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Impact of Technological Growth on Unemployment Development: A Time Series Analysis of Bahrain Economy

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Abstract - Fears existed before or during technological pushes, and that despite the continuous transformation of our societies due to the introduction of new technologies, the population explosion of the past two centuries has been mirrored by a similar creation of new jobs. It is then interesting to consider how these new jobs have been created when they have been created, and what mechanisms facilitated their increase. Therefore, the current study aims to analyze the effect of the extent of the technology growth on the unemployment in the Kingdom of Bahrain. The study used the secondary data for the last 18 years which was taken from government data streams as well as the World Bank. The unemployment used as a dependent variable and technological growth and labour force participation taken as independent variables, however, education used as a moderator variable in the current study. The study applied the ADF unit root test for stationary analysis and Johansen and Jusilious co-integration test was applied for further analysis because all the variable was stationary at level 1. The findings show that the three variables have a significant negative effect on unemployment. Thus, the study recommended that the government should spend more to improve the technology as well as provide more opportunities to educate the people related to relevant skills of those technologies.

Keywords: Technological growth; unemployment; labour force participation; education; Jusilious co-integration

INTRODUCTION

Ever since the first Industrial Revolution in the late 18th century, new technologies have been viewed ambiguously, while some welcome the prospect of increased productivity and the potential of improved wealth, there similarly exists considerable opposition, especially by those who stand to lose of a change in the status quo. Notably, this opposition is from all ages: whereas it is most commonly known from the Luddite rebellion of 1811-1816, predictions that technological progress will make humans redundant have been made regularly. In the 1920s the New York Times claimed that the 'March of the machines makes idle hands', in the 1930's Keynes coined the term technological unemployment, in the 1960's President Kennedy declared that automation is replacing men, and also in the 80s there were fears that computers would result in job losses (Economist, 2017).

This dichotomy in the perceptions of technological advancements still exists today, with considerable and increasing coverage of the impact of artificial intelligence (AI), machine learning (ML), robotization and other aspects of the current technological progress. Illustratively, CEO of SpaceX, Tesla and Neurolink Elon Musk has stated that "Robots will take your jobs", Bill Gates, founder of Microsoft, the largest software company in the world, claimed that robots that steal jobs should pay taxes, and also renowned physicist Stephen Hawking argued that AI 'will automate middle-class jobs' (Larson, 2017).

Supplementing these anecdotes, numerous papers indicate that automation and digitalization threaten an increasing number of jobs, with a widely cited paper stating that up to 47% of jobs in developed economies are threatened in the

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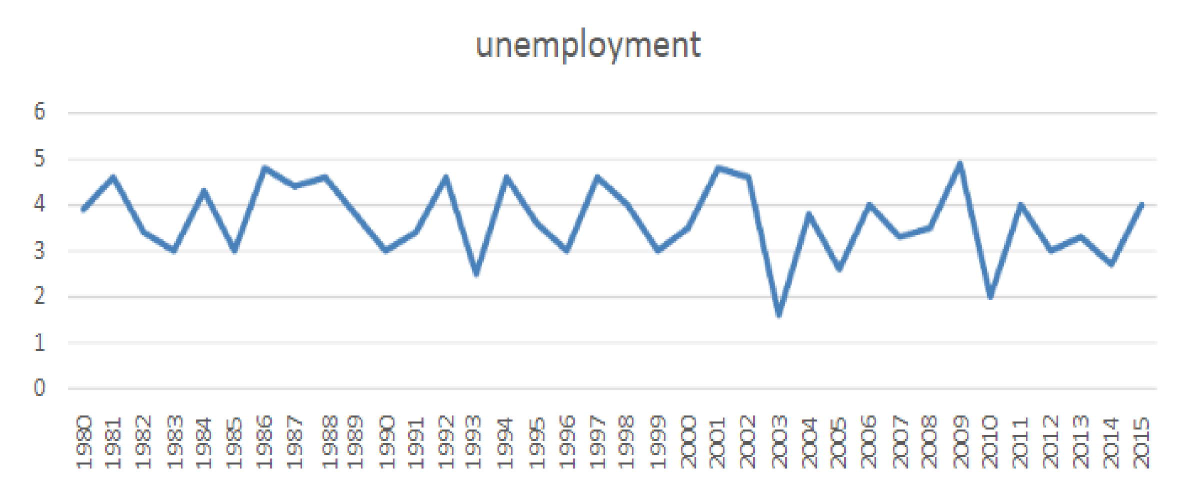
foreseeable two decades (Frey and Osborne, 2013). Yet there is considerable disagreement in the literature as well as amongst economists and economic historians as to the future of employment and the supposedly negative impact of technology or technology growth: several papers point out how similar fears existed before or during technological pushes, and that despite the continuous transformation of our societies due to the introduction of new technologies, the population explosion of the past two centuries has been mirrored by a similar creation of new jobs (Mokyr, Vickersand and Ziebarth, 2015). It is then interesting to consider how these new jobs have been created when they have been created, and what mechanisms facilitated their increase.

Moreover, whereas there is extensive literature on the impact of technological progress on labor dynamics, a considerable proportion of this is theoretical, with fewer recent papers empirically assessing the impact of technological progress on the labor market. One of the reasons for this is that it is difficult to measure technological progress, necessitating the use of imperfect proxies. These have included computer diffusion, research and development expenditure, or patents, commonly aggregating technological developments by operationalizing one, or a number of aggregated proxies.

