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TECHNOLOGICAL CHANGE AND ITS IMPACT ON THE LABOR MARKET IN EGYPT

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Abstract

The current study aims at analyzing the impact of technological change and innovations on the labor market in Egypt. Using the panel data of Egyptian Labor Market Panel Survey (ELMPS) 1998, 2006, and 2012 as well as the initial year of ELMPS 1988, a quadratic form of equation for employment is estimated and two approaches were applied. The first one is collaborated by applying the Ordinary Least Square (OLS) estimation method and taking the difference between the rounds of the ELMPS database; three regressions were estimated for the following, namely total labor force (males and females), a regression for male workers as well as another regression for female workers on wage and wage squared. The second approach is estimated by applying the panel model techniques using the Fixed Effects Model as well as the Random Effects Model to analyze the impact of technological change on the Egyptian labor market. Results of the study reveal that the impact of technological change on employment is evident in the years 2006 and 2012 causing job polarization in the Egyptian labor market as revealed in the first approach. Moreover, the findings show that in the second approach there exists a J-shaped relationship between employment growth and wage and wage squared as control variables. The present study provides an overview of the related literature; moreover, it addresses and analyzes the impact technological change has on the labor market. Finally, the paper provides policy recommendations for forward-looking labor market policies in Egypt.

Keywords: technological change, labor market, skills, digital economy, MENA, Fixed Effects Model, Random Effects Model, 3rd Industrial Revolution, 4th Industrial Revolution, Egypt.

Jel-classification: J21, J24, L96

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1. Introduction

Unquestionably, technological change entails a dominant role of Information Communication Technology (ICT), or Digital Economy (DE) that characterizes the 4th Industrial Revolution (4IR). Thus, the access and use of ICT and digital skills have gained greater momentum, especially in the labor market. Moreover, advances in Artificial Intelligence (AI), low-cost ICT prices and increased Internet penetration rates render the potential for automation to be inevitable. Furthermore, building a long-term pool of talents in Science, Technology, Engineering and Math (STEM) fields becomes an essential ingredient for forward-looking labor policies. DE creates new opportunities for trade and development and is helping smaller businesses and entrepreneurs in developing countries to connect with global markets more easily through digital platforms that consequently open up new ways to generate income. It is worth noting that until 2030, automation per se is estimated to add between 0.3 to 2.2 percent in compound annual productivity growth to the world economy. According to the McKinsey Global Institute (MGI), automation is more likely to transform human work than to replace it. Although, at least, a third of the tasks involved in 60 percent of occupations could be automated, fewer than 3 percent of occupations could be fully automated with the current automation technologies (McKinsey, 2018b).

The 3rd Industrial Revolution, which took place in the late nineties of the 20th century and the early 21st century, is also pertinent to this study. The 3rd Industrial Revolution entails the advent of using microchips, computers and Internet on a wider scale to become a general-purpose technology. There are certain challenges that relate to economic development and pertain to the evolution of digitalization and technological change. Egypt, like most Arab countries, attempted to adopt the latest technologies in its economy. However, these countries are still inadequately prepared to capture the numerous opportunities emerging as a result of digitalization, in general, and the 4IR, in particular. This raises concerns that the DE may lead to increased polarization in the global labor market and may widen income inequalities, which would affect the Egyptian context as well. Productivity gains may accrue mainly to a few already wealthy and skilled individuals. Thus, winners-take-all dynamics might be the outcome in digital economies where network effects benefit first movers.

Increased digitalization and automation is leading to new types of jobs and employment, these developments are changing the nature and conditions of work, altering skill requirements, affecting the functions of the labor markets and influencing the international division of labor. Moreover, the ability of countries and enterprises to exploit new digital resources will become a key determinant of their competitiveness.

It is worth noting that the overall effects of digitalization remain uncertain. However, these effects are context-specific, differing greatly among countries and sectors. This makes it

increasingly important for countries to ensure that they have an adequate supply of skilled workers with strong cognitive, adaptive and creative skills necessary for *'working with machines'*.

