

**THE ROLE OF HUMAN CAPITAL IN THE PRIVATE
MANUFACTURING SECTOR PRODUCTIVITY IN THE
DEVELOPING AND TRANSITION ECONOMIES**

SALEM ABDUSSALAM FARAJ GHEIT

**A thesis submitted in partial fulfilment of the requirements of
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ABSTRACT

Faculty of Management
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DOCTOR OF PHILOSOPHY

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This thesis principally seeks to provide empirical examination of the contribution of human capital, particularly in the form of education, to productivity at the micro level, through the lens of human capital and production theories, for a pooled sample of countries from the Middle East and North Africa (MENA), in comparison with both the Eastern Europe and Central Asia countries (ECA).

This research mainly aims to establish substantive empirical evidence on the varying effects of human capital on growth, across regions. It also aims to investigate the role of human capital investment in the productivity gains, mainly through efficiency and labour productivity, in the formal private manufacturing sector, in the aforementioned regions.

The thesis takes into account the variations in per capita income levels, based on the World Bank classifications of countries by income group. In addition, this research recognises and takes into account the heterogeneity which exists throughout the selected sample of countries.

The main objective of evaluating the impact of human capital is to untangle the existing differences in the firms' performance, partly on account of employing different workers with

varying levels of education, with distinctive regional socio-economic changes, and different political conditions.

The stochastic frontier analysis (SFA), as a fully parameterised model is used, in order to address and examine the determinants affecting production efficiencies, especially from a human capital point of view, and in the light of Vandebussche, Aghion, and Meghir's 2006 assumptions, on growth, distance to frontier, and composition of human capital, which remains untested in MENA and ECA at the firm-level.

The SFA was applied following the approach of Caudill, Ford, and Gropper (1995) (CFG) by estimating and testing stochastic frontier production functions, assuming the presence of heteroscedasticity in the one-sided error term (inefficiency), and by following the approaches of Hadri (1999) for cross sectional data assuming the existence of heteroscedasticity in both error terms (the one-sided inefficiency term and the two-sided symmetric random noise), in order to obtain more accurate measures of technical efficiency.

However, the rationale for this choice of the two different regions, is the heterogeneous organisational structures, and the dissimilarities between production functions across economies in different developmental phases, which can be used as a suitable platform for analysing the distinctive effects of human capital composition on efficiency, and growth in each region in comparison with the other.

In addition, the applied methodology also involves the incorporation of two matching methods consisting of a completely randomised experimental design, propensity score matching (PSM), and a fully blocked experimental design, Mahalanobis distance matching (MDM), using a cross-sectional firm level dataset, in order to examine the causal effects of formal training on productivity in MENA, and in ECA.

The main conclusion of the empirical analysis suggests that highly-educated labour proxied by workers with tertiary education and those with university degree, appear to have a positive and statistically significant impact on efficiency in the two regions. Noting that the closer is the country to the frontier, the more important this level of human capital tends to be. As a country becomes closer to the frontier, it depends more on innovation and knowledge creation, which

leads to the reallocation of labour from unskilled-complementary technology production activities, to skilled-prejudiced and technology-intensive activities.

This result appears to confirm the association between high levels of human capital and growth, and chimes with the relevant literature about the link between human capital and growth in the developing and developed countries.

It was also found that low-skilled labour component, denoted by workers who attended secondary school, seemed to have positive and statistically significant contribution to efficiency only in the less developed countries, such as MENA. This is due to the fact that the further the country is from the technological frontier, the more reliant the country becomes on imitation activities, and this seemed to corroborate the ideas posited in the literature about the sources of growth and the proximity to the world's technological frontier.

The low-skilled labour in the private manufacturing firms, in MENA, is positively associated with high levels of efficiency, and its impact appears to be significant, especially in high-technology firms. Although in the more affluent countries, such as the high-income economies in Eastern Europe, and the middle-income economies in ECA at large, the impact of secondary school workers gives the impression of being insignificant on efficiency.