Unemployment has always been a focus area in labor economics research. Researchers in the past have attempted to find the determinants of unemployment through various methodologies. For example, Maqbool et al. (2017) find that population, foreign direct investment, and inflation have a significant effect on unemployment in the long run. In addition, they find an inverse relationship between unemployment and inflation, suggesting the existence of the Phillips curve at play both in the short- and long-run. Maki and Spindler (2017) look at the post-1966 increase in measured unemployment rates in the United States and find that a large part of unemployment changes is due to the changes in unemployment benefits. Political factors come into play as well.

The second employment effect, coined by Schumpeter as 'creative destruction effect,' captures a positive relationship between technological progress and unemployment (Aghion and Howitt 1994). It highlights that the new capital will only be employed by newly created jobs, and therefore suggests that technological progress requires a transition of workers to new firms, creating lower job creation and higher job destruction flows resulted from labor reallocation (Boianovsky and Trautwein 2017). Which one of the abovementioned theoretical effects will dominate is unclear, and will be explored further in later sections through empirical research. With the inconclusive effects presented by theoretical models aside, however, the media has frequently reported and portrayed the direct, often destructive effect of technological advancement on workers ever since the first Industrial Revolution, during which spinning machines became a competitive force to human labor.

As a prominent example, the Luddite movement in the 19th century was centred around a group of English textile artisans and weavers, who feared being replaced in the industry, and protested the automation of textile production by destroying weaving machines (Skidelsky, 2014). More recently, scholars have been concerned with the popularity of computers and their potential ability to replace a significant portion of existing jobs. For example, Brynjolfsson and McAfee (2016) predict that rapid digitization brings economic disruption by eliminating companies' needs for some kinds of workers. Acemoglu and Restrpo (2016) propose the relationship to be a "stable balanced growth path in which the two types of technology growths go hand in-hand; an increase in automation reduced the cost of producing using labor, and thus discourages further automation and encourages the faster creation of new complex tasks.



Source: World Bank Country Data (2016)

Figure 1: The unemployment rate in Bahrain from 1980-2015

The importance of education for economics mainly stems from its ability to create and/or accumulate human capital and increase the aggregate productivity level of the economy (Bogetoft et al., 2017). Thus, as productivity level increases, the economy can produce more and more efficiently. These effects of human capital have led countries to invest in education and the number of educational institutions and the student population worldwide has risen dramatically. However, in order to optimally benefit from human capitals' productivity and production enhancing effects, the created human capital should be employed. But in the present conditions, it is almost impossible for all graduates to find employment as labour markets in many countries are unable to accommodate this large group of skilled labour force thus labour force participation is decreasing as time passing on. This is due to a failure in many countries to closely link the educational system to the needs of the labour market and to the large numbers of youth now reaching working age. Hence, each graduate becomes a potential member of the army of jobless and can increase the unemployment rates. In addition, the use of higher education by governments as a tool for solving labour market problems has caused the unemployed labour force to rise. The main idea behind this approach is that, if unemployment rates or the tension in the abour market are too high in an economy, they can be easily decreased by pulling idle workforce back into the university system (Plümper, Troeger and Manow, 2017).

Therefore, the importance of labour force participation has become more important for all countries especially for developing countries like Bahrain. Bahrain has over time experienced a growing number of its population being unemployed (The World Bank, 2016). From the data got from the World Bank website, the following trend line shows the patterns of unemployment in Bahrain since the year 1980 to 2015. The trend line above shows the unemployment trend in Bahrain for the year 1980 to 2015. From the trend line, it can be seen that in early 2000, the unemployment rate was declining. However, around 2005, it shot up, then down toward 2006, and then shot up for the first time high during the period of the study to about 5.6 per cent. It has since declined but has been oscillating as shown by the spikes.

Unemployment in Bahrain has over time been at low rates even though it has been fluctuating. Several studies have looked into the possible factors affecting unemployment in Bahrain (Boyce, Wood and Brown, 2012; Bogdan, 2014). Among the leading factors that different studies have fronted by these studies are the education level, economic growth, the openness of the economy to trade with external markets, and the level of technology in the country. This study appreciates the findings of these studies but will use a mixed approach to bring forth the macro and microeconomic variables in understanding the unemployment issue in Bahrain. The mixed approach will entail reliance on both secondary time series data and primary time-series data.

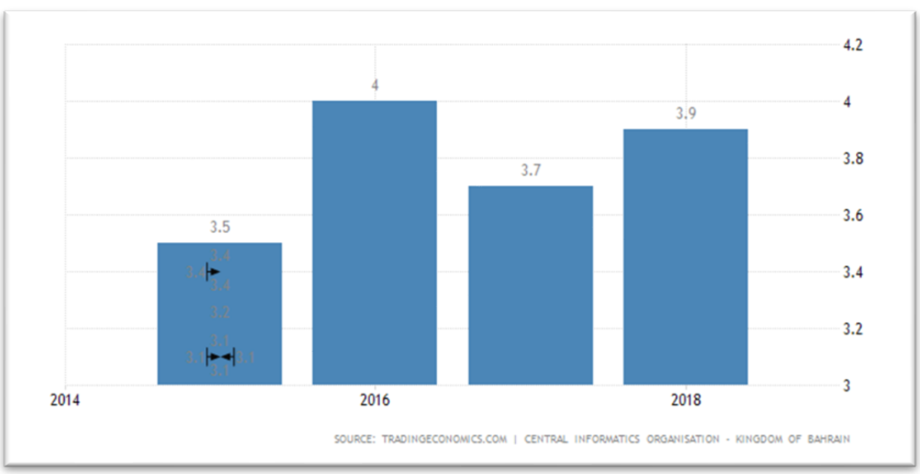


Figure 2: The unemployment rate in Bahrain from 2014-2018

Unemployment Rate in Bahrain increased to 3.90 per cent in 2018 from 3.70 per cent in 2017. Unemployment Rate in Bahrain averaged 4.09 per cent from 2006 until 2018, reaching an all-time high of 16 per cent in 2006 and a record low of 3.10 per cent in 2015. Therefore, the current study has the following objectives, 1) To analyse the extent of unemployment in the Kingdom of Bahrain, 2) to analyse the effect of technological growth on unemployment in the Kingdom of Bahrain. 3) to analyse the effect of labour force participation on unemployment in the Kingdom of Bahrain and lastly, 4) to analyse the moderating effect of education between technology growth and unemployment in the Kingdom of Bahrain.