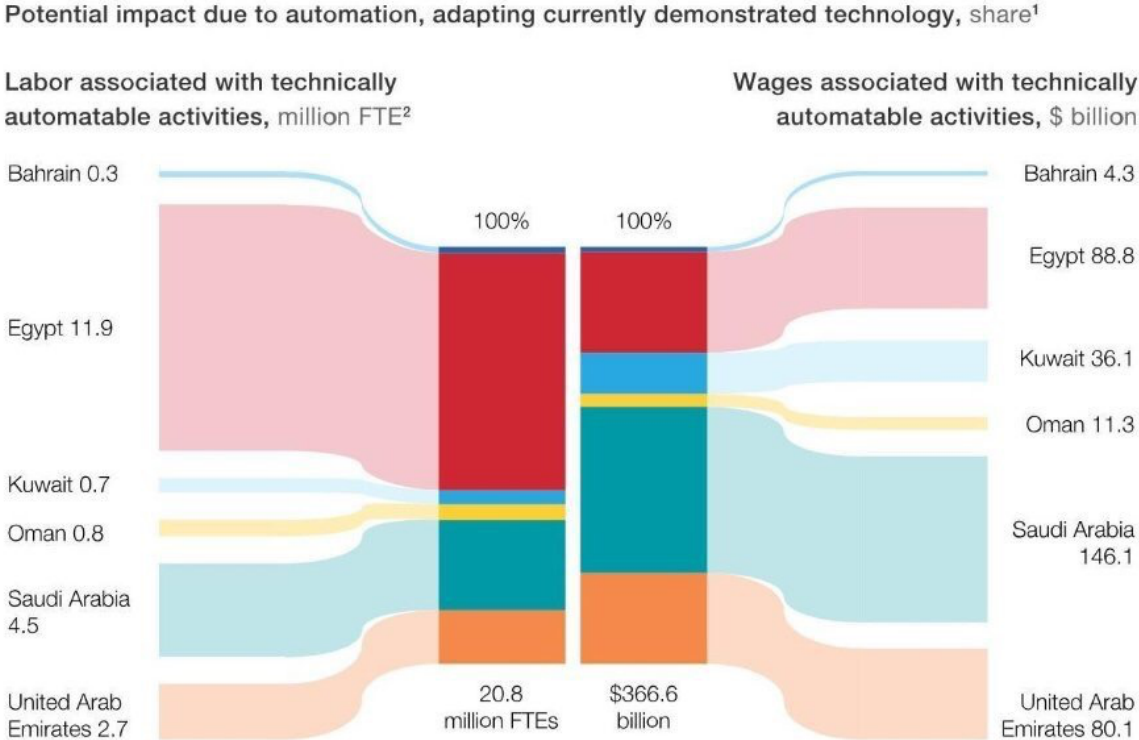
An important motivation of this paper is the findings made by a recent McKinsey study that cover six Arab countries (Egypt, UAE, Saudi Arabia, Oman, Kuwait, Bahrain). Based on currently demonstrated technology, today 45 percent of the existing work activities in the labor market are automatable. This average is slightly below the global average of 50 percent; it is also noted that only a relative small variation exists among the six countries. Based on 2015 scores of the McKinsey Country Digitization Index, the same study forecasts that workforce automation of Egypt was ranked just under UAE, the latter scored 50 percent points higher than Egypt. McKinsey's report further reckons that Egypt displays the highest potential share at 48 percent of automatable current activities, while Saudi Arabia and Oman have a lower share of automatable current activities at 41 percent in this sample. Overall, the regional average is at similar levels as the US share (i.e., at 46 percent) or the "Big 5" European countries (France, Germany, Italy, Spain, and the United Kingdom).

Furthermore, the degree of automation potential varies substantially across sectors raising doubts about the future proof of some sector job creation plans. In the region, the information sector and the intensive routine tasks sectors – such as manufacturing, transportation as well as warehousing – exhibit technical automation potential that is larger than 50 percent. However, sectors that are more dependent on human interaction, are creative as well as have non-routine activities and services – such as arts, entertainment and recreation, healthcare and education – display below average automation potential of 29 percent to 37 percent. When compared to some of the Gulf economies, this variation helps illustrate the fact that, in the region, a much higher share of the automation potential is concentrated in Egypt. This is due to its being driven by a larger absolute and relative workforce footprint in certain fields such as manufacturing and agriculture. During the first 15 years, technical automation potential for Egypt started from the highest baseline and since has been most rapidly increasing (partially even overtaking the global average). However, compared to the other countries in the sample, it is found that the projected actual adoption for Egypt is the slowest (McKinsey, 2018a).

Figure 1 depicts the forecasts of the McKinsey study showing that the Middle East automation potential would lead to about \$366.6 billion in wage incomes. This translates into an added enormous increase in economic value as well as in the opportunities resulting from the technological changes in the MENA labor market. In all six Middle Eastern countries combined, \$366.6 billion in wage incomes and 20.8 million in Full-Time Equivalent (FTEs) are associated with activities, which are already technically automatable today. The relative labor force size and current wage levels are the major factors of how this economic value is distributed among the countries. While Egypt, with almost 12 million FTEs currently employed in automatable work

activities, tops the list in terms of the labor share in the region, the economic value at stake is highest for Saudi Arabia, reflecting its higher average wage structure (McKinsey, 2018a).

Figure 1: Middle East Automation Potential:



¹Share of combined total of 6 countries studied. Figures may not sum to listed totals, because of rounding.
²Full-time equivalent.

Source: Emsi database; Oxford Economics forecasts; US Bureau of Labor Statistics; McKinsey Global Institute analysis

McKinsey&Company

Based on the above discussion, Egypt is witnessing, and will continue to experience, a change in the labor market due to the technological changes accompanying either the 3rd or 4th Industrial Revolutions. It is projected that the labor market in Egypt will undergo further changes in terms of automation and its embracement of new technologies. These technological changes would definitely have a significant impact on the future structure of the Egyptian labor market.

