoretical foundations. Yet, as far as manpower forecasting is concerned, the models differ in at least two important ways. First, the theoretical underpinning of the model's labour market behavior is either Keynesian or neo-classical theories of employment and unemployment that inform the model's wage rate and employment specifications and forecasts. The second important differentiating factor among top-down econometric models relate to how country models produce projections of employment at sector level. On one hand, a good portion of multi-sector econometric models include estimated equations for components of aggregate demand (i.e., consumption, investment, export, imports, inventories) that inform the model's projections of those variables. They are then fed into an input-output system to produce projections of industry outputs. Finally, through a variety of simple or complex methods, sector outputs and projections of other relevant variables (e.g., wage rate, labor productivity) are used to produce a model's industry level employment. On the other hand, some macroeconometric models that are used for manpower forecasting (e.g., EU, UK, South Africa) do not rely on input-output system to estimate industry output and to indirectly estimate industry employment. They use industry level estimated equations for both output and employment.

Over the years, top-down econometric approaches have been extensively used for manpower forecasting in many developed countries that have the requisite historical time series economic data (e.g., United States, United Kingdom., the Netherlands, Australia, Canada, New Zealand). As systematic macroeconomic data collection has become more internationally widespread, an increasing number of developing countries have also begun to use the approach as part of their manpower forecasting tools (e.g., Singapore, South Africa).

2.1.3.3. TOP-DOWN CGE APPROACH

Methodologically, the main difference between this top-down Computable General Equilibrium (CGE) approach and the top-down econometric approach is the use of the CGE modeling techniques to produce projections of growth and employment used for manpower projections.

CGE models are quantitative expressions of neo-classical general equilibrium theory and therefore embody strong theoretical assumptions about the working of the economy that do not necessarily reflect the reality of market economies, especially in developing economies. These assumptions include perfect competition and flexible markets with inherent tendencies to self-correct and achieve full employment general equilibrium, i.e., to simultaneously clear all goods and factor markets. These assumptions are among CGE's most debatable depictions of the working of the economy.[39]

Another set of issues related to CGE models centre on the calibration method used to develop the model's parameters (i.e., elasticities). The method is a deterministic approach to calculating parameter values from a benchmark equilibrium data set. Shoven and Whalley (1992) point out that the techniques are less than ideal and undermine the reliability of the results derived from the model since the parameters are either based on the empirical literature, arbitrary or are a set of values that "force the model to replicate the data of a chosen benchmark year." Similarly, Jorgensen (1984), Lau (1984), Jorgensen et al. (1992), and Diewert and Lawrence (1994), among others, point out flaws they have found in the parameter setting techniques in CGE models. This includes the use of industry or commodity level elasticities that are methodologically inconsistent, and/or are from other countries, and/or are old and obsolete estimates, and/or are outright guesses. They correctly point out that without reliable or credible parameter values, the utility of the empirical CGE models is compromised.

Since calibration is a process through which a model's parameters are adjusted until the model reproduces the national account for the benchmark year, the quality of the data is critical. Yet, one year of data, which empirical CGE models are usually built upon, provides insufficient grounds upon which to base generalised results. Thus, an important criticism regarding the inherently limited scope of CGE models hinges on the calibration technique itself, which causes the quality of the model to be at least partly dependent on the quality of the data for an arbitrarily chosen benchmark year. Critics also note that the calibration techniques are susceptible to errors and biases as a result of subjecting the data matrices to various scaling processes to force micro-consistency. These errors and biases will directly influence the parameters of a calibrated model.[40]

Three examples of top-down CGE approach are the models used in Australia, New Zealand and Vietnam. In Australia, occupational forecasting has been developed under the Department of Education, Employment and Workplace Relations (DEEWR) and the Centre for Policy Studies (CoPS) of Monash University. Their model has been in operation for more than 25 years. The

[39] De Canio (2003) and Ackerman (2002) review these assumptions, Barker (2004) examines their influence on the development of CGE models, and Taylor et al. (2006) provides a critique of CGE models as used in studies of impact of trade liberalisation.
[40] McKitrick (1998) provides an "econometric critique" of calibrated CGE models which is focused on the models' functional and numerical structure

predictions are made annually and for 5-year periods with the latest 2017 projections covering the period until 2022. Part 4 provides the Australian and New Zealand experience with top-down CGE approach for skills forecasting.

2.2. QUALITATIVE APPROACHES

Qualitative approaches use ‘soft’ qualitative data alongside with “harder” statistical information to anticipate future skills needs. They are easier to set up initially since they do not require extensive data series or quantitative modeling of economic relations. However, qualitative approaches can still use semi-quantitative or quantitative methods yet, contrary to the quantitative approach, their results are not expected to be fully based on quantitative methods and findings. While qualitative and quantitative skills forecasts have similar goals, they differ in the way they are implemented, their requirements in terms of input, and also in the types of output that they can generate.

A wide range of practices are employed in the qualitative approaches. These include using labor market information and signaling to guide schooling and training decisions and to assess how well the labor markets are functioning, and foresight methods that use the Delphi method, expert panels, scenarios, and other means for skills anticipation.

Some advantages of the qualitative methods to manpower forecasting are: their direct involvement of users of skills (i.e., employers, managers), focus on behavior, coverage of specifics that are not necessarily quantifiable, and their wider (holistic) scope. On the other hand, in terms of disadvantages of various methods that fall under this category, the practices can be very subjective, inconsistent, myopic, non-systematic, partial, and focused on the margins (Bakule *et al*. 2016). The next two subsections are dedicated to describing two sets of practices in manpower analysis that can be categorized under the qualitative approach to estimating skills requirements.

2.2.1. LABOR MARKET SIGNALING APPROACH

The labor market signaling (LMS) approach emerged out of a strong refutation of the rationale and usefulness of the top-down traditional manpower requirement approach (MRA) in practice (Psacharopoulos, 1991). Significantly different from the top-down approach, the LMS approach focuses on education and training qualifications rather than occupational classifications, in order to estimate pressure on economic returns on investment for specific skills. According to Middleton *et al.* (1993, p. 140), “Labor market signaling requires planners to focus on education and training qualifications rather than on occupational classifications. The reason relates to the quality of occupational statistics, the effect of technology on the concept of an occupation, and the practical link between academic specialization and occupational placement.”

By using labor market signals to gauge the pressure on economic returns to investment for specific skills, LMA is able to guide schooling and training decisions and assess how well the labor markets are functioning. The approach argues that the demand for occupations used by the top-down approach is a poor predicator of future labor market needs for qualified labor because new technologies change occupations.[41] Instead, they prefer to rely on labor market signals such as wages, employment trends by education and training, costs of education, enrolment data, programs of study, help-wanted advertisements, and unemployment rates by education, skill, training and occupation. (Hopkins 2002).

The LMS approach has been particularly used when available data is inadequate for the time series approach or to build a top-down model. In such an environment, the LMS approach has been useful for assessing mismatches between demand for particular skills (level of education) and the expected number of available workers. To assess whether the supplied skills by education institutional match what is needed, a tracer study of graduates, consensus procedures (e.g., the Delphi technique), or key informants survey are proposed.[42] As Wong (2004) points out, by using these measures predictions are not only based on calculations but supported by the strength of experts' knowledge and sources of information.

2.2.2. FORESIGHT APPROACH

Foresight can be defined as a systematic, participatory, forward looking intelligence gathering and vision building process aimed at enabling decisions and joint actions. It includes a variety of techniques to gather anticipatory intelligence in a systematic way and link it to decision-making.[43] As a tool for skills planning, especially in times of rapid changes, the forms of foresight that includes broad stakeholder involvement and an holistic approach to policy issues are considered ideally suited to address skills issues.[44]

Use of foresight techniques for skills anticipation has been a feature of foresight since the beginning and has gradually expanded from focusing on higher education to all levels and types of education. However, according to the European Union, only 16% of all foresight programmes in the world (140 out of 871 cases) specifically addressed issues relating to education. (European Commission, 2009, p.78).

[41] "However, any forecasting technique can compensate through the use of scenario analysis, that is, providing a number of alternative forecasts under different assumptions." (Hopkins, 2002, p.15).
[42] Key informants survey refers to collecting selected community-level labor market information through key informants using the local knowledge of specific categories of respondents, such as public officials, teachers, farmers, etc. (Hopkins, 2002, p. 13).
[43] JRC-IPTS, *For-Learn online foresight guide*: an A to Z of foresight http://forlearn.jrc.ec.europa.eu/guide/A1_key-terms/foresight.htm.
[44] Bakule *et al.*, 2016, p. 22.

The Foresight approach can be divided into exploratory and normative methods.[45] The exploratory methods forecast *forward* into the future from an existing situation. Scenarios that result from it are therefore extensions of the present into the future. They are primarily quantitative using calculations, producing projections, trend calculations, and probability analysis. Exploratory methods start with the present, with the pre-conditions, beliefs and social or technological possibilities that already exist.

Normative methods start with a desirable future. The process involves postulating the future and then figuring out how to get there. If exploratory methods are usually quantitative, normative scenarios show as qualitative. You are not forecasting, but backcasting, You start with the vision, with the new world, and then find a way to adapt the existing fact. (Magnus, 2012).

Bakule et al. (2016) presents a number of country case studies on the use of the foresight's explanatory and normative methods in skills anticipating. The list of countries is provided in Table 1.

2.3. MIXED (HYBRID) APPROACH

Given the strengths and weaknesses of quantitative and qualitative approaches to skills forecasting, there is a growing consensus that where data and modeling capability exist, a top-down quantitative approach should be adopted. However, the overall process should be complemented by a more qualitative approach in order to produce a more enriched view of future skill requirements. Often missing elements of quantitative skills forecasting can be substituted by simplified procedures or assumptions that can be based on qualitative methodology. At the same time, a methodology of skills anticipation that is mainly based on qualitative approaches can be supported by quantitative inputs at various stages and settings." (Bakule, 2016, 14-15).

Therefore, the emergence of Sector Councils in Canada (about 35 of them), Industry Skills Councils in Australia (10 of them since 2003), Sector Skills Council in the UK (about 35 of them), and Human Resource Development Council of South Africa (HRDC) provide the opportunity to undertake verification of the top-down forecasts. Regional and Industry Surveys in Australia and the Quarterly Labor Force Survey in South Africa are also used to verify the model based forecasts.

In **Hong Kong**, an inter-departmental task team, made of relevant government departments and training authorities, was set up to oversee the production of the latest projections of manpower requirements, which extend to 2022. The adopted approach includes two steps. The first step involved production of preliminary quantitative projections of manpower requirements for various

[45] There are also supplementary methods which are not directly considered as foresight methods, but indirectly support them in achieving their goal. This category includes SWOT analysis, literature and statistics reviews, focus groups, and brainstorming, (Bakule et al. 2016, p.29).

economic sectors and industries. These have been produced up to 2022 using the time-series extrapolation approach. The second step was to review and fine-tune the first step's preliminary projections using information obtained from various sources (e.g., consultation with businesses, trade associations, academia, government departments and statutory training bodies). This information and relevant data from the Census and Statistics Department was prepared for the inter-departmental task team to conduct the final review and fine-tune the preliminary projections (Government of the Hong Kong, 2015).