With respect to the intermediate-skilled labour, which is represented by the proportion of workers who have been trained in technical schools, or received on-the-job training, the maximum likelihood estimates point that their effects on efficiency have a propensity to be statistically insignificant, in MENA and ECA, in reducing the effects of inefficiency in firms' performance.

In fact, intermediate-skilled labour is found to have a positive and significant relationship with higher levels of inefficiency, especially in MENA. Put simply, it impedes efficiency improvements in the manufacturing firms, particularly, in the low and medium-technology plants in MENA.

Furthermore, the effects of highly-skilled workers on efficiency were found to be positive and of a high level of significance in the low and medium-technology firms, and this is quite clear, especially, in the high-technology manufacturing firms in this region.

All in all, the results of this study are in line, and compare well with the hypotheses of endogenous growth models of Lucas (1988) and Romer (1990), and with the assumptions of Benhabib and Spiegel (1994), that the economic growth is conditional on the human capital accumulation to improve efficiency and increase productivity in order to catch up with the technological frontier and shift it upward.

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DECLARATION OF AUTHORSHIP

I, Salem Abdussalam Faraj Gheit, hereby declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research;

“The Role of Human Capital in The Private Manufacturing Sector Productivity in the Developing and Transition Economies”

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:
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Date: 23/09/2018

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List of Abbreviations

• AD	Aggregate Demand
• AS	Aggregate Supply
• VAM 2006	Vandenbussche, Aghion, and Meghir 2006 Model
• SFA	Stochastic Frontier Analysis
• DEA	Data Envelopment Analysis
• DFA	Deterministic Frontier Analysis
• PSM	Propensity Score Matching
• MDM	Mahalanobis Distance/Metric Matching
• NNM	Nearest Neighbour Matching
• ES	Enterprise Survey
• TE	Technical Efficiency
• AE	Allocative Efficiency
• CD	Cobb Douglas Production Technology
• TRANSLOG	Transcendental Logarithmic Production Technology
• CRS	Constant Returns to Scale
• PIM	Perpetual Inventory Method
• OLS	Ordinary Least Squares
• MENA	Middle East and North Africa
• ECA	Eastern Europe and Central Asia
• MLE	Maximum Likelihood Estimates
• LR Test	Likelihood Ratio Test
• DTF	Distance to Frontier

Chapter 1: Introduction

1.1 Overview

In economic theory, optimisation is regarded as the foundation stone of modern production economics. This implies that the production unit's overriding objective is to maximise its feasible output given the common technology and levels of production inputs in place.

However, the empirical evidence demonstrates that not all firms succeed in achieving the optimisation target, therefore they cannot be viewed as technically efficient producers in the marketplace. In truth, some firms fall short whether in terms of experience or production techniques of maximising their output through better allocation of resources or of minimising their production cost by reducing the input used to produce the same amount of output.

Moreover, even if some firms are considered as technically efficient, they could be cost-inefficient because of their failure in allocating their inputs to reduce production expenditures and the average cost taking into account the inputs' prices.

Furthermore, some firms could be cost-efficient, but they might not be profit-efficient because they fail to maximise their profit given the amount and prices of the output produced.

The firms' choice to adopt a profit-maximising scheme will partly hinge on the price of the production inputs, which in turn is reliant on the relative abundance or scarcity of these inputs in the market. Hence the choice of the appropriate level of technology will differ from one firm to another and from one country to another. This means that in low-skilled labour abundant countries, firms will opt to operate with low-skilled complementary

technologies because the wage bill for highly skilled workers will be high for these firms.

By technical efficiency, this research seeks to discuss the relationship between the observed output and the potential output considering the differences in production circumstances due to heterogeneity across firms and countries. On the other hand, by inefficiency, this research considers the endogenous random shocks that are distributed homogeneously across firms – where the deviation of an observation from the theoretical maximum output is ascribed partly to the firm's inefficiency term. The other part of the deviation is attributable to random external shocks.