2. Literature Review

At the outset, it is worth noting that with the advent of new technologies such as the Internet and personal computers, the impact of technological change on the labor market is a recurrent

research topic, whether it dates back to the 3rd Industrial Revolution or even prior to that during the steam and water power energy of the 1st Industrial Revolution. According to Acemoglu (2002), some scholars such as Griliches (1969) indicated that capital and skills are inherently complementary. This implies that the increase in capital-intensive production techniques is associated with an increase in demand for skills (Claudia Goldin and Lawrence Katz, 1998). This relationship was shown by the increase that occurred in the roles of white-collar and clerical occupations in the American economy. However, in nineteenth-century Britain, the opposite phenomenon took place: “skilled artisans destroyed weaving, spinning, and threshing machines during the Luddite and Captain Swing riots, in the belief that the new machines would make their skills redundant” (Acemoglu, 2002, p. 3). Products that were previously manufactured by skilled artisans started to be produced in factories by workers with relatively fewer skills; moreover, many previously complex tasks were simplified, thereby reducing the demand for skilled workers. This phenomenon is referred to as ‘deskilling’; or unskill-biased; a major purpose of technical change was to expand the division of labor and “simplify tasks previously performed by artisans by breaking them into smaller, less skill-requiring pieces” (Acemoglu, 2002, p. 9). The early nineteenth century was characterized by skill-replacing developments because the increased supply of unskilled workers in the English cities (resulting from migration from rural areas and from Ireland) made the introduction of these technologies profitable. However, according to Acemoglu (2002), technological advances in the twentieth century – 3rd Industrial Revolution – have been skill-biased, which has induced the development of skill – complementary technologies. This is correlated with the fact that the development and use of technology is, at least in part, a response to profit-driven incentives. The recent acceleration in skill-biased technical change is, in turn, likely to have been a response to the rapid increase in the prevalence of skills during the past several decades. Thus, Acemoglu (2002) argues that acceleration in skill-bias is associated with the types of technologies that are being developed and not with the technological change per se. So, the trend shows that workers were seeking education to improve their average educational level, which would overcome the low wages related to being unskilled. In the US, there was a sharp increase in the return to more skilled workers, suggesting that skill-biased changes in technology continued throughout the postwar period. There are two distinct approaches/theories that provide an explanation to the impact of technological change on the labor market structure. The first approach would view technology as *exogenous*, stemming from advances in science or from the behavior of entrepreneurs driven by a variety of nonprofit motives. This approach maintains that the demand for skills increased faster during the past thirty years because of the technological revolution led by the microchip, personal computers, and the Internet. Moreover, new technologies of the early nineteenth century were skill-replacing (unskill-biased) because the technological frontier then only enabled the invention of skill-replacing techniques (i.e., technology that was considered exogenous). An alternative theory maintains that new technologies are *endogenous* and respond to incentives. This approach claims that the large increase in the supply of skilled workers induced acceleration in the demand for skills. Additionally, skill-biased production techniques are more profitable and firms will have greater motivations to deploy these techniques. A key determinant of the profitability of new technologies is their market size; machines that can be sold in greater numbers will be more profitable, where market size plays the significant role in this theory (Schmookler, 1966).

In another paper by Goos et al. (2008), two models that explain the relationship between employment and skills were reported. The first is the Skill-Biased Technical Change (SBTC) introduced in 1999. This model claims that the technology is biased in favor of skilled workers against unskilled workers. The SBTC is placed in the top half of the wage distribution. The second model is the Autor, Levy and Murnane (ALM) introduced in 2003. This model states that technology can replace human labor in routine tasks, be they manual or cognitive, but cannot replace human labor in non-routine tasks. According to this hypothesis, skilled workers are found in both routine and non-routine jobs. As a result, job polarization or hollowing out of the labor market takes place. There is an increase in demand for well-paid skill requiring jobs that typically involve non-routine cognitive skills, such as jobs in the area of finance and business services; these are the high paying jobs. There is a decrease in demand on middling jobs that typically require routine, manual, or cognitive skills such as the clerical jobs and manually skilled jobs in the field of manufacturing. Then the lousy jobs are those with lousy pay or are low paying service labor. Job polarization takes place in non-routine manual occupations that lead to a decrease in wages, resulting in very low wages. Whereas, non-routine cognitive and interactive jobs have higher wages, routine jobs receive middle level wages.

It is worth noting that, according to the US Dictionary of Occupational Titles (DOT), there are 5 types of skills or tasks.

1. Non-routine cognitive
2. Non-routine interactive
3. Routine cognitive
4. Routine manual
5. Non-routine manual

Where type 1 and type 2 are lovely jobs and type 5 is the lousy job, types 3 and 4, which are automated, are considered low routine skills or middling jobs. Unemployment would increase in middling jobs, but there is employment growth in both lovely and lousy jobs. For the latter, the increase is explained in terms of performing non-routine manual tasks.

According to work by Bessen (2016), major new technologies today should increase employment if they improve productivity in markets where there is a large unmet demand. This appears to be the case in computer technology. In the short run, as long as there is a large unmet consumer demand, automation will sufficiently raise demand for labor in the relevant industries to create job growth. However, in the long run, the consumer demand will become inelastic, hence, these technological changes may result in major job losses.

In a third paper about robots and jobs, by Acemoglu and Restrepo (2018), there is indeed a large and negative impact of robots on wages and employment in the USA. Moreover, in the 1930s, Keynes coined the concept of “Technological Unemployment”. Industrial robots are

programmed to perform several manual tasks such as welding, painting, assembling, handling materials or packaging. They are automatically controlled, reprogrammable and are multi-purpose machines. According to the paper, robots have 2 effects on employment: first, the displacement effect, which is negative in impact; second, the productivity effect, which is positive in impact. The latter leads to an increased demand for labor in other industries. In another paper by Goos (2018), he explains that the current 4IR and the digital revolution have an impact on the relationship between worker skills and digital capital where they are completely intertwined in the labor market, thus, affecting job mobility for workers and output prices. The paper focuses on how present worker-technology dynamics and the equilibrium effects permeate job polarization. Continuous technological change would eventually result in winners and losers in the labor market.