The BLS in the **US** uses extensive consultation with academic, business, and government officials to prepare the inputs for the models that it uses and to evaluate all quantitative manpower related projections. BLS uses its consultations with academics and officials to fine tune model inputs, model operations, and model outputs, prior to making the results public. The sequence of inter-related steps that the BLS follows may be repeated multiple times to allow feedback and to ensure consistency. Initial estimates of key economic variables (inputs), as well as the underlying exogenous assumption, are reviewed by a panel of economists. For the most part, the determinants of industry employment are expressed both in the structure of the models' equations. However, adjustments are sometimes imposed on the specific equations to ensure that the models do indeed make a smooth transition from actual historical data to projected results. According to the BLS "one of the most important steps associated with the preparation of the BLS projections is a detailed review of the results by analysts who have studied recent economic trends in specific industries. In some cases, the results of the aggregate and industry models are modified because of the analysts' judgment that historical relationships need to be redefined in some manner."[46]

3. CONCLUSIONS

The literature on manpower forecasting approaches is extensive. The aim of this section was to provide a brief overview of various approaches and their estimation techniques. Criticisms of the original manpower requirement approach (MRA) led to the emergence of a number of additional approaches over the last 50 years which we classified as quantitative, qualitative, and hybrid approaches. In this section, we shed light on the overall distinction between these approaches and on the differences within and between the approaches in terms of the estimation methods for forecasting skilled manpower at the national level.

[46] BLS website on Employment Projections, https://www.bls.gov/emp/ep_projections_methods.htm#industry_employment.

PART 3

COUNTRY EXPERIENCES WITH SKILLS FORECASTING

Part 3 summaries manpower forecasting approaches used in ten developed and developing countries. The case studies provide an opportunity to present the diversity of implementation approaches to skills demand and supply forecasting. Although international experience with manpower planning goes back far and covers many countries, information on the details of the techniques used is much more limited. Moreover, given space limitations, our primary objective for this section is to provide a small sample of recent country experiences with manpower skill forecasting. For this purpose, we have chosen the following countries: United States, Canada, Australia, Germany, United Kingdom, Hong Kong, South Africa, New Zealand, and the Republic of Korea.

In Part 2, we identified the top-down approach as the dominant methodology in skills forecasting, especially at the national level. The estimation of likely future trends in employment is the first step in a ten-step process. Within the top-down approach, we also delineated between those practices that use macro-econometrics modeling techniques and those that use CGE techniques to deliver forecasts of employment and other macroeconomic indicators to the manpower estimation process. Broad country experiences with the top-down approach suggest growing consensus on following additional steps to produce manpower forecasts by systematically using the outputs from the first step (i.e., the macro model):

- Estimating future employment by occupation
- Estimating expansion demand by occupation
- Estimating future employment and expansion demand by educational qualification
- Estimating future replacement or separation demand by occupation and by qualification
- Estimating future job openings by occupation and by qualification
- Estimating future size of labor force by occupation and by qualification
- Estimating job seekers by occupation and by qualification
- Comparing estimates of labor demand (stage 1) with estimates of labor supply (stage 2) to estimate imbalances by occupation and by qualification
- Determine future outlook for skills demand, supply, (im)balances, and mismatches by occupational and qualification

South Africa has produced one of the latest top-down models and will currently serve as a platform to explain each of the above steps. Other country experiences will then be presented to elaborate on additional features of skills forecasting practices.

SOUTH AFRICA

A key goal of the third National Skills Development Strategy (NSDS III) in South Africa was to establish a credible institutional mechanism for skills planning. The Strategy notes that "[t]here is currently no institutional mechanism that provides credible information and analysis with regard to the supply and demand for skills. While there are a number of disparate information databases and research initiatives, there is no standardised framework for determining skills supply, shortages and vacancies, and there is no integrated information system for skills supply and demand across government."[47] Then Minister of Higher Education and Training stressed the need for better information and integration of the holistic needs of the economy in planning the university, vocational college and skills sub-systems. He went further to state "[w]hat is needed is knowledge and planning instruments for the system and research-based intelligence for strategic decision-making for the post-school system." [48]

The Linked Macro-Education Model (LM-EM) is a forecasting tool built for South Africa in response to the call for instruments needed by government and policy analysts for their strategic decision-making. Specifically, LM-EM and its user-friendly web-platform enable policy analysts to design economic and education policy scenarios, quantify their impact, and project future trends in economic indicators along with the demand for and supply of educational qualifications. Overall, LM-EM aims to supports skills planning and systematic decision making by providing credible foresight about the skill needs of future jobs.

LM-EM was created by linking the Applied Development Research Solutions (ADRS) multi-sector Macroeconomic Model of South Africa (MEMSA) to models of supply and demand for occupations and educational qualifications. The model, based on the top-down approach, has a modular design where the overall system is subdivided into smaller parts (modules) by functional partitioning of the model. Each module is designed to carry out a particular set of functions within the larger system, using inputs from other modules and feeding its outputs into the rest of the system. The LM-EM is made up of eight modules:

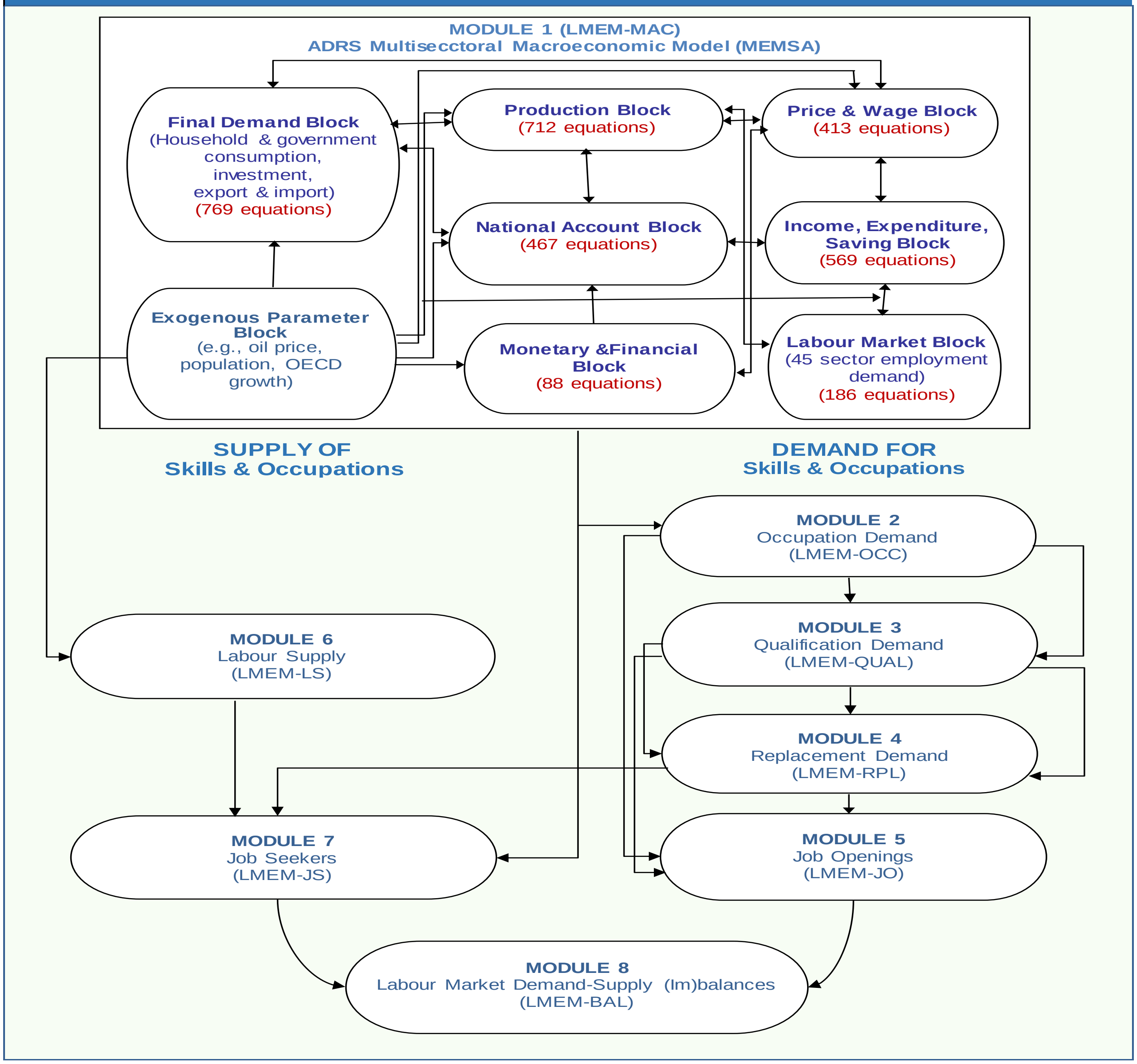
- LMEM-MAC: Multi-Sectoral Macroeconomic Model of South Africa
- LMEM-OCC: Occupational demand module
- LMEM-QUAL: Qualification demand module
- LMEM-RPL: Replacement demand module

[47] Department of Higher Education (2011), National Skills Development Strategy III, page 12, http://www.nationalskillsauthority.org.za/wp-content/uploads/2015/11/NSDSIII.pdf.
[48] Budget Vote speech by Minister of Higher Education and Training Dr Blade Nzimande, 2010, page 4.

- LMEM-JO: Job openings module
- LMEM-LS: Labour Supply module
- LMEM-JS: Job seekers module
- LMEM: BAL: Balance and imbalance module

Diagram 1 presents a simple flowchart of the LM-EM.

Diagram 1: LM-EM Module Structure



Module 1: Macroeconomic Model (LMEM-MAC)

ADRS' Macroeconomic Model of South Africa (MEMSA) is the first and core module of the LM-EM. It is a multi-sector bottom macro-econometric model with more than 3200 equations that captures the structure of the National Income and Product Account (NIPA) at sector and aggregate levels and produces projections that are consistent with various national accounting identities in nominal and real terms. The model's more than 400 time series estimated equations use the time series econometrics techniques of cointegration and error correction, originally advanced by Engle and Granger (1987) and Hendry et al (1984), to capture the behaviour of the private and household sectors as part of expressing the workings and dynamics of the economy from its production, expenditure and income perspectives. The basic structure of the model is presented Module 1 of Diagram 1.[49]

A distinct feature of MEMSA is that it captures behaviour of the private sector through the sector level econometric estimation of investment, output, employment, export, import, real wage rate, and prices. Therefore, for each of these seven variables, the model includes time series estimated equations for 41 sectors, composed of 4 primary sector, 28 manufacturing sectors, and 9 service sectors. The model's forecasts of aggregate sector variables (total primary, total manufacturing, total services, and total economy) are simply the sum of relevant sub-sectors.[50]

Given the heterogeneity among sectors of the economy, LM-EM uses the broad theoretical and empirical literature on the subject for the specification of each sector level variable (e.g., employment, investment), thereby avoiding the *a priori* imposition of one theoretical stand on the determination of a given sector level variable. The adapted broad specification approach is employed because the model's focus is not to test or assert the validity of a particular theoretical proposition, but to capture the potential differences in the law of motion (i.e., behavioural differences) among sectors of the economy, using a combination of econometric test criteria and economic theory. Therefore, the model's analytical approach is in the tradition of pluralism of heterodox economics.

The model's list of exogenous variables includes a number of domestic and international variables.[51] Among other LM-EM projections, it generates projections on investment, output and employment (expansion demand) for 45 sectors of the economy.

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[49] The key underlying behaviour of the economy is captured through the model's econometric estimations of determinants of short and long term dynamics of a large number of variables related to components of aggregate demand, production, labour market, prices and wages, and monetary and financial variables.
[50] The model includes 45 employment equations, 41 of which are estimated equations consisting of 4 primary, 28 manufacturing and 9 servicessubsectors. Four employment equations are for the total primary, manufacturing, and services sectors, and the total economy. Each aggregate variable is the sum of those in its subsectors.
[51] Among exogenous inputs to the model are: general government and public corporation investment; monetary and fiscal policy rules; government current spending; tax and subsidy rates; population; oil prices; gold prices;

When a run is initiated with LM-EM, the macroeconomic module first simulates the impact of the user defined scenario and generates projections of macroeconomic and industry indicators. Subsequently, a sub-module of LMEM-MAC translates LM-EM's 41 sector employment projections to employment and output for 21 Skills Education Training Authorities (SETA).