LITERATURE REVIEW

Bahrain has over time experienced challenges in employment. Youth unemployment remains a major long-term economic challenge. Despite this, Bahrain has maintained economic resilience and continues to be a regional leader in economic freedom. The kingdom's challenging transition to greater openness, diversification, and modernization continues (Alrayes & Wadi, 2018). There are a number of factors that are expected to affect unemployment in Bahrain. These include economic growth, total investment, total government expenditure, and inflation.

Economic Growth and Unemployment

Gross Domestic Product (GDP) is the money value of all goods and services produced in a given period of time. It is expected that when the GDP of a country increases, more employment opportunities are created. By pursuing policies that affect GDP, the country is, in essence, pursuing the unemployment challenge (Alrayes & Wadi, (2018). Economic growth, methinks, is a determinant of unemployment. The policy implications are that countries that want to dress the unemployment problem must target GDP grow policies. The author concludes that the relationship between GDP and unemployment is negatively related. There is a significant relationship between economic growth and the unemployment rate in Bahrain. When the national income increases, firms respond by increasing the supply of goods and services. As this occurs, more labor units are demanded so as to take part in the production of increased production demands. Thus, GDP and unemployment are negatively related (Abrar ul Haq, Akram, Ashiq, & Raza, 2019). Other policies to promote employment through pursuing economic growth policies include the employee training which would ensure that the country at any one time has sufficient pool of employees (Hanlon, 2019). The economy should also be open to trade to the external world to promote trade through increasing export demand which enhances the growth of the economy (Abrar ul haq, Jali, & Islam, 2019). It is also important that all the growth policies as suggested in the literature be pursued including promoting basic and intermediate level education among and pursuing policies to attract foreign direct investment (Waqas et al., 2017). All these would ensure there is a flow to capital by enhancing economic growth which is an important channel through which employment can be promoted (Alrayes & Wadi, 2018).

Technological anxiety and the labour market

As the anecdotes from the introduction illustrate, there has been increasing interest in the impact of technological progress on our societies; while recent decades have seen the introduction of numerous technological devices and technology growths in our daily lives, the societal impact of these technologies has been significant, but relatively gradual. While this initially was reflected by the introduction of widespread consumption goods such as increasingly powerful phones and computers, there is growing concern that the current technological progress will not just supplement our daily lives, but increasingly will substitute for human labor (Murtaza, Abrar Ul Haq, & Ali, 2015).

Indeed, Frey and Osborne, in a widely cited paper by both scholars as well as the mainstream media, assessed the likeliness of jobs in the U.S. being automated, particularly considering the recent advances in Machine Learning and Mobile Robotics (Frey & Osborne, 2013). Notably, controlling for education, wages and in particular the requirements of job descriptions they argue that 47% of jobs in the U.S. are susceptible to automation (Idem, 2013). Replicating their methodology, Pajarin and Rouvinen (2014), argue that 35% of jobs in Finland are susceptible to automation. Similarly reproducing this methodology for more European countries Bowles (2014) found that 45% to 60% of the jobs in European countries are at risk of being substituted in the coming two decades (Bowles, 2014).

Hence, the potential for automation to substitute laborers and its supposedly increasing threat towards the foundation of industrial societies seems substantial, and therefore important to consider. Yet it should be noted that there is no consensus on the impact of technology on future employment, with statements regarding the risk of automation and their actual substitution requiring critical evaluation (Abrar Ul Haq, Jali, & Islam, 2018).

Indeed, weakening some of Osborne and Frey's (2013) as well as Bowles (2014) assumptions, Arntz, Gregory and Zierahn (2016) argue that in the OECD on average only 9% of the jobs is automatable. They argue that it is important to consider heterogeneity within occupations, rather than purely focusing on the description of the jobs as a homogenous unit (Arntz, Gregory and Zierahn, 2016). It appears then that the impact of technology on future employment is difficult to estimate, especially when considering that not only the direct effects on employment but also the indirect effects in the form of compensation mechanisms should be accounted for when assessing the impact of technology on employment (Bhatti et al., 2016).

In order to guide our understanding of current technological processes and their impact on the nearby future, it warrants assessing the economic past, potentially providing guidance as to how to best address with the issues we face today (Rehman, Ullah, & Abrar-Ul-Haq, 2015). After all, the microeconomic theory proposes that labor-replacing capital is introduced for the simple fact that it is cheaper than the labor it replaces. Yet, despite the ever-increasing quantity and quality of capital due to technological progress since the industrial revolution, there still is full employment. Moreover, if anything, the industrial revolution and its aftershocks have supplemented our lives, contributed to increasing standards of living all around the world and have boosted the overall development of society (Qasim, Abrar ul Haq, Hussain, & Roshan, 2018).

It is then important to consider how technological progress has been influencing society and labor markets in the past. Doing so allows us to understand whether the current technological progress in the form of digitalization, automation and robotization represent a break from the past similar to the first industrial revolution or is a continuation of trends manifested in a new form.