Finally, a recent report by McKinsey (2018a) about the future of jobs in the Middle East concluded: “In the 6 Middle East countries, 45 percent of the existing work activities in the labor market are automatable today based on currently demonstrated technology. This average is slightly below the global average of 50 percent, and there is only a relatively small variation among the 6 countries (with Saudi Arabia and Oman having a slightly lower share of automatable current activities at 41 percent, and Egypt a higher share of 48 percent).” The report reached the conclusion that in all 6 Middle Eastern countries under investigation, a total of \$366.6 billion in wage incomes and 20.8 million FTEs are accompanying actions, which are presently technically automatable. The report also concludes that the average technical automation potential for workforce with just high school or less than high school education is about 55 percent to 50 percent, respectively. Furthermore, the average automation potential for higher education degrees or their equivalent is around 22 percent.

Hence, with the exception of the McKinsey report, a conclusion may be drawn from the literature review indicating that previous studies focused on the impact of the technological change on the labor market in developed countries. Thus there exists a research gap in this area concerning the MENA region and more precisely Egypt. This current study aims to fill this knowledge gap.

2.1 The Empirical Analysis Data

ELMPS is an extensive, nationally representative panel survey that investigates numerous areas such as job dynamics, employment, unemployment and earnings in typical labor force surveys. In addition to the survey’s panel design, which permits the study of various phenomena over time, the survey also contains a large number of retrospective questions about the timing of major life events such as education, residential mobility, jobs, marriage and fertility (Assaad, and Krafft, 2013). The survey provides detailed information about the labor market in Egypt.

ELMPS 2012 is the third round of this longitudinal survey, which was earlier carried out in 2006 as well as in 1998.

2.2 The Empirical Model:

The empirical study is based on collaborating two distinct approaches. The first one is based on taking the difference between the rounds 2006 and 2012 of the ELMPS database and applying the OLS method of estimation to model (1). We use 3 years of the survey 1998, 2006 and 2012 in the OLS regression.

We model the wage in the quadratic form to reflect the nonlinear relationship - J-shaped relationship - between employment growth and median wage, due to the relative forces of income and substitution effects (Goos, 2008). The estimated model is a quadratic form of the employment equation:

$$\Delta n_j = \beta_0 + \beta_1 w_{j0} + \beta_2 w_{j0}^2 + \beta_3 D_1 + \beta_4 D_2 \text{ -----(1)}$$

where, Δn_j is the change in log employment in job j and w_{j0} is the log median wage in the job j that defines the quality of jobs, and D_1 and D_2 are two dummy variables for the years 1998 and 2006, respectively where 2012 is the reference year. Then, three regressions were estimated, namely the total labor force (males and females), a regression for male workers and the last one for female workers on wage and wage squared, $n= 208$ observations.

Using the OLS estimation method and taking the difference between the rounds of the ELMPS database, three regressions were estimated using OLS. Preliminary results reveal that the years between 2006 and 2012 witnessed a job growth where wage and wage squared came out statistically significant. Attempting to verify the J-shaped relationship that should appear in the regression results. In the regression, we measure employment using 2-digit occupation codes with a 1-digit industry code. However, results revealed a different outcome. The linear term (w) in equation (1) is negative and the quadratic term w squared is positive implying a *U-shaped* relationship between employment growth and the initial level of wages. This is explained in terms of the existence of substantial numbers of workers in the downward-sloping part of the relationship. These regressions emphasize the fact that there has been polarization in the quality of jobs, with the employment growth being at the extreme ends of the distribution. Data Analysis also reveals that the impact of technological change is evident in years 2006 and 2012 in terms of positive job growth that is associated with an increase in certain occupations such as science and engineering associate professionals, and administrative and commercial managers. However, there was a dramatic decrease in certain occupations such as agricultural laborers, forestry laborers, fishery laborers as well as business and administrative associate professionals.

In the second approach, both the estimated Fixed Effects Model as well as the Random Effects Model were applied. The effect of technological change on the Egyptian Labor market was investigated for the years 1998, 2006 and 2012, where 1998 is the reference year.

Panel data techniques have their advantages, for instance they are used when taking heterogeneity into account to estimate individual specific estimates. The use of panel data techniques is especially suitable to study the dynamics of change such as the impact of technological change on the labor market in Egypt. Besides, it is widely applied in complex behavioral models and techniques that minimize bias due to aggregation (Green, 2003). The panel data of the underlying model is unbalanced due to the fact that as a result of technological change some occupations disappear, while others emerge. (Green, 2003)

$$\ln(\text{empl}_{it}) = \beta_0 + \beta_1 \ln \text{Wage}_{it} + \beta_2 \ln \text{Wage}_{it}^2 + \beta_3 \text{Gender}_{it} + \varepsilon_{it} \quad (2)$$

where $\varepsilon_{it} \sim (N, \sigma)$ iid (identically independent, distributed errors)

The Random Effects Model assumes that the entity's error term is not correlated with the predictors, which allows for time-invariant variables to play a role as explanatory variables. In the Random Effects Model you need to specify those individual characteristics that may or may not influence the predictor variables. An advantage of the Random Effects Model is that you can include time invariant variables (i.e., gender). In the Fixed Effects Model these variables are absorbed by the intercept (Torres-Reyna, 2007).