Module 2: Occupational Demand (LMEM-OCC)

The occupational module of LM-EM captures the links between LM-EM's macro module, that produces projections of sector employment, and the occupational structure of economic sectors in order to translate the model's projections of employment to projections of demand for occupations.[52]

Internationally, most occupational employment forecasts are based on the simple extrapolation of past trends, mainly due to significant data limitations.[53] Where relevant data is available, it is possible to utilise a more sophisticated approach. In South Africa, the availability of Quarterly Labour Force Survey (QLFS) data allowed regression techniques to be used to establish the statistical links between the occupational structure within economic sectors and economic and demographic factors. The theoretical and empirical literature on factors that influence the occupational choice of individuals in the labour market provided the bases for the identification of factors that potentially explain occupational demand in South Africa.[54] This led to the initial specification of the multinomial logistic (mlogit) model for occupations in South Africa that included the following list of explanatory variables (i.e., regressors): sector employment, gender, age, province, race, average national real wage rate, export and import shares, investment-output ratio, and capital-labour ratio.

Computer codes of the occupational module transform the estimated log-odds of the multinomial logistic model for occupations to dynamic probabilities related to demand for 10 occupations whose values adjust each period to changes in sector employment and demographic explanatory variables used in the mlogit model. The module's computer codes build the bridge between the LMEM-MAC annual projections of sector employment and projections of demographic factors to produce annual forecasts of occupational composition of sector employment and net additions to employment (expansion demand). Moreover, two

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annual growth rates of world and regional import demands; U.S. interest and inflation rates; fiscal and monetary policy measures.

[52]We have followed the tradition of referring to the occupational composition of employment as 'occupational demand' and the qualification of employment as 'qualification demand.' However, it should be noted that employment levels, as captured by historical data or generated by models as projections, are the outcome of a combination of both demand and supply factors. Similarly, we have referred to the projected changes in the levels of employment between any two years as 'expansion demand' even though in some years the change may be negative.

[53] For a review see Wilson, R.A. (2001).

[54]Additional literature on this topic includes Briscoe and Wilson (2003); Gregory *et al.* (2001); Machin (2001); Acemogly (2002); Autor*et al.*(2002); Wong *et al.* (2004), Woolard *et al.* (2003), Whiteford *et al.* (1999), and van Aardt (2001).

transition-probability matrices translate LM-EM's projections of employment by the main occupational categories to demand for about 400 lower occupational categories and employment by occupation for 21 SETAs.

Module 3: Qualification Demand (LMEM-QUAL)

Qualification demand refers to the educational qualification shares within occupations, and across industries.[55] The aims of the qualification demand module of LM-EM are: to capture the educational qualification structure within occupations; to capture the qualification composition of new job opportunities due to the expansion of the economy (i.e., expansion demand); to facilitate the interactions between the qualification module and other modules of LM-EM; and to produce detailed annual projections of demand for qualifications for the economy as a whole and for the SETAs.

The model uses the mlogit regression technique to estimate 9 equations for the 10 qualification categories, not including the reference category. For each equation, the estimated log-odds are based on an employee's occupation (1 to 10), province (1 to 9), gender (1 to 2), race (1 to 4), and age group (1 to 10).

Within the module, for every year of the forecast period, the module combines LM-EM's projections of variables used as explanatory variables in the multinomial logistic regression for qualifications with the transformed log-odds ratios of parameters of the estimated equation to produce period specific sets of probabilities related to the range of skills composition (educational qualifications) within each occupational group. The calculated occupation-qualification probability matrix for each period and the vector of demand projections for 10 occupations for the same period, provide projections of demands for specific and all educational qualifications.

The LMEM-QUAL generates a range of annual forecasts related to the qualification demand. This includes projections of demand for 7 educational qualifications based on the multinomial regression model, 27 educational qualifications based on the transition-probability matrix, and 7 educational qualifications for each of the 21 SETAs. Outputs of the qualification module feed into at least two other modules of LM-EM, namely the job openings and skills gap modules.

[55] CEDEFOP, 2009, p.118. Even though it is understood that skill is a complex concept that embodies tangible and intangible attributes, it is assumed that skills significantly reflect and positively correlate with formal educational qualifications and thus the module used the highest educational qualifications of individuals within national surveys as close proxies for their skill levels. Despite its limitations (e.g., its shortcomings to measure various generic skills and competences), this is an internationally established practice in modelling the education sector that relates to the availability of data and relative ease of measurement.

Module 4: Replacement Demand (LMEM-RPL)

Replacement demand refers to job openings that result from the departure of workers that need to be filled by new workers.[56] The LMEM-RPLD provides projections of the number of employees in each occupation that will be replaced due to labour turnover related to retirement, migration, mortality or through career changes, which together constitute replacement demand. Therefore, the aim of the replacement demand module is to estimate replacement demand rates within each occupation for the forecast period and by educational qualification.

The methodology used is based on the the cohort component approach (Willems and de Grip, 1993) that involves using multiple surveys that include detailed information on the demographic and labour market of individuals.[57] The approach uses the size of a population cohort at two different points in time to estimate the numbers of leavers from that cohort. If the size of the cohort has decreased, then there has been a net outflow. If the net flow is positive, then the method assumes that there has been no outflow and hence no replacement demand. The method therefore examines the net flows and is based on summing the net outflows over all cohorts where there is an outflow. The cohort component method was applied using pseudo cohorts, since the data did not track the same individuals. At the same time, demographic information such as age and gender was used because many of the flows, especially retirements and mortality, are age and gender specific.

The above approach was used to calculate baseline values for the replacement demand rates that were used as exogenous parameters for retirement, mobility, mortality and migration to produce projections of the annual flow of replacement demand by occupation and qualification. Therefore, the LMEM-RPLD module generates projections of the scale of vacancies, i.e., replacement demand, that are expected under a given economic scenario by occupation and qualification.

Module 5: Job Openings (LMEM-JO)

The purpose of this module is simply to provide an aggregate view of total job openings in the economy, which is the combination of job openings due to economic growth (i.e., the expansion demand) and job openings due to the replacement demand. The module thus produces annual projections of total job openings by occupation and qualification. The module's outputs also facilitate identification of occupations and qualifications that are in high and/or low demand in the future.

[56] Willems and de Grip, 1993, p. 173.

[57] The methodology has been used to calculate the net replacement demand in the Netherlands (Willems and de Grip, 1993), Australia (Shah and Burke, 2001), Ireland (Sexton et al., 2001), and the United States (Eck, 1991, and Bureau of Labour Statistics, 2006).

Module 6: Labor Supply (LMEM-LS)

The labour supply module of LM-EM is designed to produce annual projections of the labour force and its breakdown by educational qualification (i.e., skills supply). The output of this module also feeds into the model's generation of forecasts of job seekers. Therefore, the aims of the labour supply module of LM-EM are: to produce annual projections of the available skills, measured by the highest level of education, in the labour force, using the expanded definition of unemployment; to produce annual projections of the available skills in the labour force by the occupation of employed and the occupational preference of unemployed.

In order for the LMEM-LS to produce projections of the labour supply (labour force), the module requires a number of inputs. Therefore, current and future values of three categories of inputs are fed into the module as part of producing projections of the labour force: (a) annual projections of population by gender, race, age groups and provinces; (b) current and future values for the labour market participation rate (LFPRs) by gender, race, province and age group; and (c) current and future values for the Average Matric Rate and the Higher Education Graduation Rate by race.

The multinomial logistic regression techniques were used along with the "10 Percent Census" data for 2011 to conduct statistical analysis of factors that influence adult participation in the labour force. The LMEM-LS uses the above three categories of inputs and the estimated equations of the multinomial logistic regression to produce annual projection of the labour force for ten educational qualifications. The annual projections of the total labour force are calculated as the sum of projections of the labour force for ten educational qualifications. The LMEM-LS also uses the estimated relationships between qualification and occupation from the qualification module (LMEM-QUAL) to approximate estimates of the labour force by occupation.

Module 7: Job Seekers (LMEM-JS)

Job seekers refer to the portion of the labour force that is not employed and seeks employment, using the broad definition of unemployment. The aim of the job seekers module (LMEM-JS) is to produce annual projections of the size of job seekers in the economy and its breakdown by qualification of unemployed and their occupational preference.

For each forecast period, the module simply calculates the size of job seekers by using the mathematical relationship between the labour force, employment, and the replacement demand, all expressed by occupation and qualification. The module's projection of job seekers by occupation and qualification are consistent with the results from other modules of the LM-EM.

Module 8: Labor Balance/Imbalance Skills Gap (LMEM-BAL)

The skills gap module of LM-EM uses the model's annual projections of job openings and job seekers to estimate the extent of labour market imbalances, skills gap, and unemployment over time. At the aggregate level, the module produces an annual estimate of the labour market imbalance (i.e., unemployment or excess supply of labour) as the difference between the model's estimates of job seekers and job openings. Skills gaps are estimated for all educational qualification categories by calculating the difference between the model's projection of job seekers and job openings for the qualification categories. Finally, the module estimates skills gap by occupation by calculating the difference between the number of job seekers with different occupational preference and the number of job openings by occupation. Overall unemployment, and unemployment by qualification and occupation, are represented by corresponding excess supply estimates.

Positive (negative) overall excess supply of labour in a given year implies that the projected number of job seekers is more (less) than the number of job openings in that year. Similarly, excess supply of (excess demand for) labour by qualification shows the number of job seekers segmented by educational qualification with the number of job openings that requires those qualifications. Negative excess supply or positive excess demand expressed by qualification implies the extent to which demand outpaces supply (job openings are greater than the number of job seekers) in various skill (educational qualification) categories. Finally, the overall unemployment rate for the economy is calculated as the share of the labour force that is unemployed, and moreover, unemployment rates for various qualifications (skills) and occupations are calculated as the unemployment shares of corresponding segments of the labour force.

As a whole, the module utilises results related to sector employment, occupations, qualifications, replacement demand, labour supply, job openings and job seekers to present the effect of a given scenario on labour market balances and imbalances over time and by educational qualification and occupation. The module also estimates future unemployment rates by qualification and occupation.

Despite the various advantages and utility of LM-EM to assess labour market imbalances and skills gaps using projections of both demand and supply for occupations and skills, it is important to note that in reality analysis of skills imbalances involves issues that are not always quantifiable and often demand much richer data than is currently available.

LM-EM Outputs

LM-EM produces forecasts in six principle categories: macroeconomic and industry indicators, employment, demand/supply of educational qualifications, demand/supply for occupations, skills (im)balances by educational qualifications and by occupations, and (im)balances in the labour market.

Public Access to LM-EM

LM-EM is probably the first manpower planning model with a user-friendly web-platform.[58] It allows the public direct access to the model to design and simulate their own scenarios. This feature is possible because the ADRS macroeconomic model of South Africa (MEMSA) has a web platform (which has been live since 2006) and the LM-EM utilises MEMSA and its web infrastructure for its user-friendly interface. This online facility enhances accessibility to LM-EM for policymakers, analysts, researchers, students and others.

The principal goal of building LM-EM and its website is to have users engage more on policy questions, and specifically to generate answers to 'what if' questions that inform the policy processes. Scenario testing of trends in the economy, the educational sector and the future demand and supply of occupations and educational qualifications can ultimately assist decision-makers with the foresight to see and understand the potential outcomes of alternative policies. Projections of important economic, education, skills and occupation demand and supply indicators, provide users with evidence-based intelligence for detailed and systematic decision making.

EUROPEAN UNION

An ambitious use of the top-down econometric approach has been spearheaded by the European Union. The Lisbon agenda, followed by several related policy initiatives, gave high priority to anticipation of evolving skill needs. CEDEFOP began to work on early identification and anticipation of skills needs in 2001-02. The first pan-European projection of skills demand was produced in 2008. It provided consistent and comprehensive projections of employment and skill needs across Europe until 2015. The next year, the projections were extended to 2020. The overall aim of the project was "to develop a system of regular, detailed and consistent projections of future skill demand and supply across Europe" (CEDEFP, 2010). The model encompasses 27 European countries together with Norway and Switzerland as a single entity, where countries are represented as regions in the model.