Technological Progress and Societal Impacts: Labor Substitution

Following the post-WWII 'Golden Age of Capitalism', the end of the 70s heralded a different economic era: after the numerous shocks to the global economy, Western income structures experienced a substantial widening of the wage inequality, particularly so during the 80s (Autor, Katz and Kearney, 2006). This increasing wage inequality has been reflected in widening wealth inequality as well, resulting in a number of papers assessing the 'squeeze', 'hollowing' or 'decline' of the middle classes, for the U.S. Pressman (2017) similar to papers on the EU and a number of other cross-country comparisons (Piketty, & Saez, 2018).

While the actual definition of the middle classes is open to interpretation – one could measure it using wealth (Piketty, & Saez, 2018), income, or other variables such as health or education (Putnam 2015), Pressman in a comprehensive overview maintains that the middle class has indeed decreased in a number of developed countries, including the U.S. While observing that for some industrialized countries their middle class actually prospered (e.g. France since the 80s) or underwent relatively few changes (e.g. Italy and Norway), he notes that these are exceptions and that there is a negative trend in OECD countries (Pressman, 2017; Ullah, Abrar-ul-haq, & Shah, 2016).

This 'decline' of the middle classes are difficult to attribute to one particular factor and concurrent with a number of global trends; yet there is a general consensus in the literature that this primarily can be attributed to 1) globalization and 2) technological change. Both factors are important, and difficult to completely separate (e.g. technological progress is one of the factors that facilitate globalization due to the introduction of communication technologies that allows for outsourcing and offshoring) (Malik, H. A. M., Mahmood, Usman, Rziwan, & Abid, 2019). While also the impact of globalization on labor markets is important to consider, this paper focuses primarily on the impact of technological progress on employment and our very societies (Shah, Abrar Ul Haq, & Farooq, 2015).

Skill Biased Technical Change

As referred to above, recent decades have seen an increase in interest in the decline of the middle classes. Notably, this has been attributed to several potential causes and has been related to a number of other trends that have proliferated over the past forty years. These include decreasing blue-collar occupations, changes in the supply of college and non-college- educated employees, offshoring and outsourcing, declines in labor union membership, as well as the biting impact of automation (Autor, 2015). While several of these trends and processes interact, automation arguably is one of the fundamental processes underlying these phenomena (Autor, 2015; Shah, Shahzad, & Abrar Ul Haq, 2015).

Indeed, concurrent with an academic interest in the 'hollowing' middle classes, there has been considerable growth of literature on the concept of skill-biased technical change (SBTC). This notion of skill-biased technical change implies that further increases of technology result in higher overall economic output, but simultaneously decrease the demand for certain types of labor, depending on the skill level of the employees (Autor, Levy and Murnane 2003). This is generally associated with an increasing skill-premium, a stagnation of low wages and widening wage-polarization (Hemous and Olsen, 2016).

While there are sub-strands in the SBTC literature, the theory is grounded on the notion that skilled workers are more capable of adapting to technological change, and are thus less likely to be replaced by it. Vice versa, low-skilled laborers are less capable of adapting to technological change, are more likely to perform simple tasks, and are therefore more susceptible to the risks of automation (idem) (Akram, Abrar Ul Haq, & Umrani, 2019). Thus, proponents of SBTC consider high- skilled labor and capital as complementary, but low-skilled labor and capital as substitutes, and therefore argue that due to technologically driven decreases in the price of capital, low- skilled labor has become less competitive compared to capital (Hemous and Olsen, 2016).

Routine/ Task Biased Technical Change

Proponents of the routine biased model assess the content of tasks in more detail, classifying them not only according to their skill level (low, medium and high) but also on their complexity (Acemoglu and Autor, 2011).3 An important aspect of this framework is the so- called 'routineness' of jobs, which they argue is an important indicator of jobs substitutability by technology (Autor, Levy and Murnane, 2003). Indeed, Autor, Levy and Murnane's framework is grounded on the notion that technologies are more likely to substitute tasks that involve limited, straightforward and well-defined tasks, both cognitive and manual, and that can be completed while adhering to explicit rules (Akram et al., 2017).

They moreover state that technology complements tasks that are less well defined, require more interpretive or creative actions, and are thus more difficult for computers to do, relative to the price of labor (idem, 2003). Expanding on these more basic papers, David Autor and Daron Acemoglu propose a model that further expands on this: they offer five task measures for jobs, allowing researchers to categorize occupations accordingly: 1) routine cognitive (e.g. accounting), 2) routine manual (e.g. manufacturing), 3) non-routine cognitive analytical (e.g. sales, medical), 4) non-routine manual (e.g. janitorial services), and, non-routine cognitive interpersonal (e.g. managerial), (Autor and Acemoglu 2011).

Technological Progress and Employment

There have been a number of studies that have evaluated the link between technology growth and employment. This relationship, however, is complex, difficult to adequately measure, and therefore has large variety with regard to the scope of studies (micro- vs. macro-data; on the local, regional or national level; differing econometric models, amongst other factors) as well as varying proxies for technology growth. Unsurprisingly then, there is considerable contention in the literature as to the exact specificity of this relationship. Illustratively, the impact of technology growth depends on a number of factors, notably including institutional mechanisms, which differ at the micro-, and macro- level, and vary in different economic contests due to the diverging enforcement of Intellectual Property Right (IPR) laws and employment protection in the form of labor laws (Vivarelli, 2014). While a number of macroeconomic studies have evaluated this link, these were mainly done in the 80's and 90's, generally finding that a positive impact of innovation on employment. While a number of macroeconomic studies have evaluated this link, these were mainly done in the 80's and 90's, generally finding that a positive impact of technology growth on employment depended on sufficient elasticity of demand, and were moreover largely conditional on the respective institutional structures (Layard and Nickell 1985; Vivarelli, 2014). Seeking to assess this relationship more directly, more recent papers have utilized the increasing availability of data with a micro econometric approach, taking the firm as the level of analysis. Notably, Lachenmaier and Rottmann utilized a dynamic employment equation of German manufacturing firms over the period 1982-2002, with their estimates suggesting positive impacts of technology growth on jobs (Lachenmaier and Rottmann, 2011).