In the second approach, the pooled regression with no fixed effects was estimated, followed by the Random Effects Model and then the LM test was conducted to choose between pooled OLS and the Random Effects Model. Finally, we estimated the Fixed Effects Model and chose the best model based on results of the Hausman test. In the Random Effects Model, the number of the observations amounted to 251. The overall R^2 is 16%. All explanatory variables are statistically significant. Compared to males, the females' share in employment has decreased in the years 2006 and 2012 in comparison with 1998. Table 3 represents the OLS regression. Table 4 reports the results of the estimated Random Effects Model. Then the LM test was conducted to choose between the pooled OLS model and the Random Effects Model (Table 5). Results of the LM test reveal that panel effects exist, that there are significant differences across years and that the Random Effects Model is more suitable than the pooled OLS. Finally, the Fixed Effects Model is estimated (Table 6), and the Hausman test is conducted in order to choose between Random Effects Model and the Fixed Effects one. Results of the Hausman test confirm that the Random Effects Model is the right model to use where the Hausman test came out to be insignificant in favor of the Random Effects Model. The second approach based on panel data techniques, namely, the Fixed Effects Model as well as the Random Effects Model, reveals that wage is statistically significant where wage has a nonlinear relationship with employment. Gender is also statistically significant with a negative impact on the employment rate in Egypt. However, this approach depicts the expected J-shaped relationship between employment and wages. In general terms, panel models take into account heterogeneity and are suitable for

modeling the impact of technological changes; additionally, the panel model minimizes bias due to aggregation.

3. Conclusion & Policy Recommendations

The first approach i.e. the pooled model that took the difference between 2006 and 2012 employment levels, shows that the impact of technological changes on the Egyptian labor market is evident between years 2006 and 2012 in terms of creating polarization, where there was positive job growth associated with the increase in certain occupations such as science & engineering associate professionals, administrative and commercial managers. However, there was a dramatic decrease in certain occupations such as agricultural laborers, forestry laborers, fishery laborers as well as business and administration associate professionals. So, a U-shaped relationship between employment and wages appeared between 2006 and 2012, revealing the existence of job polarization. Compared to males, the females' share in employment has decreased in the years 2006 and 2012 where 1988 is the reference year and both wage and wage squared were highly statistically significant. The second approach founded on panel data techniques, i.e., the Fixed Effects Model as well as the Random Effects Model shows that wage is statistically significant in the case of a nonlinear relationship with employment. Gender is also statistically significant and it has a negative effect on the employment rate in Egypt. Furthermore, this approach illustrates the J-shaped relationship between employment and wages. By default, panel models take into account heterogeneity and appropriately model the influence of technological changes on the market; moreover, the panel model reduces bias due to aggregation.

With respect to policy recommendations for adopting a forward-looking approach to the Egyptian labor market, it is expected that the 4IR in Egypt will take a longer time to materialize. This is due to the fact that Egypt is lagging in automation and relies more on labor-intensive technologies. However, it is anticipated that globalization will have an impact. Major disruptions are expected to take place due to Egypt's rapid technological adoption and the existence of large numbers of routine occupations. On a regional level, Egypt is one of the countries that are more susceptible to the automation of the labor-intensive production techniques. Egypt has the advantage of learning from other countries', which earlier faced similar challenges as well as experiences and adjusted properly to these disruptions. To this end, it becomes critical to promote a second wave of digital disruptions of jobs. The ICT sector in Egypt has a major opportunity and responsibility to invest in creating a second wave of technology disruptions with the aim of enabling everyone to participate in the 21st century's new or DE. The effect of automation is clear especially in the case of unmet demand or consumer needs, where automation will raise the demand sufficiently to create jobs in the relevant industries. Whereas,

in the short run, there would be no major job losses because the demand is elastic, in the long run, there would be major job losses because the demand would be inelastic.

There is little doubt that technological changes have, and will continue to have, an impact on the Egyptian labor market. The result would be a change in the demand for labor and hence the structure of the labor market will also change. New jobs and new skills will be in demand. While, in the past, digitalization put medium-skilled, routine jobs at a particularly high risk of being automated (Acemoglu and Autor, 2011), future digitalization may put low-skilled jobs at significantly higher risk of unemployment (Bode et al., 2018). The digital technologies will create many new jobs, too. But most of these new jobs will emerge in different occupations or industries. Moreover, they will require skills that differ from the skills demanded by current jobs (Brynjolfsson and McAfee, 2011; Autor, 2015; Acemoglu and Restrepo, 2018). The resulting skill mismatches may fuel significant technological unemployment in the short and medium terms. To retain their employability and strengthen their resilience to the technological change in the digital age, even more workers in the Age of Computerization will then need to continuously update and upgrade their skills to complement the new technologies. Doing so will improve their mobility across tasks, jobs, occupations and industries. The notions of adult learning developed for the Age of Computerization need to be re-focused to meet the challenges of the digital age (Bode et al., 2018).