The basic methodology used to forecast Europe's future skill needs and supply is top-down econometric modeling using time series data. It adopts the modular approach to achieve the necessary customization of the utilized multi-sector macroeconomic model to include modules related to skills demand and supply.

The interaction between the economy and labor market is captured by E3ME (Energy-Environment-Economy Macro-Economic Model), which is an established model of the European economy built by Cambridge Econometrics. The model delivers detailed projections of employment by sector and country and of the economically active labor force by age (and

[58] LM-EM's web platform is located under the ADRS website: www.adrs-global.com.

gender) that drive the more detailed skills modules. E3ME treats Europe as a multiregional area, with each country treated as a region within the whole. The entire system covers all sectors and regions (countries).

The model is based on empirical relationships and econometric estimation. The main data source is Eurostat and the model has recently been updated for NACE revision 2. The revised model distinguishes 69 industrial sectors (to be aggregated for presentation to around 40 industries). It is compatible with ESA-95 accounting classifications. Labor supply is segmented by gender and five-year age bands.

E3ME includes a detailed treatment of the labor market, with sets of equations for employment (treated as labor demand), labor supply, average earnings and hours worked. The equations for labor demand, wages and hours worked are estimated and solved for each economic sector, defined at NACE two-digit level. Labor participation rates are disaggregated by gender and five-year age band, and multiplied by Eurostat population data to obtain labor supply information.

The model has a Keynesian structure that incorporates an input-output system for its output at sector level. Each region is modeled separately. The model is large primarily because of the input-output system's level of disaggregation. At its centre is an input-output matrix, which deals with the flows of goods and services between industries and determines total industrial outputs.

A key relationship in E3ME is between industry employment and output. The error correction estimation technique is used to capture this relationship. In this form, the residuals from the first stage 'co-integrating regression', which represent the long run relationship between employment and its determinants, are used in a second stage dynamic specification, which incorporates various lagged terms to reflect adjustment lags. The inclusion of the residuals from the first stage ensures that the long run solution, given by the co-integrating regression, is imposed.

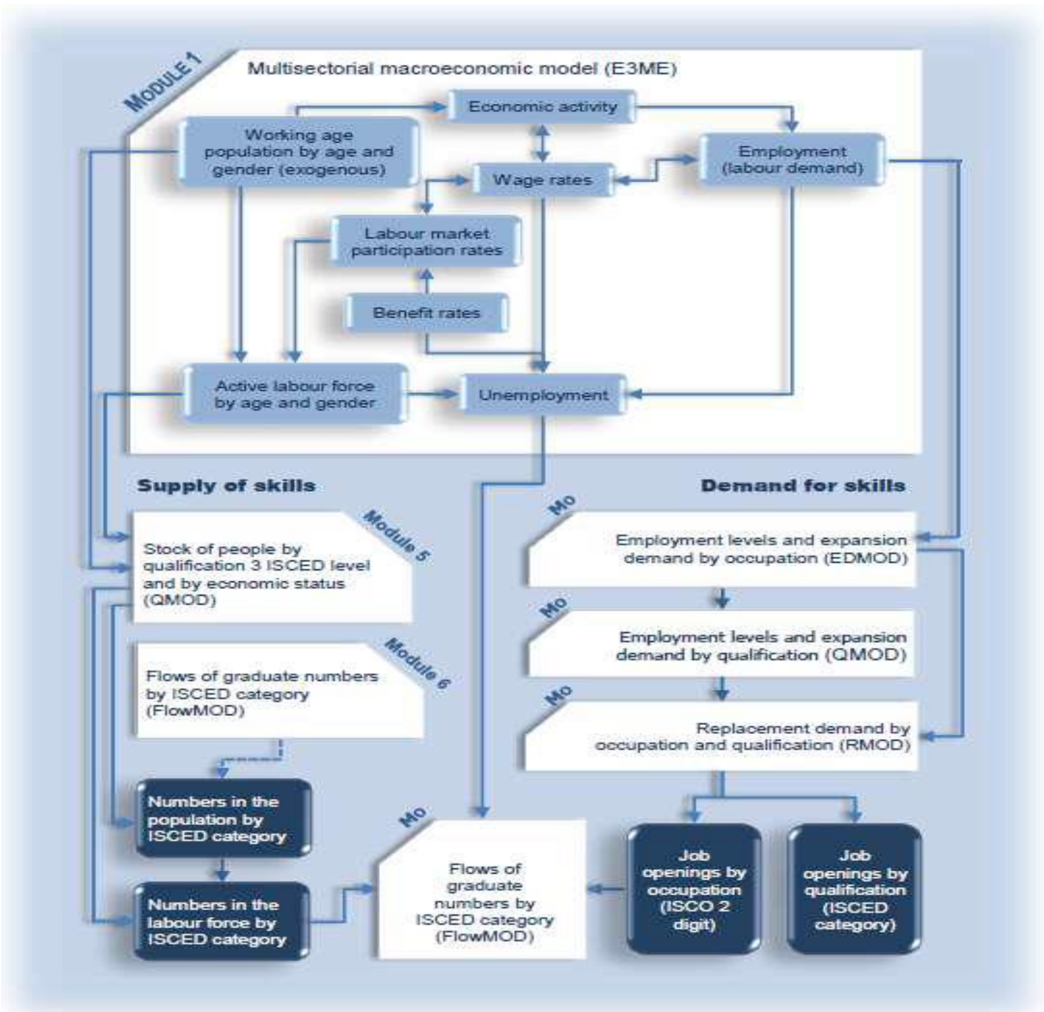
The E3ME, which does not directly address either skills or qualifications, was needed to link the labour market to the economy and set the aggregate context for the overall skill demand and supply projections (CEDEFOP, 2012:34). The E3ME has therefore been extended to include modules that translate its sector employment projections to demand for occupations and qualifications. Relative to the core model, which is characterized by many feedbacks within the system, these 'sub-models' are based on much less data and do not feed back into the main macroeconomic model.

Diagram 2 highlights how the E3ME was extended to include modules related to the demand and supply of skills.

The Demand side is composed of four modules, the E3ME, the expansion modules by Occupation (EDMOD) and Qualification (QMOD) and the Replacement module (RDMOD). The Supply side is comprised of the macroeconomic Module (E3ME) together with the stock of people by qualification (StockMOD, 5), and the flows of graduate numbers by ISCED category

(FlowMOD). A pseudo-cohort model estimates the stock of people in Module 5. The number of the population by ISCED category is determined by the inputs of both Module 5 and Module 6. The numbers in the Labour Force by ISCED category is then determined. Module BALMOD balances the labour market.

Diagram 2: CEDEFOP Model, 2012



Empirical methodologies that have been used to build the above modules and establish the necessary links between them can be summarized as follows:

- Occupational Demand: To obtain occupational shares for industries in each of the EU countries, CEDEFOP applied the multinomial logistic regression technique with time as the only regressor. The models were estimated for each of the 41 sectors and eah of the EU-25+ countries. The results of the multinomial logistic regression analysis are then used to estimate national predictions for future occupational shares (two-digit level), as well as shares of qualifications for each occupation, within the 41 industries.

- Qualification Demand: Similar multinomial logistic regression models were estimated for obtaining qualification shares within occupations, across industries and countries.
- Replacement Demand: The cohort-component method was used to estimate the rates associated with the replacement demand, i.e., the retirement rates, emigration rates, mobility rates, etc.
- In the module that balances the labor market, BALMOD, the SORT algorithm reconciles the demand for qualifications model with the stock of supply of qualifications and sorts them into occupations. It raises or lowers the qualification shares within occupations until there is matching of the demand and supply numbers (CEDEFOP, 2012: 86).

UNITED KINGDOM

The UK, following the footsteps of USA and Canada, has a long history in Labour Market forecasting. The publicly funded organization that currently provides leadership on skills and employment in the United Kingdom is the UK Commission for Employment and Skills (UKCES). At the time of the generation of Working Futures 2014-2024[59], the UK was still a part of the European Union. The UKCES vision is to create the best opportunities for the skilled workers in the UK in order to improve their competitiveness in the global economy (UKCES, 2014: 5). Working Futures 2014-2024 provides information for employers, individuals, education and training providers and policy makers and focuses on employment prospects for close to 75 industries, 369 occupations and 6 broad qualification levels. UKCES projections and analyses were prepared by the Institute for Employment Research (IER) and Cambridge Economics (CE) in 2014. The modelling procedures in the UK also incorporate the results from the Sector Skills Councils and those from 47 local Learning and Skill Council areas within England (CEDEFOP, 2007:149).

The UKCES follows the top-down modelling approach, where employment is derived from an economic model that produces projections of the labour demand. The labour supply is estimated as a stock-flow model and the matching of demand and supply is on the basis of qualifications.

The MDM-E3 is a macroeconomic model of the UK built by Cambridge Economics. It is a Keynesian model using an econometric time series cointegration methodology. The National Accounts data peg 2011 as the reference year and utilize chained volume measures and the Standard Industrial classification 2007 (SIC2007). The database is constructed with data from

[59] Working Futures 2014-2024 is the fifth report that was prepared. A subsequent study looks at different scenarios of jobs and skills in 2030.

the ONS National Accounts, Regional Accounts and other key ONS statistics (UKCED, 2014:15). The input-output supply and use tables (SUTS) are used to process information on inputs, outputs, gross value added, income and expenditure.

Employment is estimated with time series methodology and occupation employment is produced first by estimating industry employment and then the occupational structure of employment within each industry. The IER's occupational models are linked to the employment results to generate the occupational employment projections. Future projections of occupational employment share are developed from the occupational by industry employment share (SIC-SOC) matrices (UKCES, 2012:39).

Modules on the demand side are the Main Occupational Model (OCCMOD), the Qualifications Model and the Replacement Demand Model (REPMOD). The OCCMOD and the Qualifications Model both feed into the Replacement Demand Model. The estimates of the replacement demand for skills, which are reported to be an important measure for assessing education and training provision, is a key feature of the IER occupational projections.

On the supply side is the Qualifications Supply Model. Qualifications reported are the highest qualification held by age group, gender and region. Separate time trends are identified for the propensity to hold a given level of qualification which is in NQF level equivalents. These time trends are then used to generate projections of qualification attainment over the forecast period, the shares of which are then mapped onto labour force projections to generate the numbers holding qualifications by age category and gender (WF(2004):77).

The Qualifications Sorting model balances the demand and supply side. The way in which they are brought together is with an iterative procedure which adjusts the total number of qualified reports from the occupational/qualification shares and matches these to the results from the supply side stock-flow model. The process of scaling changes the occupational employment totals which then have to be readjusted. The qualification levels also have to be readjusted and the process repeated until the qualification profile matches the stock-flow model results and the original occupational results are restored (WF 2004-2014:78).

UNITED STATES

The forecasting methodology currently being used by the Bureau of Labor Statistics (BLS) in the U.S. is an example of the top-down econometric approach. The BLS publishes medium-term or 10-year employment projections every two years. These projections, that were introduced as early as 1960, were originally based on the MRA. Presently, these projections cover 530 occupations and 50 industries at the national level. The BLS projections of industrial and occupational employment are developed in a series of six interrelated steps, each of which is based on a different procedure or model and related assumptions: labor force, aggregate economy, final demand (GDP) by consuming sector and product, industry output, employment by industry, and employment by occupation. The results produced by each step are key inputs to subsequent steps, and the sequence may be repeated multiple times to allow feedback and to ensure consistency.[60]

BLS develops macroeconomic projections using the Macroeconomic Advisers (MA) model, which is a structural econometric model of the U.S. economy.[61] The model is comprised of more than 1,000 variables, behavioral equations, and identities. Central characteristics of MA are a life-cycle model of consumption, a neoclassical view of investment, and a vector autoregression for the monetary policy sector of the economy. The model is explicitly designed to reach a full-employment solution in the target years. Within MA, a submodel calculates an estimate of potential output from the nonfarm business sector; the calculation is based on full-employment estimates of the sector's hours worked and output per hour. Error correction models are embedded into MA, so that the model's solution is aligned with the full-employment submodel.