Similarly, using micro data from 15.000 French firms in the manufacturing sector, Greenan and Guellec suggest that innovating firms (as designated through a survey) create more jobs than no innovative firms – an effect which however disappeared when controlling for the socalled 'business-stealing effect' (Greenan and Guellec, 2000). This is the notion that supposedly positive effects of technology growth often also have a negative effect on business in the same sector due to changing relative competitiveness, with more innovative firms growing their market share at the costs of others, resulting in overall small net positive effects on employment (Vivarelli, 2014). This is one of the reasons why a sectorial level of analysis is arguably more appropriate, as it better accounts for the business-stealing effect – and thus the effect of both product and process technology growths – facilitating a more comprehensive understanding of the impact of technology growth on employment, including also the compensation mechanisms and indirect effects discussed above.

Yet also when assessing literature that considers industrial sectors as the unit of analysis the results are ambiguous, with different regions, time periods and proxies of technology growth giving different results. Pianta (2000) as well as Antonucci and Pianta (2002) for example evaluate the impact of technology growth on employment in manufacturing sectors in Europe, finding that technology growth generally has a negative impact on overall employment. This is however countered by a similar analysis from Boglaciano and Pianta, who find a positive impact of technology growth on employment for both services and manufacturing in a sample of 8 European countries (Boglaciano and Pianta, 2010). In another study, Boglaciano and Vivarelli, using R&D expenditures as a proxy for technology growth, find that for the period 1996-2005 in 16 countries there is a positive effect of technology growth on employment. Notably then, while an assessment of the literature that investigates the empirical effect of technology growth on employment is inconclusive, a number of notable aspects can be derived: the data used, the time period considered and features such as regional and institutional factors are relatively similar in this literature, and lend themselves to further empirical analysis. Indeed, the data and methodology of the papers using sectors as the unit of analysis are quite similar: they use a variant of the Generalized Method of Moments (GMM) methodology, generally selecting the variant of the system over the differences variant (Boglaciano and Vivarelli 2012; Piva and Vivarelli 2003, 2005; Akram, Abrar ul haq, & Raza, 2018).

The previous literature presented the delve analysis on the study variable such as technological growth and employment. The prior literature presents the mix findings about the relationship of abovementioned study variables where few studies reveal positive relation and other unfolded vice versa. Therefore, more empirical examination of the study variables is required in order to determine the relation especially in the context of Arab countries like Kingdom of Bahrain.

Conceptual Framework

Based on the immense and thorough discussion regarding study variables following is the conceptual framework of the current study:

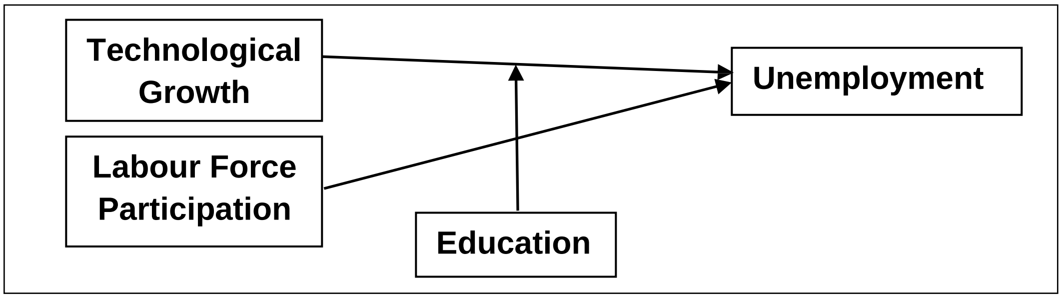


Figure 3: Conceptual Framework

Unemployment is a situation wherein people are willing to work but unable to find suitable work to earn for their living. Unemployment is a global phenomenon that is prevailing and of course, Bahrain is not spare of that phenomenon. The problem of unemployment has been clearly addressed in the problem statement section that provides ample evidence about the unemployment in the Kingdom of Bahrain. In addition to this, prior theory identified several predictors of unemployment in an economy however, technological growth and labour force participation is among the most crucial that may curtail or boost the unemployment in the presence or non-presence of the education. Therefore, Figure 3 shows the conceptual framework of the current study that has deep roots in the established theories of economics and has been empirically investigated.

Research Hypothesis

H01: There is no significant effect of technological growth on unemployment in the Kingdom of Bahrain.

H02: There is no significant effect of labour force participation on unemployment in the Kingdom of Bahrain?

H03: There is no significant moderating effect of education between technology growth and unemployment in the Kingdom of Bahrain.

METHODOLOGY

The data can be gathered via Primary or Secondary Source, where Primary Source is where the researcher is the first/primary individual to acquire the data via multiple means, whereas the Secondary source is where the researcher acquires data that has been collected/obtained by others (Mesly, 2015). While using time-series analysis we have acquired secondary data one which relates to the past, where secondary data is nothing but just the analysis and interpretation of the primary data. The major secondary data collection sources are government publications, websites, books, journal articles etc. Therefore, data (unemployment, technological growth, labor participation) for the study have been extracted from data stream repository, government data bank, ministry of finance and national economy (Bahrain) and World Bank data.