Hence, it becomes critical to promote a second wave of the digital disruptions of jobs. The technology sector has a major opportunity and responsibility to invest in creating a second wave of technology disruptions with the aim of enabling everyone to participate in the 21st century's new or DE. To achieve this, it is essential to adopt the following critical changes in Egypt's labor market: first, job openings must specify the skills needed for specific jobs and not just the qualifications and/or experience; this would help job seekers in identifying and understanding the potential skills that they are missing. In this respect, it is worth noting that the Google Cloud Job Discovery in the USA enables smarter job searches and provides recommendations. Moreover, it leverages the huge data sets owned by technological companies. Second, job openings must apply mapping technology to benefit the labor market. These job maps could reveal potential job openings and specify the exact skills needed. Moreover, job maps also show the time to fill a job with the lowest or greatest-skilled job seekers; additionally, job maps link this data set to salary data and related information. Third, job opening must include an assessment of the required skills that meet the wants and needs of the customers, followed by automatically offering training opportunities to meet the needs of job seekers. This service may be performed by the technological sectors, or the product teams with experience in a given specific area. Fourth, social media and online content must play an important role to showcase careers that people would aspire to. They would actually help people imagine themselves involved in higher-skilled work. More workers need to continuously update and adjust their skills to complement the new

technologies. This includes encouraging mobility across tasks, jobs, occupations and industries, through Lifelong Learning (LLL).

In addition, it is recommended that policymakers develop initiatives that foster continuously changing skill requirements of the Age of Computerization by emphasizing LLL (Bode et al., 2018). It is worth noting that LLL is recognized as one of the Sustainable Development Goals, namely Goal 4. In developed countries, the current programs focus on providing education and training to highly skilled workers in their current jobs, rather than addressing their mobility needs across tasks, jobs, occupations or industries. Studies stress the positive benefits of adult training on low-skilled individuals. Participating in adult training is significantly lower among older workers, workers with lower proficiency in digital skills, and workers with fixed-term contracts. Adult training currently focuses too little on enhancing general skills. More public support is needed to increase participation of employed workers in general training, particularly of those with skill deficiencies.

Hence, the goal should be to enable workers to complement technology rather than compete with it. Digitalization provides manifold opportunities to increase labor productivity even in the case of low- and medium-skilled workers. With digitalization, new tasks emerge that require cooperation between man and machine more so than being a holder of a college degree. New and smarter intelligent technologies need workers with skill advantages to carry out tasks. New types of skills have been introduced in the digital age. These focus on general as well as specific skills and are classified into three main categories: General Skills – Specific Skills – Digital Skills (Bode et al., 2018). General Skills can be used in a broader variety of jobs and occupations and are meant to complement the new technologies rather than replace them. General Skills include theoretical skills, which comprise formal school and university education in addition to soft skills training. Examples of these skills are punctuality, reliability, responsibility, integrity, honesty, values, behaviors, self-discipline, self-confidence, social (i.e., interpersonal) skills and communication skills. Specific Skills are a set of skills related to a worker's domain. Finally, Digital Skills encompass ICT skills, software and programming skills as well as digital literacy. Adult training programs should generally aim at simultaneously enhancing all three-skill types as well as help workers with particular deficits in certain areas to enhance their job competence. Motivating individuals to voluntarily participate in LLL adult programs is the most crucial and difficult task (Bode et al., 2018).

The LLL programs must devote utmost effort to motivate the target workers to participate voluntarily. Motivation-enhancing measures should include disseminating information and raising awareness. The adult training programs should specifically target workers who are highly susceptible to automation (Bode et al., 2018).

Egypt has a youth bulge that constitutes its precious resource for implementing as well as benefiting from the 4IR (Badran, 2014). The uptake of ICT in Egypt is among the top in the region, in terms of users and producers of technology. Thus one policy objective is to entice the young people to use their human capital and not to leave the country. Furthermore, drafting updated regulations that are technologically neutral for the labor market and other economic sectors is essential to harness the momentum of the 4IR in Egypt. Fostering the young generation of developers in ICT and technology through updating school and university curricula as well as promoting R&D initiatives are all imperative measures that need to be adapted among the fast technological changes associated with the 4IR (Ahram online, 2018).

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Table 1A: Top 10 occupations by job growth rates between 2006 and 2012

Top 10 occupations by job growth rates				
2 -Digit Occupation Code	Median wage	employment		% change in employment
	2006	2006	2012	
31 Science and Engineering Associate Professionals	992.9	2413	634047	100
12 Administrative and Commercial Managers	1573.0	9458	1789111	99
71 Building and Related Trades Workers	1022.4	23352	2292332	99
21 Science and Engineering Professionals	1628.7	18674	354580	95
34 Legal, Social, Cultural and Related Associate Professionals	917.6	69234	1243294	94
24 Business and Administration Professionals	1119.4	66532	1113171	94
23 Teaching Professionals	1573.0	186862	1671241	89
22 Health Professionals	1649.6	39873	251908	84
74 Electrical and Electronics Trades Workers	852.0	131975	805851	84
32 Health Associate Professionals	742.6	58911	359419	84