As inputs into producing the macroeconomic projections, BLS elects to determine values for certain critical variables that determine, in large part, the trend that the GDP will follow. The BLS elects to determine these critical variables through research and modeling, and then supplies them to the MA/US model as exogenous variables. These include the in-house labor force projections, energy prices and assumptions about fiscal and monetary policy. Initial estimates of key economic variables, as well as the underlying exogenous assumptions, are reviewed by a panel of economists. The final solution is evaluated for consistency with the detailed output and employment projections.[62]

The MA model supplies BLS with the aggregate projections of 11 categories of GDP.[63] BLS uses several behavioral models as well as distributional trends and/or assumptions separating the eleven categories of GDP supplied by the macro model into the detailed matrix of final demand data. It then uses projected final demand data to produce annual projection of the input-output table's two basic matrices: a "use" table and a "make" table. BLS uses the relationships between the two tables and the projection of commodity demand developed in preceding steps into a projection of domestic industry output.

The next step is to project the industry employment necessary to produce the projected output. To do so, projected output is used in regression analysis to estimate hours worked by industry. The regression model utilizes industry output, industry wage rate relative to industry output

[60] This section is extensively based on the BLS' website page on Employment Projections and other related pages, https://www.bls.gov/emp/ep_projections_methods.htm#industry_employment.
[61] For more information, see the MA website, http://www.macroadvisers.com/.
[62] BLS, Employment Projections, Projection Methodology. https://www.bls.gov/emp/ep_projections_methods.htm#industry_employment.
[63] These are personal consumption expenditures (PCE), private investment in equipment (PEQ), private investment in intellectual property products (IPP), residential and nonresidential construction, change in private inventories (CIPI), exports and imports of goods and services, as well as consumption and investment of federal defense, nondefense, and state and local government.

price, and time. Additionally, average weekly hours are derived as a time trend for each industry. From these hours' data, projected wage and salary employment by industry is derived.

Detailed industry employment projections are based largely on econometric models. For the most part, the determinants of industry employment are expressed both in the structure of the models' equations and as adjustments imposed on the specific equations to ensure that the models are indeed making a smooth transition from actual historical data to projected results. However, one of the most important steps associated with the preparation of the BLS projections is a detailed review of the results by analysts who have studied recent economic trends in specific industries. In some cases, the results of the aggregate and industry models are modified because of the analysts' judgment that historical relationships need to be redefined in some manner.

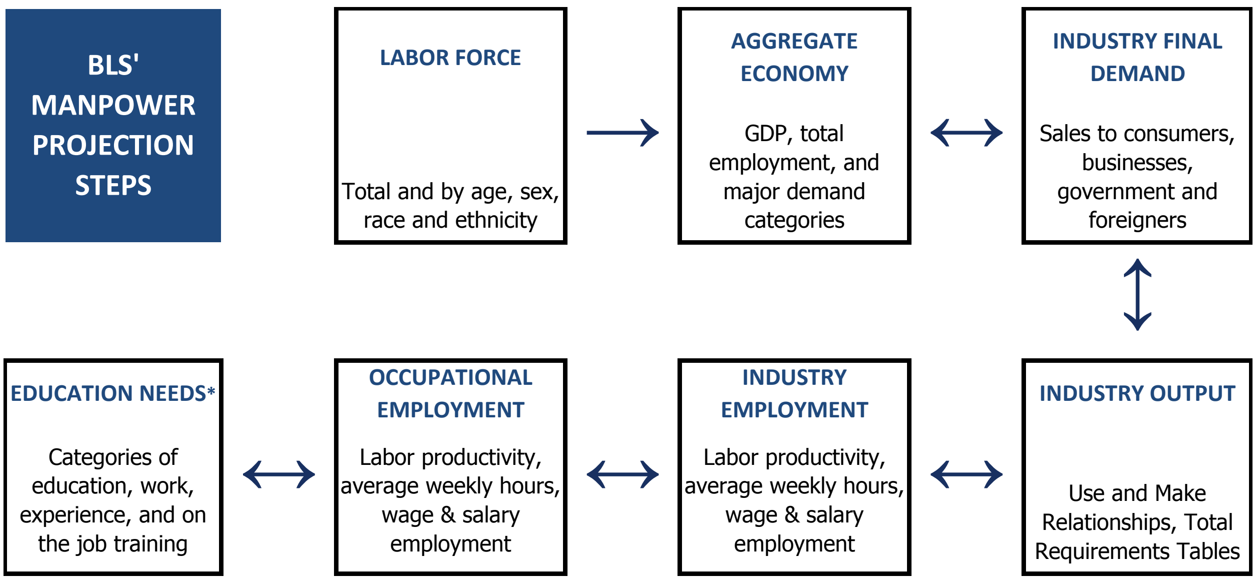
Next, BLS creates occupational employment projections, called the National Employment Matrix, that show the employment of detailed occupations within detailed wage and salary industries and different classes-of-workers, including those who are self-employed or employed by a private household. Each occupation in the matrix is analyzed to identify factors that are likely to cause an increase or decrease in demand for that occupation within particular industries. This analysis incorporates judgments about new trends that may influence occupational demand, such as expanding use of new manufacturing techniques like 3D printing that might change the productivity of particular manufacturing occupations, or shifts in customer preferences between different building materials which may affect demand for specific construction occupations.

The results of this qualitative analysis form the quantitative basis for making changes to occupational shares of industry employment. The structural changes suggested by different trends are compared to determine if they will cause demand to grow or shrink, and if so, by how much. The effects of the projected trends are then combined into an overall numerical estimate which describes the change in an occupation's share of industry employment.

In most occupations, openings due to separations of existing workers provide many more opportunities than employment growth does. To project occupational openings, the BLS calculates an estimate of separations caused by workers exiting the labor force, due to retirement or other reasons, and separations caused by workers transferring to different occupations. Projections of separations are combined with projections of employment change to determine occupational openings. This estimate of openings does not count workers who change jobs but remain in the same occupation.

BLS projects occupational separations using two different models, one for labor force exits and another for occupational transfers. Both models use a regression analysis of historical data to identify the characteristics of a worker, such as age and educational attainment, that make them likely to separate from their occupation. These patterns from historical data are then applied to the current distribution of employment for each occupation to project future separations.[64]

Finally, BLS provides information about education and training requirements for each projected occupation. In the BLS education and training system, each of the occupations is assigned separate categories for education, work experience, and on-the-job training. Occupations can be grouped to create estimates of the education and training needs for the labor force as a whole and estimates of the outlook for occupations with various education or training needs. In addition, educational attainment data for each occupation are presented to show the level of education achieved by current workers.[65]



Source: BLS website on Employment Projections: https://www.bls.gov/emp/ep_projections_methods.htm#labor. *
The BLS diagram does not include this step, even though its presentation includes the derivation of education needs.

CANADA

At the Symposium on Closing the Skills Gap in Canada – Mapping a Path for Small Business in 2012, the then Deputy Minister stated that the growing skills shortfall presented a threat to the country's prosperity, and that the key to making progress on skills related challenges was to bring together government, business, educational and training institutions, workers and policy people. In Canada, two trends creating the skills shortages are the aging population and the

[64] Further detail is available in https://www.bls.gov/emp/ep_separations_methods.htm.
[65] More information about the replacements methodology is available from https://www.bls.gov/emp/ep_replacements.htm.

retiring baby boomers. It is projected that by 2025 jobs would be more specialized thereby increasing the demand for educated and skilled workers (Chamber of Commerce, 2012: 5, 17).

In Canada, the Canadian Occupation Projection System (COPS) model generates occupational outlooks, which are based on the National Occupational Classification (NOC). Detailed 10 year forecasts are produced every 2 years by the Employment and Social Development Canada (ESDC)[66]. Initially only demand side projections were produced with supply side projections introduced in the mid-1990s. Moreover, the Job Bank, which is an online ESDC labour market information system, is designed to basically link job seekers and job openings across Canada.

The methodology for manpower projections in Canada could be described as being a hybrid of the market signaling and top-down approaches. It can be viewed as a market signalling approach when imbalances in the labour market are analyzed. Labour market indicators such as changes in the unemployment rate, wage growth, employment growth and overtime and Employment Insurance information are used to identify occupations showing signs of imbalance. For each occupation then, projected gaps between job openings and job seekers are identified by estimating the number of both openings and seekers over the projected period. In the final step, the projected conditions for each occupation are analyzed by using the results from the previous two steps (COPS, 2016:2).

Canada could also be described as having a top-down methodological approach since it uses models to estimate the occupational demand and supply and reconciliation of the two. The macro-model which is used by COPS is the quarterly MTFM (Medium Term Forecasting Model) of the Conference Board of Canada, which is an econometric model. This model is designed for forecasting and simulations for the short, medium and long-term analysis[67]. The steps for estimating occupational demand include: estimating future output by industry, estimating employment by industry and occupation and estimating Expansion and Replacement demand by occupation. There are four steps for estimating the occupational supply starting with estimating the population by age, sex and educational level in a stock-flow model.

The determination of skills and knowledge is one extension to the occupational model. In the case of Canada, the National Occupational Classification (NOC)[68], currently NOC 2016, is structured by skill and educational level, hence, implicitly includes an aspect of skill forecasting (The Centre for Spatial Economics, 2008: vii). More than 30,000 occupational titles are gathered into 500 Unit groups according to skill levels and skill types in the NOC 2016. The NOC is based on four principles of classification which are the skill level, the skill type, occupational mobility and industry, according to Roberts (2003), cited in (C4SE, 2008:57).

[66] Employment and Social Development Canada came into existence in 2003 and replaces the Human Resources and Skills Development Canada.
[67] Conference Board of Canada webpage.
[68] The NOC is a collaborative partnership between Employment and Social Development Canada and Statistics Canada

The NOC is used as a tool to classify occupations according to the Skill level and Skill Type with a four-digit code to identify the occupation. The skill type, according to the website, is the broadest occupational category which is based on the type of work performed. In addition, it reflects the educational area of study required as well as the field of training or experience required for entry into the occupations. Occupational descriptions have been developed for all 500[69] current occupational groupings. The information on skill types, in columns, and skill levels, in rows, are represented together in the NOC matrix.

Skill levels correspond to the amount of education or training that would be required to work in an occupation, in the NOC context. Four skill levels from A to D are identified with each level receiving one of two numerical codes from 0 to 7 (NOC website).

AUSTRALIA

Historically, occupational forecasting in Australia was developed under the Department of Education, Employment and Workplace Relations (DEEWR[70]) and the Centre for Policy Studies (CoPS) of Monash University. The macro-model, MONASH, a dynamic computable general equilibrium (CGE) informed the projections with a top down methodology and the sequence of steps closely following the US. SriRamaratnam and Zhao, (2010:2) assert that these efforts were facilitated by the DEEWR and several federal and state training authorities who subscribed to the forecasting efforts as well as the "Job Outlook" website. As a member of The Centre for the Economics of Education and Training (CEET) at Monash University, Prof Shah produced a set of projections "The Demand for Qualifications and the future Labour Market in Australia 2010 – 2025" for the DEEWR.

Historically, the occupational projections in Australia involved the collaboration of the private and public sectors. Recent projections are undertaken both in the public sector, the Department of Jobs and Small Business, as well as at the private sector, the National Centre for Vocational Education Research (NCVER)[71] at Victoria University.