Econometric Model

The Research to further proceed, it is necessary to first define the chosen methodological model upon which this study is built. Which it is necessary to consider while choosing the research philosophy: this approach is employed to conduct the secondary research and the way the research was conducted on the collected data. The current study developed the model of unemployment rate in relation with technological growth and labor participation rate in country.

$$\boldsymbol{Unemploymentrate_t} = \boldsymbol{\beta_{0t}} + \boldsymbol{\beta_{1t} TecnologicalGrowth} + \boldsymbol{\beta_{2t} LabourParticipationRate} + \boldsymbol{\beta_{2t} TecnologicalGrowth * education} + \mu_t$$

Where, the unemployment is affected by threevariables (technological growth, labour participation and technological growth*education) and an error term. The error term represent all the factors that affect the unemployment however, not considered in current research model. As per our econometric model, the study identified the hypothesis that consists of two independent variables that effect the most the unemployment in the country.

Unemployment Rate

Unemployment occurs when people are without work and are actively seeking employment. In an economy, the labor force is the actual number of people available for work. Economists use the labor force participation rate to determine the unemployment rate. The unemployment rate is calculated by expressing the number of unemployed persons as a percentage of the total number of persons in the labour force. The labour force (formerly known as the economically active population) is the sum of the number of persons employed and the number of persons unemployed.3 Thus, the measurement of the unemployment rate requires the measurement of both employment and unemployment. In current research, the unemployment rate is calculated as follows:

$$Unemploymnet\ rate = \frac{personunemployed}{Labourforce} * 100$$

Technological Growth

A common measure of technological progress (the one used in this graph) is growth in total factor productivity (TFP). This is the relative efficiency with which an economy produces goods and services given a certain quantity of labor and capital. The current research will take a proxy of government spending on technology over the time period to measure the technological growth in Bahrain.

Labour Participation rate

The labour force participation rate is a measure of the proportion of a country's working-age population that engages actively in the labour market, either by working or looking for work; it provides an indication of the size of the supply of labour available to engage in the production of goods and services, relative to the population at working age. The breakdown of the labour force (formerly known as economically active population) by sex and age group gives a profile of the distribution of the labour force within a country. The labour force participation rate is calculated by expressing the number of persons in the labour force as a percentage of the total population in the country. The labour force is the sum of the number of persons employed and the number of persons unemployed. Thus, the measurement of the labour force participation rate requires the measurement of both employment and unemployment. In current research, the unemployment rate is calculated as follows:

$$LabourParticaptionRate = \frac{LabourForceofthecountry}{Totalpopulationofthecountry} * 100$$

Education

Education is the process of facilitating learning, or the acquisition of knowledge, skills, values, beliefs, and habits. Educational methods include teaching, training, storytelling, discussion and directed research. The data is extracted and compared with the data from multiple sources such as statistical website, government data bank and World Bank. The data was cleaned and transformant into an appropriate format ready for processing.

Data Processing and Statistical Treatment of Data

The current study applied either ARDL or Regression Model for empirical analysis and this is totally depended on the assumptions whether the extracted date is stationary or not through. As we are using time series data for the identified employment factors hence we will be checking the stationary of data at first place by using ADF unit root test. Considering the level and order of the stationary of data (0 order, 1stdeference or 2nddeference) to choose the appropriate econometric model. If after carrying out the unit root test the data is stationary at 0 order, then regression analysis is suitable of current data, else if some variable get stationary at level and some get stationary at 1st difference then ARDL Model is suitable, however, the co-integration method is perfect if all the variables get stationary at 1st difference. In current study, all variables are non-stationary at level, however, stationary at first difference. So, when all variables of a model are stationary at first difference or integrated at level one then suitable technique to estimate the model is Johansen and Jusilious co-integration test.

RESULT AND DISCUSSION

The results of ADF unit root test depict that all the variables are non-stationary at level but stationary at first difference. Therefore, we used Johansen and Jusilious co-integration test for current analysis to analyze the impact of technological growth, labor participation rate on unemployment rate along with moderating role of education between technological growth, and unemployment rate. The results of the unit root test and Johansen and Jusilious co-integration testare as follows:

Table 1: *ADF Unit Root Test employment*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.072198	0.0265
Test critical values:	1% level	-4.616209	
	5% level	-3.710482	
	10% level	-3.297799	

Null Hypothesis: D(UN_EMPLOYMENT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)
*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations

Table 2: *ADF Unit Root Test for Labour Force Participation*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.327977	0.0953
	1% level	-4.616209	
Test critical values:	5% level	-3.710482	
	10% level	-3.297799	

Null Hypothesis: D(LABOUR_FORCE_PARTICIPATI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

Table 3: *ADF Unit Root Test for Technological Growth*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.994159	0.0305
	1% level	-4.616209	
Test critical values:	5% level	-3.710482	
	10% level	-3.297799	

Null Hypothesis: D(TECHNOLOGICAL_GROWTH) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

Table 4: *ADF Unit Root Test for Education*Technological Growth*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.351120	0.0917
	1% level	-4.616209	
Test critical values:	5% level	-3.710482	
	10% level	-3.297799	

*MacKinnon (1996) one-sided p-values.
Null Hypothesis: D(EDUCATION* TECHNOLOGICAL) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

In statistics and econometrics, an augmented Dickey–Fuller test (ADF) tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is used, but is usually stationarity or trend-stationarity. It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models.The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence.
Considering the ADF Unit root test, the current findings of table 1 shows that the unemployment rate is stationary at first difference 1(1) as t-statistic value is -4.072198 with 0.0265 probability value. Similarly, the labor force participation is also stationary at first difference as its t-statistic value is -.327977 with 0.0953 probability value. Moreover, the technological growth is stationary at fist difference with -3.3994159 t-value and 0.0305 probability value. Lastly, the education and technological growth is stationary at first difference as the t-value is -3.351120 and probability value is 0.0917.