Source : ELMPS 2006, 2012, author's calculations

Table 1B: Bottom 10 occupations by job growth rates between 2006 and 2012

Bottom 10 occupations by job growth rates				
2 -Digit Occupation Code	Median wage	employment		% change in employment
	2006	2006	2012	
92 Agricultural, Forestry, Fishery Labourers ,	766.8	62227	705	-99
33 Business and Administration Associate Professionals	1006.0	464786	14958	-97
73 Handicraft and Printing Workers	852.0	732545	183895	-75

13 Production and Specialized Services Managers	1523.8	273719	91811	-66
62 Market-oriented skilled Forestry, Fishery and Hunting workers	540.7	8899700	3412731	-62
72 Metal, Machine and Related Trades Workers	852.0	1480940	664173	-55
42 Customers services Clerks	835.6	279251	163936	-41
51 Personal Services Workers	686.2	1356713	973977	-28
82 Assemblers	613.5	461516	643844	40
83 Drivers and Mobile Plant Operators	1179.7	1012124	1564528	55

Source : ELMPS 2006, 2012, author's calculations

Table 2: Description of Variables:

Variable	Description	Number of Observations	Mean	Std. Dev.	Min	Max
round	1988, 1998, 2006 and 2012 (base group 1988)	2,201	1999.60	8.93	1988	2012
gender	1=male 2=female (base group male)	2,201	1.31	0.46	1	2
crocp1d	current occupation 1 digit (9 categories) 0 Armed Forces 1 Managers 2 Professionals 3 Technicians and associate professionals 4 Clerical support workers 5 Service and sales workers 6 Skilled agricultural, forestry and fishery workers 7 Craft and related trades workers 8 Plant and machine operators, and assemblers 9 Elementary occupations	2,201	4.29	2.41	1	9
crecac1d_cl	Economic activity of prim. job (1-digit, based on ISIC4, ref. 1-week) 0 A:Agriculture, forestry and fishing 1 B:Mining and quarrying 2 C:Manufacturing 3 D:Electricity,gas,steam and air conditioning supply 4 E:Water supply;sewage,waste management and remediation activities 5 F:Construction 6 G:Wholesale and retail trade; repair of motor vehicles and motorcycles 7 H:Transportation and storage 8 I:Accommodation and food service activities 9 J:Information and communication 10 K:Financial and insurance activities 11 L:Real estate activities 12 M:Professional, scientific and technical activities 13 N:Administrative and support service activities 14 O:Public administration and defense; compulsory social security 15 P:Education 16 Q:Human health and social work activities 17 R:Arts, entertainment and recreation 18 S:other service activities 19 T:Activities of extraterritorial organizations and bodies 20 U:Activities of extraterritorial organizations and bodies	2,192	8.81	5.67	0	20

crocp2d_all	Economic activity of prim. job (2-digit, based on ISIC4, ref. 1-week)	2,201	44.72	27.93	1	99
RmnthwGAllJobCPII2	Real Monthly wage for all jobs in 2012 prices (mean by occupation)	2,196	1339.25	1715.06	30.13	35129.38
crempl	number of employment by occupation	2,201	18752.87	85323.55	0.00	1810498.00
Inwage	Natural Log. of real Monthly wage for all jobs in 2012 prices (mean by occupation)	2,196	6.92	0.69	3.41	10.47
Inwage_sq	Square of natural Log. of real Monthly wage for all jobs in 2012 prices (mean by occupation)	2,196	48.37	9.67	11.60	109.55
ln_cremp	Natural log. For current employment variable	1,549	8.78	1.45	4.98	14.41

Table 3A: Pooled OLS Model (Males and Females Regression Results)

Employment	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
median_wage	-1312.48***	488.0698	-2.69	0.008	-2275.31 -349.647
median_wage_sq	0.32885**	0.170494	1.93	0.055	-0.00749 0.665189
Year					
1998	-7222.3	160855.6	-0.45	0.654	-389547 245102.5
2006	441560.2***	183325.5	2.41	0.017	79908.38 803212.1
_cons	1119819	320385.8	3.5	0.001	487783.9 1751854

N=201

F-stats= 4.23

R-squared=8%

*** p<0.01, ** p<0.05, * p<0.1

Table 3B: Pooled OLS Model (Males Regression Results)

Employment	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
median_wage	-558.23***	155.3015	-3.59	0.000	-864.641 -251.818
median_wage_sq	0.121082***	0.046097	2.63	0.009	0.030133 0.212031
Year					
1998	-14222.9	60319.84	-0.24	0.814	-133235 104788.8
2006	281757.8***	69427.94	4.06	0	144775.7 418740
_cons	546680.6	111948.4	4.88	0	325805 767556.1

N= 188

F-stat: 8.4%

R-squared=15.5%

*** p<0.01, ** p<0.05, * p<0.1

Table 3C: Pooled OLS Model Females Regression Results:

Employment	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
median_wage	-902.892	617.9741	-1.46	0.146	-2125.75 319.9674
median_wage_sq	0.313013	0.309223	1.01	0.313	-0.29888 0.924909
Year					
1998	-7032.06	174198.4	-0.04	0.968	-351739 337675.1
2006	180569.3	177237.2	1.02	0.31	-170151 531289.8
_cons	594005.7	286794.8	2.07	0.04	26490.63 1161521