The Department of Jobs and Small Business[72] produces employment projections by industry, occupation, skill level and region each year. These projections are annual and for five-year periods. The most recent projection is from 2017 to 2022. Two of the outputs are the Employment Outlook (relevant till May 2022) and the "Job Outlook" website.

[69] 500 occupational groupings, reduced to 292 by combining the smaller groups, according to NOC 2016.
[70] This Department was formed in October 1998 and dissolved in November 2001.

[71] The chief architects of this research are Prof Shah from the Centre for International Research on Education Systems and J.Dixon from the Centre of Policy Studies.
[72] Previously known as the Department of Employment, this Department was formed on 20 December 2017. The name was changed because of an Administrative Arrangements Order.

The methodology can be described as having elements of the time series approach. Since in 2012, the Department adopted a univariate time series estimation methodology for their analysis. The Autoregressive Integrated Moving Average (ARIMA) time series model together with the Exponential Smoothing with Damped Trend (ESWDT) model which describes the time series by its evolving slope[73] have been adopted.

The Department is also undertaking research on skill shortages in the country which involves a Survey of Employers who have Recently Advertised (SERA), generating both qualitative and quantitative information about the skills needs of employers. The research is for larger occupations and for skills that require at least three years of post-secondary education and training[74]

The methodology of NCVER can be described as being a top-down approach. The three steps involved for generating the employment forecasts are firstly, the economy wide projection with the VU[75], the dynamic computational general equilibrium model, to produce the forecast of employment (by headcount) as well as the expansion demand by industry and occupation. Replacement[76] demand is forecast in the second step. In the third step job openings are derived from the previous two steps (Shah and Dixon, 2018:9). Job openings provide an indication of the minimum number of additional persons to train for a particular occupation. Job openings in a particular occupation are the sum of the expansion and replacement demand when the employment is increasing in the occupation. The job openings are equal to the replacement demand when the employment in an occupation is decreasing.

The VU model differs from the MONASH model in that it does not include an unconstrained labour supply. Instead, the supply of labour by occupation is linked to an exogenously determined supply of skills[77]. One advantage of the model is that feedback from labour supply shortages and surpluses are enabled since the supply side of the market is explicit. The growth in the number of people with particular skills is projected by using historical data together with adjustments for demographic changes. Skill groups are defined by the level and field of education.

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[73] O'Regan C from the Department of Employment, Australian Government.
[74] Skill shortage research methodology, Australian Government, Department of Labour.
[75] The VU CGE model is a development from the MONASH CGE model, which was developed in 1993 from the ORANI model. Each model is more advanced than its predecessor.
[76] The cohort-component method is used to estimate the replacement rate (Shah and Dixon, 2018:24). This is generally done by occupation, but, sometimes by qualification.
[77] Wittwer and Dixon 2015, cited in Shah and Dixon. 2018:22.

GERMANY

The unification of East and West Germany and the recent influx of refugees have impacted the approach to manpower forecasting in Germany. Attempts are being made to incorporate them into the modelling process. One of several modelling approaches in Germany is presented below.

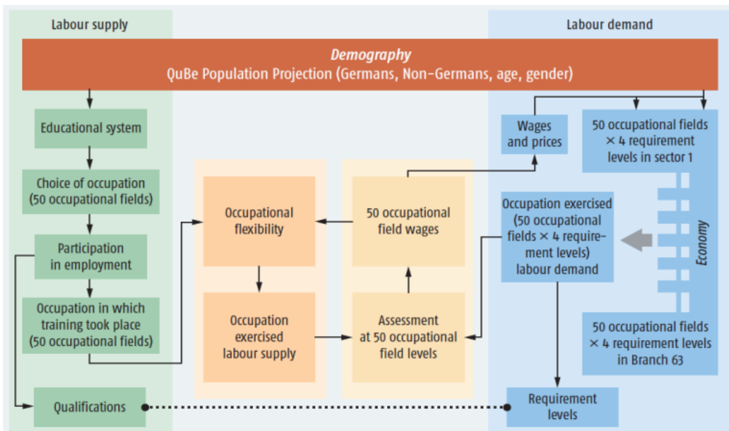
A public and private partnership between four institutions in Germany has produced Qualifications and Occupational Field Projections.[78] This collaboration has allowed for the unique linkage of two projection models, IAB/INFORGE and BIBB/FIT[79]. The objective of the group is to map out the development of the supply and demand for qualifications and professions over the long term. The Fourth Wave projections[80] of the group forecast until 2035.

The methodology used in a previous modelling exercise by Maier et al, where yearly forecasts were provided for 2007 to 2025, involved the use of the IAB/INFORGE multisectoral model. The steps that were involved in this process are assumed to be similar to the steps for the BIBB-IAB projections. The steps on the demand side included using the model for the forecasting of employment by industries, thereafter, employment by occupation and by qualification. Two sub-modules[81] were generated, one for the conversion from employment by industries to employment by occupational fields, and the second for the projection by qualification levels. The methodology for these processes has been described as being bottom-up in terms of the way in which the models are constructed, but top-down in terms of the overall modelling approach (Maier et al, 2015:7).

A brief description of the IAB/INFORGE[82] model shows that it is really two single multisectoral macroeconomic models which are linked to allow for the exchange of data. Although the INFORGE model has many features, in common with CGE models, its theoretical foundations are different and its parameters and their elasticity values are estimated econometrically using a time series methodology. The features that are similar to the CGE models are the basic data set of input-output tables and NA as well as the simultaneous solving of the equations (Maier, 2015:9).

[78] The partnership is between BIBB (Federal Institute for Vocational Education and Training), IAB (Institute for Employment Research), GWS (Institute of Economic Structures Research), and FIT (Fraunhofer Institute for Applied Information Technology).
[79] Economic and Social Affairs Projects of the GWS website.
[80] These projections are every 2 years since 2010, hence the First, Second and Third Waves before.
[81] The sub-models are “Employment by Occupation”, which requires input from the Model and “Employment by Qualification”, which requires input from Sub-Module 1.
[82] The fundamentals of the two models, which belong to the INFORUM modelling family, are that the construction is bottom-up with total integration (Maier et al, 2015:8).

The Model structure of the QuBe Project is presented in the diagram on the next page. The Labour Supply by qualifications is developed from the participation in employment which is fed from the occupational field, which in turn is fed from the educational system. The level of aggregation on the supply side is of 50 occupational fields[83] (20 Major) as well as 4+1 qualification levels[84]. On the demand side, the employment by occupation is developed from the macromodel, described above. The level of aggregation on the demand side is 50 occupational fields (20 Major), 63 Sectors (NACE), and 4 requirement levels[85]. The matching is at the level of qualification on the supply side and occupational requirement level on the demand side[86].



Model Structure of QuBe-Project: Source: Maier et al, 2016

NEW ZEALAND

In New Zealand, the government believes that the effective use of knowledge, skills and capital in firms is the driver for innovation and growth[87]. It is believed that the interaction between skilled people and innovative firms from the present to 2025 should provide the largest scope for economic growth. Work on constructing a broad occupational forecasting framework in New Zealand commenced as late as 2006[88].

[83] 50 BIBB Occupational fields are introduced with the implementation of the KldB 2010 Occupational Classification. The requirement levels are an innovation of this categorization.
[84] ISCED 0-3a/3b,4/5b/5a,6/ + persons in education
[85] The requirement levels are: un or semi-skilled tasks/skilled tasks/complex tasks /highly complex tasks.
[86] Maier et al, 2016
[87] From the Website
[88] SriRamaratnam and Zhao, 2010:2, who cite Papps, 2001.

The Ministry of Business, Innovation and Employment (MBIE)[89] regularly embarks on short-term employment forecasts for the purpose of informing the Ministries on priorities for tertiary education and industry training as well as immigration priorities[90]. The MBIE conducts medium to long-term forecasts as well[91]. The Ministry of Education (MOE) has also developed four year plans, the last one being from 2015 – 2019, to fit in with the overall policies of the country. An occupational outlook application and a job profile tool have been developed. The government is also working towards assessing the value of the tertiary education qualifications based on the feedback it receives from the employers and graduates (2015:27).

The Department of Labour uses a top-down economy wide approach with an in-house Computer General Equilibrium model, developed by Business and Economic Research Limited (BERL). The BERL model is a multi-industry model, of 60 industries, as well as the inter-relationships between the industries.

The macro-economic forecasts underpinning the settings have been informed by the NZIER[92] Consensus forecasts for the 2017-20 periods. These included the private consumption growth of 2.7 per cent, export growth of 3.4 per cent and Government consumption growth of 1.5 per cent on average for the 2015-20 period (MBIE, 2017:11). GDP growth forecasts together with estimates of future productivity growth in each industry are used to develop industry employment growth. Future changes in occupational employment are obtained from historical changes in occupational shares within industries. Changes in the qualification shares for each occupational group are used to derive qualification based occupation employment forecasts.

The supply of skills is represented with a stock-flow model, with the stock represented by the current skills and the flows being the working age population flowing in and out of the labour force through net migration, retirement or those leaving the education system. Population projections together with the projected data on age, gender and qualifications are used to derive the labour supply by qualification.

Replacement Demand is estimated using 5-year census data. A cohort component method for 5 year age cohorts has been applied to project the likely retirements and replacement levels in the five year projection periods (SriRamaratnam and Zhao, 2010:2).

For short-term projections, a short-term forecasting model drawing on the Treasury's GDP and macroeconomic forecasts is used. Regional employment forecasts by industry are derived by using recent changes in levels and shares of employment and the model based forecasts of industry level economic activity and productivity. Forecasts of employment growth by occupations and skill level are obtained from the industry employment forecasts

[89] This MBIE combines the former Ministries of Economic Development, Science and Innovation with the Departments of Labour and Building and Housing
[90] The most recent forecast cover the period from 2017 to 2020 and was published in February 2018.
[91] The most recent forecast covers the period from 2017 to 2025 and was published in February 2017.
[92] New Zealand Institute of Economic Research

(MBIE,2018:10).

HONG KONG

According to Fung (2001), Hong Kong has progressed from being like a fishing village, which lacked natural resources, to a robust manufacturing and trading centre, due in large part to its focus on the establishment of a system of vocational education and training (VET). In order for Hong Kong to remain competitive in the international marketplace, it has been essential for the country to continue fostering and promoting the education and training of the labour force. Since the 1970s, Hong Kong has used manpower projections as a tool to facilitate the efficient working of the labour market.

The recent Report on Manpower Projections to 2022, released in 2015 by the government of the Hong Kong Special Administrative Region, uses a two-step process, a quantitative projection and a qualitative review, to project the manpower needs of the economy by estimating the needs of economic sectors and industries and the potential manpower imbalances at different education levels.

The first step involved production of preliminary quantitative projections of the manpower requirements of various economic sectors and industries (i.e., demand projections) up to 2022 using the time-series extrapolation approach. As part of the quantitative process, preliminary forecasts of the manpower requirements in 2022 were derived by fitting the historical data series (from 2000 to 2012) to various statistical projection models such as the linear model, parabola model, log linear model and reciprocal linear model. For sectors and industries in which the above trend-fitting statistical approach did not work, other alternative statistical processes (e.g., truncated data series or historical average annual rate of change) were used to estimate their projected annual average rates of change, which were applied to base year employment figures to arrive at the projection by economic sector.

The projection for the manpower requirement (demand) by occupation category is obtained by applying the historical average growth rates to the base-year figures. The projection by education attainment is obtained when the occupational category is split into eight major levels of educational attainment for the projected period.

For labor supply projections, the starting point is the population projection. Fertility, mortality and migration trends are factored into the population projections which have an age-sex composition. In the 2018 projections with base year of 2010, the educational level is also included.