Table 5: Max and Trace Eigenvalue (Co-integration analysis)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.830471	65.68880	47.85613	0.0005
At most 1 *	0.674066	35.51832	29.79707	0.0098
At most 2 *	0.440033	16.46028	15.49471	0.0357

At most 3 *	0.321841	6.602355	3.841466	0.0102

Trace test indicates 4 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.830471	30.17047	27.58434	0.0227
At most 1	0.674066	19.05805	21.13162	0.0952
At most 2	0.440033	9.857923	14.26460	0.2214
At most 3 *	0.321841	6.602355	3.841466	0.0102

Table 6: *Long Run and Short Run Relationship*

Cointegrating Eq:	**CointEq1**
_UN_EMPLOYMENT(-1)	1.000000
TECHNOLOGICAL GROWTH(-1)	-3.60E-07 (1.3E-07) [2.67302]
EDUCATION* TECHNOLOGICAL GROWTH (-1)	-3.969685 (1.31437) [3.02021]
LABOUR_FORCE_PARTICIPATI(-1)	-6.187585 (1.93256) [-3.20176]
C	130.0686

Error Correction:	**D(Un_Employment)**	**D(Education* Technology)**	**D(Technology growth)**	**d(Labour_force_participati)**
CointEq1	-0.022240 (0.04598) [-0.48364]	-0.089551 (0.01964) [-4.55906]	-169271.8 (526186.) [-0.32170]	0.003822 (0.03397) [0.11250]
D(_UN_EMPLOYMENT(-1))	-0.171733 (0.28243) [-0.60806]	0.034317 (0.12064) [0.28446]	-5329294. (3231751) [-1.64904]	0.065741 (0.20863) [0.31511]
D(EDUCATION(-1))	-0.609046 (0.39242) [-1.55203]	0.174496 (0.16762) [1.04100]	1571284. (4490370) [0.34992]	0.235910 (0.28988) [0.81383]
D(GOVT_SPENDING_ON_TECHNOL(-1))	-7.28E-09 (2.8E-08) [-0.26407]	6.40E-09 (1.2E-08) [0.54368]	0.063667 (0.31541) [0.20185]	2.86E-08 (2.0E-08) [1.40460]
D(LABOUR_FORCE_PARTICIPATI(-1))	-0.094163 (0.55695) [-0.16907]	-0.185640 (0.23791) [-0.78031]	-851089.4 (6373102) [-0.13354]	0.362385 (0.41142) [0.88082]
C	0.221830 (0.30633) [0.72416]	0.579223 (0.13085) [4.42660]	-289230.6 (3505259) [-0.08251]	0.054350 (0.22628) [0.24019]
R-squared	0.210043	0.831831	0.282666	0.331046
Adj. R-squared	-0.149029	0.755390	-0.043395	0.026976
Sum sq. Resids	4.878218	0.890096	6.39E+14	2.661904
S.E. equation	0.665939	0.284461	7620214.	0.491926
F-statistic	0.584961	10.88207	0.866910	1.088718
Log likelihood	-13.51027	0.949977	-289.8091	-8.361497
Akaike AIC	2.295326	0.594120	34.80107	1.689588
Schwarz SC	2.589401	0.888196	35.09515	1.983663

Mean dependent	-0.070588	0.610597	740167.2	0.343294
S.D. dependent	0.621253	0.575156	7460067.	0.498699
Determinant resid covariance (dof adj.)		1.18E+11		
Determinant resid covariance		2.06E+10		
Log likelihood		-298.3585		
Akaike information criterion		38.39512		
Schwarz criterion		39.76747		

Cointegration tests analyze non-stationary time series processes that have variances and means that vary over time. In other words, the method allows you to estimate the long-run parameters or equilibrium in systems with unit root variables (Rao, 2007). Two sets of variables are cointegrated if a linear combination of those variables has a lower order of integration. For example, cointegration exists if a set of I(1) variables can be modeled with linear combinations that are I(0). The order of integration hereI(1) tells you that a single set of differences can transform the non-stationary variables to stationarity.This implies that variables will move closely together and will not drift arbitrarily over time and the distance between them will be stationary. The concept of cointegration mimics the existence of a long-run equilibrium relationship to which the variables converge over time. In current study, the table 6 shows the Max and Trace eigenvalue values which indicate that there is cointegration among variables.

In current study, the co-integration findings of table 6 shows that the technological growth has negative impact on unemployment of the country as the co-integration values is -3.60E- 07 which is statistically significant with t-value of 2.67302. The result is in line with the various previous studies such as Autor (2015) found that there is no long-run increase in unemployment caused by technological progress but changes in technology affect the types of jobs available. Some people (according to their occupation's probability of computerization) are at a high, medium or low risk (Frey and Osborne 2017). Furthermore, Brynjolfsson and McAfee (2011) also acknowledge ideas about the deep changes that computerization is bringing but, as the authors note, these changes can become more valuable because people who had the wrong skills now can find more valuable skills and be more desirable for employers. Marcolin et al. (2016) came up with the similar findings and proved that technological innovation has a positive effect on employment.