N=152

F-stats= 1.2

R-squared=3%

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Pooled OLS Model:

In_crem1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnwage	3.196***	0.518	6.170	0.000	2.180 4.21
lnwage_aq	-0.217***	0.036	-6.040	0.000	-0.287 -0.146
round					
2006	0.289***	0.081	3.55	0.000	.1292 .448
2012	0.520***	0.088	5.94	0.000	.348 .691
Female	-0.474***	0.078	-6.08	0.000	-.627 -.321
_cons	-3.419	1.877	-1.82	0.690	-7.102 .263
crocp1d					
Professionals	0.416	0.125	3.33	0.001	.171 .662
Technicians and associate professionals	0.588	0.135	4.36	0.000	.323 .852
Clerical support workers	0.308	0.136	2.26	0.024	.041 .575
Service and sales workers	0.686	0.151	4.56	0.000	.391 .982
Skilled agricultural, forestry and fishery workers	0.841	0.285	2.95	0.003	.391 .982
Craft and related trades workers	0.437	0.145	3.01	0.003	.152 .722
Plant and machine operators, and assemblers	0.282	0.163	1.73	0.083	-.037 .602
Elementary occupations	0.886	0.190	4.66	0.000	.513 1.259
crecac1d_cl					
B: Mining and quarrying	-1.052	0.257	-4.09	0.000	-1.555 -.548
C: Manufacturing	0.566	0.187	3.03	0.003	.199 .932
D: Electricity, gas, steam and air conditioning supply	-0.624	0.226	-2.76	0.006	-1.068 -.180
E: Water supply; sewage, waste management and remediation activities	-0.422	1.840	-1.84	0.066	-.871 .028
F: Construction	0.182	0.217	0.84	0.400	-.242 .607
G: Wholesale and retail trade; repair of motor vehicles and motorcycles	0.158	0.199	0.79	0.427	-.233 .549
H: Transportation and storage	0.031	0.209	0.15	0.881	-.378 .440
I: Accommodation and food service activities	-0.749	0.228	-3.28	0.001	-1.197 -.302
J: Information and communication	-0.151	0.218	-0.69	0.489	-.579 .277
K: Financial and insurance activities	-0.242	0.223	-1.08	0.279	-.680 .196
L: Real estate activities	-2.355	0.671	-3.51	0.000	-3.670 -1.039
M: Professional, scientific and technical activities	-0.409	0.239	-1.71	0.088	-.878 .060
N: Administrative and support service activities	-0.890	0.274	-3.24	0.001	-1.428 -.352
O: Public administration and defense; compulsory social security	0.823	0.190	4.33	0.000	.450 1.195
P: Education	0.532	0.200	2.67	0.008	.140 .923
Q: Human health and social work activities	0.323	0.204	1.58	0.114	-.077 .724
R: Arts, entertainment and recreation	-0.664	0.231	-2.88	0.004	-1.117 -.211
S: other service activities	0.131	0.235	0.56	0.578	-.329 .591
T: Activities of extraterritorial organizations and bodies	0.237	0.377	0.63	0.529	-.502 .975

U:Activities of extraterritorial organizations and bodies	-2.836	0.672	-4.22	0.000	-4.154	-1.520
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Number of obs = 1,544
 Prob > F = 0.0000
 F(33, 1510) = 12.32
 R-squared = 0.2122
 Adj R-squared = 0.1949
 *** p<0.01, ** p<0.05, * p<0.1

Table 5: Random Effects Model:

In_cremp	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
lnwage	6.539***	2.315	2.820	0.005	2.001 11.077
lnwage_aq	-0.461***	0.170	-2.710	0.007	-0.794 -0.128
Female	-1.204***	0.232	-5.190	0.000	-1.658 -0.749
_cons	-11.860	7.903	-1.500	0.133	-27.351 3.632

Number of obs = 251
 R-Square: overall = 0.1633
 Wald chi2(3) = 48.22
 Prob > chi2 = 0.0000
 *** p<0.01, ** p<0.05, * p<0.

Table 6: LM Test

Breusch and Pagan Lagrangian multiplier test for random effects

	Var	sd = sqrt(Var)
ln_cremp	3.433	1.853
E	3.341	1.828
U	0.000	0.000
Test: Var(u) = 0		
chibar2(01) = 0.00		
Prob > chibar2 = 1.0000		

Table 7: Fixed Effects Model

In_crem	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnwage	7.615*	3.852	1.980	0.051	-0.0335511 15.26271
lnwage_aq	-0.518*	0.279	-1.850	0.067	-1.072532 .0366383
Female	0 (omitted)				
_cons	-17.039	13.309	-1.280	0.204	-43.46344 9.385337

Number of obs = 251
R-squared overall = 0.0718
F(2,94) = 2.64
Prob > F = 0.0764
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Hausman Test

---- Coefficients ----				
	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lnwage	7.614	6.539	1.075	3.078
lnwage_aq	-0.518	-0.461	-0.057	0.222
b = consistent under Ho and Ha; obtained from xtreg B = inconsistent under Ha, efficient under Ho; obtained from xtreg Test: Ho: difference in coefficients not systematic chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 0.89 Prob>chi2 = 0.6400				