The Labour Force projection is generated when the age-sex labour force participation rates are obtained from the statistical extrapolation of past trends. These are then applied to the population projection across various age-sex groups and then summed to produce the projection of labour supply. This is applied to only workers who are citizens of Hong Kong.

The manpower supply projection by educational attainment is determined according to the eight major levels of educational attainment. The stock of the manpower is influenced by the effects of ageing and mortality. This labour supply model is a stock flow model. In 2018 three sets of education statistics were used to estimate the education profile of labour supply[93].

The matching of demand and supply of labor by educational attainment provides the quantitative measure of potential future imbalances in the labour market by qualification.

The aim of Hong Kong's two step approach to manpower forecasting is to review and fine-tune the first step's preliminary projections using information obtained from various sources, such as, consultation with businesses, trade associations, academia, government departments and statutory training bodies. This information, along with relevant data from the Census and Statistics Department, was prepared for the inter-departmental task team to conduct the final review and fine-tuning of the preliminary projections (Government of the Hong Kong, 2015).

REPUBLIC OF KOREA

The tremendous success which the Republic of Korea has enjoyed as a result of its education policy has been one which other countries of lesser income would like to emulate.
One of the four pillars on which the education system in the Republic of Korea rests, according to Bermeo (2014) is the linkage of education to its development strategy, in particular, its industrial policies. According to the Human Capital Index of 2016, which was developed by the World Economic Forum, the Republic of Korea is number 32[94] out of 130 countries. There has been simultaneous investment in the labour market and the attempt to achieve a 70% employment rate rests on another four pillars which includes the reform of working hours and work arrangements as well as job creation through creative economy[95].

The methodology for occupational projections adopted by Korea closely follows the BLS methodology of the US. The methodology they use for the labour supply – demand forecasting system, could be described as being a top-down approach and it is the responsibility of the Korea Employment Information Service (KEIS), which was formed in 2006. These forecasts have a policy function in that they inform policies on employment, education and industry, as

[93] These are the students taking courses in Hong Kong, the students returning from studying overseas and the workers taking courses to upgrade their academic qualifications (2010:6).
[94] This index is a tool capturing the complex relationship between education, employment and workplace dynamics.
[95] Jaeheung, Lee (2013), "Major Policy tasks …."

well as having an information function in assisting individuals with career selection and counselling.

Korea followed the example of the *Occupational Outlook Handbook* of the USA, the *Job Bank* of Canada and the *Occupational Handbook* of Japan for the development of the *Korean Occupational Outlook Handbook,* which was first published in July 1999[96]. The Handbook includes sections on: Nature of the Job; Working Conditions; Education; Training and Other Qualifications; Employment; Earnings; Job Outlook; and Related Information Sources. The job outlook over the period of the projection is described in terms of whether the employment would increase, decrease or remain the same.

The projections are for a 10-year period and are updated every two years. There is the labour supply (labour force, which encompasses the productive population and the economically active[97]) forecast, the labour demand (employment, by industry and by occupation) forecast and the new entrant supply-demand mismatch forecast. The match is determined by educational attainment, field of study/ major and occupation. (KEIS, 2011:5)

Further, for medium and long-term forecasting, the labour supply forecast starts with population projections. The first step is the generation of the productive population which are persons aged 15 and over. The second step is the participation rate and the third step is the forecast of the economically active population by gender, age (in five year increments) and educational attainment (four groups including two-year college degree and four-year university degree or higher).

On the labour demand side, employment is forecast first in aggregate and then by industry. An industry-occupation matrix is used to convert the employment by industry into employment by occupation. The disaggregations are according to the Korean Standard Industrial Classification and the Korean Standard Occupational Classification.

There are three steps in the new entrant labour supply forecasting procedure. First, there is the “Graduate” forecasting which may be completed either by forecasting using trend lines or establishing the number of enrolled students. Second, the “Field of Study” forecasting is established from the new entrant supply and participation rate. Third, the new entrant supply by occupation is generated from the field of study-occupation matrix. New entrant demand forecasting involves the estimation of expansion demand[98] and replacement demand. Replacement demand is forecast using employment size by education and occupation and is estimated using the methodologies of the Research Centre for Education and the Labour Market which includes inflow-outflow pattern analysis.

[96] Seok, J-W, Monthly Labour Review, May 2000.
[97] This is completed by gender, age and educational attainment.
[98] This is estimated from the annual net increase of demand by occupation.

Matching the new entrant supply and demand forecasts constitutes the final step. The mismatch forecast is for a 10-year period and is by the size and excess supply (demand) ratio. This forecast is performed by education (2 year college or higher), by field of study and by occupation.

PART 4

RECOMMENDATIONS

India has a long history of manpower forecasting and planning. Local experts in the country are best positioned to deliberate on the issue of how to expand or enhance India's manpower forecasting capability. After careful consideration (perhaps with insight from the current review), India may find that its current models are sufficiently sophisticated to meet the needs of the country. However, there may well be need for improvement in specific areas. The "correct" approach or model is more than an academic matter. Indeed, since the same policy can have different effects in different models, having the appropriate model deeply matters for policy purposes. In that context, the following ten recommendations are centered on key attributes of an effective long term approach to skills forecasting.

1. Key criticisms of the original manpower requirement approach (MRA) relate to its employment projection methodology, whose cascading shortcoming further weaken projections of occupational demand, skills demand, and imbalances. This critique along with recent country experiences emphasize that a good manpower projection system needs good conceptualization (e.g., clear and realistic goals), good analytical foundations, good data, and good use of empirical techniques.

2. Though for various reasons, as explained in this report and other reviews (Wilson, 2012, Bakule et al. 2016), the top-down quantitative approach based on large scale multi-sector models is considered 'best practice' worldwide, country experiences show that such methods must be complemented by other more qualitative approaches. As second largest population in the world and its tremendous diversity makes India particularly well suited to use a hybrid approach to skills forecasting.

3. An important pre-requisite for credible skills forecasting is to have access to quantitative projections of industry level employment under alternative 'what if' scenarios. The quality of sectoral employment is especially important since statistical analysis of demand for skills relies heavily on the estimation of demand for occupations that are based on sector employment projections. In effect skills forecasting needs and stands to benefit from access

to a well developed multi-sector macroeconomic model.

4. Good models effectively capture the dynamic of the actual economy they are meant to replicate. Whether the macroeconomic dynamics of the Indian economy is best captured by neoclassical or non-neoclassical economic paradigms will inform whether the manpower forecasting system for the country should be founded on the CGE or econometric modeling technique.

5. As Bakule et al. (2016) points out, the success of skills forecasting depends on whether it is embedded into a structure in which the results are developed, discussed and used by the various stakeholders and decision-makers. As important as the development and the instruments of generating forecasting results are, so too are the networks and institutions that work with the data, feed back into them, and participate in the development of initial discussions and ongoing evaluation of results.

6. For the public sector, skills forecasting must not be a one-time exercise but rather a sustained, long-term effort that is regularly undertaken to allow both for the development of a methodology for generating skills forecasts *and* an understanding of how to use the results. This means, among other things, that for long term effective use and sustainability of a manpower forecasting program, it is essential that executives understand the utility of forecasting and support the end users, that policy analysts within the public sector receive substantial training on the system's underlying empirical and analytical foundation, and that the executives periodically receive tailored briefs and inputs on the future of work and the skills requirements of the country.

7. To the extent that the informal sector and migration are considered important for the future of work in India, particular attention should be given to skills forecasting techniques that properly take account of these issues to ensure that their effects on the outlook for manpower are not excluded.

8. Country experiences show that the utility of the outputs of skills forecasting program can go beyond its traditional usefulness as inputs into policy making. It has been shown that the public as a whole can directly utilize and benefit from skills forecasting output (e.g., O*NET in the U.S., the Job Bank in Canada, LM-EM in South Africa, Australia's Department of Jobs and Small Business)[99]. Therefore, dissemination of results across various channels in an accessible language is increasingly beneficial and important especially in the changing global economy.

[99] Addresses of the country web portals are: United States: https://www.onetonline.org/, Canada: https://www.jobbank.gc.ca/home, South Africa: https://www.adrs-global.com, Australia: https://www.jobs.gov.au/.

9. Securing long term support, especially financial support, is crucial to ensure that the work that is initiated is completed and built upon further, rather than forgotten or being reinvented.

10. It is important that the architecture of the adopted quantitative approach has the flexibility (e.g., use module system) to adapt to changing environments and requirements over time.

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ANNEXURE 1. COUNTRY SKILLS FORECASTING PROFILE

(Preliminary – do not quote)

UNITED STATES					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down economy wide approach FREQUENCY 10 year projections every 2 years	MA/US (from 2012) Multi-sectoral Macroeconomic Model OUTPUT Occupational Outlook	1. Labour Force Determined 2. Aggregate Economic Growth 3. Commodity Final Demand 4. Input-Output Matrix 5. Industry Output & Employment 6. Occupational Employment & Job Openings	Assumption of full employment. Only the demand side is estimated Concept of skill embedded in Occupation definitions	Census Labour Force Current Population Survey Current Employment Statistics American Community Survey National Centre for Education Statistics INDUSTRIAL **2017 NAICS** North American Industry Classification System Chained Volume OCCUPATION **2018 SOC** **3 Categories** for entry into occupations 1. Entry-level education 2. Work experience in occupation 3. On-the-job training	NIPA National Income and Product Accounts EDUCATION ISCED-2011 LOCATION

CANADA					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Hybrid Top-down economy wide approach and Market Signalling FREQUENCY 10 year Projections Every 2 Years Latest: 2017 - 2026 **Population Projections** 2013 - 2063 R.Date: 2015 Population Projections every 5 years	**MTFM** Quarterly model used by COPS Multi-sectoral Macroeconomic Model OUTPUT **Occupation Handbo**	**COPS MODEL** **OCCUPATIONAL DEMAND** 1. Estimating future GDP 2. Estimating Output by Industry 3. Estimating Employment by Industry 4. Estimating employment by Occupation 5. Estimating Expansion Demand by Occupation 6. Replacement Demand by Occupation **OCCUPATIONAL SUPPLY** 1. Estimating population by age, sex, educational level 2. Estimating number of graduates by age, sex, educational level 3. Labour force participants by age, sex, educational level participation rates 4. Estimating occupational supply: Ed - Occ Matrix **MATCHING DEMAND -SUPPLY** The **Cumulative Shortage** **CS = OD - OS** OD = Occupational Demand OS = Occupational Supply	Analysis on whether Labour Market imbalances persist **Market Indicators** Unemployment rate Wages Employment Overtime EI Claims Job Vacancies Stock - Flow model Education modelling has four levels 5 skill categories	Census Labour Force Survey National Graduate Survey SLID LAD INDUSTRIAL **2017 NAICS** North American Industry Classification System OCCUPATION **2016 NOC** 500 Occupations grouped into 292 occupational groups The NOC is used as a tool to classify occupations into Skill level (4) and Skill type (10). NOC Matrix	**NEA** National Economic Accounts based on SNA2008 EDUCATION **ISCED** LOCATION **SGC 2016** Standard Geographical Classification