This research also indicated that the education is significantly moderating the relationship between technological growth and unemployment of the country as the co-integration values is -3.60E-07 which is statistically significant with t-value of 2.67302. This result is also coherent with the prior literature like Schomburg (2000) assesses the relationship between higher education and unemployment in Germany and states that, in general, the expansion of higher education was accompanied by a growing problem of graduate unemployment. Woodley and Brennan (2000) consider the higher education and unemployment nexus in the UK and showed that the rapid expansion of higher education coincided with the economic recession of the early 1990s, producing a rise in graduate unemployment and a decrease in permanent employment. Mora et al. (2000) analysed the higher education and unemployment issue in Spain and revealed that the negative face of the recent development in educational achievement of the young population is unemployment. According to the authors, while the picture is completely different for older graduates, unemployment is very high for the youngest groups of higher education graduates. Moreau and Leathwood (2006) examined the employment status of graduates across Europe and stated that they enhanced unemployment in most European countries and that this was not a temporary process. Plümper, Troeger, & Manow (2017) investigated the relation between unemployment and higher education in Germany by using state level data and revealed that state governments misused higher education as a labour market instrument against unemployment. Findings show that the States which experience larger enrolment ratios in higher education also have higher unemployment rates.

Furthermore, the current findings also reveal that the labor participation has negative impact on unemployment of the country as the cointegration values is - 6.187585 which is statistically significant with t-value of 3.20176. The results of the current study corroborate with the past studies by revealing the similar results as the long-run relation between unemployment and labour-force participation appears to be negative: countries with low unemployment have high participation rates, with Japan and, at least until recently, Sweden as notable examples; at the other end of the spectrum, high unemployment coincides with low participation in Spain and Ireland.In general, therefore, cross-country evidence does not support the notion of a long-run trade-off between levels of unemployment and non- participation.

CONCLUSION AND RECOMMENDATIONS

Ever since the first Industrial Revolution in the late 18th century, new technologies have been viewed ambiguously, while some welcome the prospect of increased productivity and the potential of improved wealth, there similarly exists considerable opposition, especially by those who stand to lose of a change in the status quo. Technology replacing the humans with high tech machine and software that are productive and accurate that human beings thus people are losing their jobs. The current study likely to contribute in the exiting literature by examining the nexus between technology growth, labor force participation, education and unemployment in the Kingdom of Bahrain.

Therefore, the current study developed the model of unemployment rate in relation with technological growth and labor participation rate in country. Therefore, in current study the unemployment rate was considered as a dependent variable and technological growth, labor participation rate were considered as independent variables. Meanwhile, education was used a moderator variable between unemployment and technological growth. At the first stage, the stationary of all the variables through ADF unit root test using E-views was checked to confirm that which model is suitable (regression, ARDL or Co-integration).The results of ADF unit root test depict that all the variables are non-stationary at level but stationary at first difference. Therefore, we used Johansen and Jusilious co-integration test for current analysis to analyze the impact of technological growth, labor participation rate on unemployment rate along with moderating role of education between technological growth, and unemployment rate.

The result of first hypothesis unfold the negative association between technological growth and unemployment in the Kingdom of Bahrain. It can be concluded pertinent to the first hypothesis that technological growth is a significant determinant that play its crucial role to eradicate the unemployment in the Kingdom of Bahrain. Whereas, the current study revealing the significant moderating effect of education on the relation between technological growth and unemployment in the context of Kingdom of Bahrain. Therefore, the conclusion may be presented as investment in education and uplifting the education may contribute significantly to strengthen the nexus between labor force participation and unemployment in Kingdom of Bahrain.

Furthermore, the third hypothesis showed the positive relationship between labour force participation and unemployment in the Kingdom of Bahrain. The empirical evidence-based results are pivotal to draw conclusion for the current study as it is indicating the significant role of labor force participation to reduce the unemployment in the Kingdom of Bahrain. Overall, this study concludes that the technological progress associated with developments in the current innovation cluster and labor force participation coupled with education should be assessed carefully by academics and the private sector, discussed by policymakers and the public alike, but not dreaded or opposed. After all, whereas there will be major employment market changes in the coming decades due to innovations and technological progress, this is not new, and likely can be accommodated by a combination of adequate policy response and gradual changes in society.

Overall, the results from this thesis are no final answer to the debate surrounding the nexus between technological growth, labor force participation, education and unemployment. It strongly recommends that government must focus on the current technological cluster of computational advances and robotics – while likely having major societal impacts in the medium to long term, including a transformation of the employment sectors – does not yet merit widespread technological anxiety. In fact, for the time period considered, technological growth seems to be mildly positively related to employment therefore, Kingdom of Bahrain must take it into considerations while formulating and implementing related policies. It should be noted that while we perhaps do not have to worry about technological unemployment in the near future, it is important to continue assessing the drivers of the current trends of wage and job-polarization – including technological progress – thus facilitating adequate responses that ensure that overall society benefits, rather than a select group of high-skilled employees and entrepreneurs. Moreover, the impact of technological growth on unemployment necessitates future research with more recent data, as well as warrants continued interest from policymakers. This study also put forward the recommendation for enhancing the investment in the education sector as empirical results are showing the crucial role of education as a moderator. Therefore, policy makers must understand the importance of investment in education and give it top priority to eradicate the unemployment. Furthermore, labour force participation must also be increased. Empirical results showing that its greater effect to curtail the unemployment in the Kingdom of Bahrain. Therefore, policy makers also need to increase labour force participation of both male and female in Kingdom of Bahrain. Moreover, unsurprisingly then, this thesis recommends further research on this complex relationship, particularly so for technologies that have been designated as so potentially disruptive to the labour market and labour force participation.

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