UNITED KINGDOM					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down economy wide approach Bottom-up treatment of Regional Economic Prospects FREQUENCY 10 year projection 6 monthly cycle of updates	**MDM-E3 BY CE** Keynesian Econometric analysis of long time series data > 5000 Equations Modular Structure	**1. Macroeconomic Model** estimating Employment and Population and Labour Force **2. Demand for Skills** 3. Occupational Model generating forecasts from Employment estimation 4. Qualifications Model 5. Replacement Demand **Supply of Skill** Population and Labour Force from Macromodel 6. Qualifications Supply Model **Reconciliation** 7. Qualifications Sorting Model RAS to sort Occupation (25) Gender (2) Qualification 6 levels	**Stock - Flow model** **OCCMOD** Employment by Region (12) Industry (75) Gender (2) Status (3) Occupation (25) **QUALIFICATION DEMAND** Employment by Region (12) Industry (41) Gender (2) Status (3) Occupation (25) Qualification 6 levels **QUALIFICATION SUPPLY** **Population and Labour Force** Gender (2) Qualificaiton level (6) Age (single year age groups	Employment ONS LM quarterly converted to annual National Employer Skills Surveys LFS Census of Population CoP INDUSTRIAL **SIC2007** **UKSIC** OCCUPATION **SOC2010** 4 digit 369	**ONS NA** with Chained Volumes Conforms with ESA 2010 SNA 2008 EDUCATION **ISCED-2011** LOCATION **NUTS** Nomenclature of Territorial Units for Statistics

AUSTRALIA					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down economy wide approach FREQUENCY Annually with 5 year projection **Time-series** Approach	MONASH A Dynamic Computational General Equilibrium Model CGE 3 components Database Theory and Parameters Department of Jobs and Small Business 5 year Projections OUTPUT JOB OUTLOOK HANDBOOK	1. Labour Force Determined 2. Aggregate Economic Growth 3. Commodity Final Demand 4. Input-Output Matrix 5. Industry Output & Employment 6. Occupational Employment **Projections of Employment** for 158 industries, 340 occupations. 8 educational attainment levels. 47 qualification fields 24 demographic groups by age and sex 9 categories of hours worked per week Projected Employment growth by State and Territory	Monash model converts the forecast of aggregate output to forecasts of industry output **Employment Growth is** Growth in Agg Employment Industry Share Effect Occupation Share Effect **Ministry Model** Projections are based on trended or smoothed data ARIMA and ESWDT (Exponential Smoothing with Damped Trend)	Australian Bureau of Statistics (ABS) Labour Force Survey INDUSTRIAL **ANZSIC** Australia and New Zealand Standard Industrial Classification OCCUPATION **ANZSCO** Australia and New Zealand Standard Classification BY OCCUPATION Skill based with one of 5 skill levels attached to each Occupation	Australian System of National Accounts EDUCATION **ASCED** Australian Std Classification of Education by Level and Field aligned to Australian Qualifications Framework LOCATION Australian Standard Geographical Classification **ASGC** Released in 2011

HONG KONG					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Time-Series **Bottom-Up** approach used for MRP (Labour Demand) FREQUENCY 10 YEAR Projections		**M. SUPPLY PROJECTION (MSP)** Estimation of Supply in Base year by age, sex and education level **Projection** on Population by age and sex in target year **Projection** on Population by age, sex and education level **Projection** of Supply by age, sex and education level **M. REQUIREMENT (DEMAND) PROJ (MRP)** **Estimation for Base year by** Economic Sector, Occupation Group & Education level **Projected Requirements** for sectors and industries in target year **Projected Requirements** for Sectors and Industries by occupational group and educational level **M. RESOURCE BALANCE** by Education Level Supply minus Demand	**Population Projections** from Census and Statistics Departments from Base year to Projected eg 2012 to 2041 No interdependence between MSP and MRP Uses a weighted exponential smoothing time series forecasting technique for it's 22 industry sectors	Census Population projections of Statistics Department Labour force projections General Household Survey Quarterly Survey of Employment and Vacancies Vocational Training Council's Manpower Surveys INDUSTRIAL **HSIC** Hong Kong Standard Industrial Classification OCCUPATION **ISCO-88**	**SNA2008** In 2012-2022 12 Economic Sectors EDUCATION **ISCED-2011** **Education Levels** <Lower Secondary Upper Secondary Diploma Sub-degree First degree Post-Graduate LOCATION

EU EUROPE (CEDEFOP)					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down economy wide approach FREQUENCY	**E3ME** Multi-sectoral Macroeconomic Model Modular Structure	1. Multisectoral model estimates Employment **Demand for Skills** 2. Employment levels and Expansion demand by Occupation 3. Employment levels and Expansion demand by Qualification 4. Replacement Demand by Occupation and Qualification **Job Openings by Occupation** **Job Openings by Qualification** **Supply of Skills** Labour Force by Age and Gender from Model 5. Stock of People by Qualification level and Economic Status 6. Flow of Graduates by Quaification (ISCED) **Numbers of Population by** **ISCED category** **Numbers in Labour Force by** **ISCED category** **Supply and Demand Matching** **Flows of Graduate Numbers by** **ISCED Category**	Estimation of Model using Time Series Cointegration Techniques Each module has it's own database and models 29 Countries are modelled as regions **Stock-flow model** DEMAND FOR SKILLS **NACE-ISCO-EDU-age-** **Gender** SUPPLY OF SKILLS **ISCO-EDU-age-gender** **EDU - age-gender** The imbalances between the Demand and Supply reconciled on basis of Qualifications	Eurostat Data EU LFS OECD Stan database INDUSTRIAL **NACE-Rev2** Statistical Classification of Economic Activities 60 Sectors OCCUPATION **ISCO- 3 Digit** European Skills/ Competencies Qualifications Occupations **ESCO** 3 Pillars ESCO is mapped to ISCO-08 ISCO-08 to Top four ESC) to bottom five.	**ESA95** EDUCATION **ISCED 2011** International Standard Classification of Education 3 Broad levels **FIELD OF STUDY** 15 Categories **7 Educational** **Categories** LOCATION **NUTS 2016** Nomenclature of Territorial Units for Statistics

SOUTH AFRICA					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top -down Bottom up multi-sector macro model 10 year forecast	**LM-EM (Linked Macro-Education Model)** Multi-sectoral Macro-econometric Model Modular Structure	**1.Macroeconomic Model** Labour Market - Employment Demand **Demand for Skills** 2. Occupation Demand 3. Qualification Demand 4. Replacement Demand Job Openings from 4 Job Opening by Occupation from 4 **Supply of Skills** **Supply of Skills** 5. Projection of Labor Force by qualification 6. Flows of Graduate Numbers 7. Supply of Skills in Population and Labour Force **Skills gaps or imbalances** by qualification are estimated for all educational categories by the difference between job seekers and job openings for the qualification categories	MEMSA is a non-linear macro-econometric model which is a bottom-up model capturing the National Income and Product Account in a disaggregated fashion. It has more than 3200 equations It uses the time series ARDL methodology for 400 equations **Stock-flow model** **Multinomial Logistic techniques for estimation**	Census 2011 Quarterly Labour Force Surveys INDUSTRIAL **SIC** Standard Industrial Classification based on ISCO-88 OCCUPATION **SASCO** SA Standard Classification of Occupations (based on ISCO-88)	**SNA2008** EDUCATION **ISCED** LOCATION

GERMANY					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Hybrid **Bottom-up** approach with **Top-down** elements FREQUENCY Continuous Update to the 4th Wave forecast every 2 years since 2010	**IAB/INFORGE** 4th Wave of Model Aggregation from Sectoral to Aggregate	1. QuBE Population Projection **Labour Supply** 2. Educational System 3. Choice of Occupation (50 fields) 4. Participation in Employment 5. From Occupation to Occupation flexibility 5a. From Flexibility to Occupation exercised labour supply 6. Qualification from (4) **Labour Demand** 1. From Economy and Population Projection 2. 50 Occupation fields * four Requirement levels 3. Requirement levels **Reconciliation** of Qualification of Labour Supply with Requirement level of Labour Demand QUALIFICATIONS **ISCED (4 + 1)**	Balance Supply and Demand on Skill level and on Occupational level SUPPLY OF SKILLS **LEVEL OF AGGREGATION** 50 Occupational Fields 4 +1 Qualification levels DEMAND FOR SKILLS **LEVEL OF AGGREGATION** 50 Occupational Fields 63 Sectors (NACE) 4 Requirement levels DEMAND-SUPPLY RECON 50 Occupational Fields 4 +1 Qualification levels 4 + 1 Requirement levels	2011 Census LFS Microcensus Educational Statistics Employment History Data INDUSTRIAL **NACE-Rev2** Statistical Classification of Economic Activities OCCUPATION **KldB 2010** 50 Occupational Fields 4 Requirement levels * Requirement level is an indicator of the complexity of the task 1. Semi or Unskilled tasks 2. Skilled tasks 3. Complex tasks 4. Highly complex tasks	**ESA 2010** EDUCATION **ISCED 2011** International Standard Classification of Education LOCATION **NUTS 2016** Nomenclature of Territorial Units for Statistics

NEW ZEALAND					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down economy wide approach FREQUENCY 5 and 10 years annually and ad-hoc	**CGE by** BERL	1. Population Projection 2. Labour Force Projections 3. Total hours workable for labour force Supply estimated by gender, age cohorts and highest qualification levels	Cohort component method for Projections taking deaths, migration and births into consideration Stochastic approach, creating 2000 simulations Population times the labour force participation rate Multiplying projected labour force by average hours workable by age and sex QUALIFICATIONS 4 levels **Stocks and flows of skill is** the stock of current skill plus the flows in and out of the labour force.	Census of Population and Dwelling Household Labour Force Survey 2013 Census INDUSTRIAL **ANZSIC** Australia and New Zealand Standard Industrial Classification 28 Industries OCCUPATION **NZSCO** New Zealand Standard Classification of Occupations 96 Occupations	**SNA 2008** Chained volume indices EDUCATION **NZSCED** New Zealand Standard Classification of Education LOCATION **SSGA18** Statistical Standard for Geographic Areas 2018

REPUBLIC OF KOREA					
APPROACH	MODEL	STEPS	METHODOLOGY	DATA	NA
Top-down approach FREQUENCY 10 year period updated every 2 years Population Projections 2010 - 2060	OUTPUT **Korean Occupational Outlook Handbook**	1. Economic Growth Employment Coefficient Forecasting by Industry **2. Labour Demand by Industry** 2. Industry / Occupation Matrix Forecasting (Employment Occupation Classification) 2. Industry /Job Matrix Forecasting (Standard Occupational Forecasting) **3. Labour Demand by Occupation/Job** 3. Labour Demand by Occupation (Employment Occupation Classification) 3. Labour Demand by Job (Standard Occupational Classification) **Labour Supply** 1. Population Projection by age / gender 2. Productive Population by age/gender/ education 3. Economically Active Population by age/gender/ education Labour Force Participation rate Labour Force Supply **Labour Supply-Demand Matching** The mismatch is forecast by Education, Field of Study and Occupation	Based on the BLS of the USA 1.The employment size in aggregate and by industry is calculated by using the industry growth rates and the employment coefficient by industry. 2. The industry- occupation matrix converts the employment by industry to employment by occupation 3. The total unemployment rate, participation rate and employment rate is obtained from the labour force forecast and employment results. QUALIFICATIONS 2 - year College 4- year College Graduate School **Field of Study** Eight Fields	Statistics Korea's Population Projections Economically Active Population Survey Local Area Labour Force Survey Other Employment and mobility statistics Population and Household Census Higher Education Graduate Statistics from KEDI Korea Labour and Income Panel Survey Graduates Occupational Mobility Survey INDUSTRIAL **KSIC** Korean Standard Industrial Classification 2-Digit 76 Industries	Bank of Korea NA EDUCATION **KEDI** Korean Educational Development Institute LOCATION OCCUPATION **KSOC** Korean Standard Occupational Classification **KECO** Korean Employment Classification of Occupations

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Contact Information:

Tel: (+1) 916-987-5660
Cell: (+1) 916-505-4874
Website: https//www.adrs-global.com
email: info@adrs-global.com

Authors

Asghar Adelzadeh, Ph.D.
Director and Chief Economic Modeller
asghar@adrs-global.com

Cynthia Alvillar
CEO and Senior Labor Economist
c.alvillar@adrs-global.com

Madhu Kanji
Senior Economist and Econometrician
mkanji@adrs-global.com