Skilled human capital is identified as efficiency-driver in advanced economies and in underdeveloped economies alike. It is viewed – according to the endogenous growth theories – as a crucial ingredient for innovation growth and as an endogenous factor in production.

However, the importance of human capital accumulation and its role as a catalyst promoting firm's efficiency and growth has been long examined and is well documented throughout developed economies in contrast with less developed economies – the Middle East and North Africa economies for example – where the empirical examinations of growth have done little to identify the dimensions of relevant human capital or any policy implications. The role of this growth ingredient has not been given sufficient attention in the development discussions as the relevant literature is rather scarce in this particular region.

This thesis concentrates on the importance of labour force skills, measured by educational attainment. By linking education levels to technical efficiency by means of stochastic frontier analysis, firm-level evidence is established across developing, transition, and developed economies.

1.2 The Middle East and North Africa Region (MENA)

The Middle East and North Africa economies (MENA) seem to be underperforming and trailing behind other regions in several global competitiveness

indexes, human resources utilization, labour productivity growth, and total factor productivity included. Even though the degree of openness is not a problem per se because firms in this region are able to trade with the rest of the world more than many of their counterparts in other developing countries, the scale of trade is an issue of concern due to several quantitative trade-confining policies and the lack of an encouraging investment atmosphere or regulations.

Moreover, it is also found that the average firm size and productivity differences between the exporters and non-exporters are smaller in comparison with other regions. Where in MENA most firms reported higher output per worker in comparison with other middle-income economies, total factor productivity is lower in MENA than in other similar economies. This might be partly attributed to the fact that this region was not able to draw from the world technology frontier to use production factors and advanced technologies efficiently.

Another major feature of the MENA economies is that the formal private sector is not sizeable, yet it still plays an important role in the labour market and in economic development.

This thesis principally aims to investigate the contribution of human capital to productive efficiency in private manufacturing firms in MENA and in transition economies in Eastern Europe and Central Asia (ECA). In doing so, it considers the advantages that the optimisation of human capital can provide to facilitate technology transference and financial capital accumulation in order to enhance a firm's competitiveness both in the domestic and international markets which will trigger more investments in the physical capital in these regions. It will take into consideration the fact that the MENA region in general utilises and captures only about 62% of its human capital potential according to the World Economic Forum's human capital index (2017).

There are several conditions and circumstances that put the MENA region in a favourable position in terms of the abundance of natural resources, the similarities in language and culture, the geographical proximity to the European Union and to the southern European economies, in particular, and

the large labour force with different levels of education. Despite these circumstances, MENA nations appear to have missed important opportunities to converge and catch up with the technological advancements that have taken place across the adjacent regions in Europe and Asia, let alone those in the North America region.

The MENA region could not recuperate its losses after being among the fastest growing in the world throughout the 1970s. In truth, it is lagging behind the Advanced Economies and the Asian Tigers in terms of its technological adoption, efficiency enhancers, and the institutional frameworks needed for innovation and knowledge dispersal.

In 2009 and during the financial crisis the scale of international trade in the MENA region decreased significantly and labour productivity declined dramatically. Before 2009 output per worker was higher in MENA than in other regions in the same developmental stage and relatively exposed to similar technical diffusion. Although, the region did not entirely go down in the flames of the financial crisis, it did not survive its profound repercussions on domestic financial systems, intra-regional and international trade progress, or the growth pace.

The global financial recession was followed by a pivotal event called the Arab Spring in 2011, where many countries were shaken to their core by revolts and economic havoc stretching from Tunisia to Libya and Egypt on the west side of the Arab world to Syria and Yemen in the East. This event caused a great deal of weak democratically elected regimes, political instability and military conflicts across the region which spelled massive disruption for the business environment, the performance of firms and efficiency as well as growth in the whole region.

The ripples of this social-political earthquake were felt all around the region and growth fell sharply from 6% on average before the crisis, during the years from 2003 to 2007, to less than 3% on average in the period between 2013 and 2017. However, GDP growth has still not returned to the levels it had in 2010 in the countries that endured the Arab Spring experience.

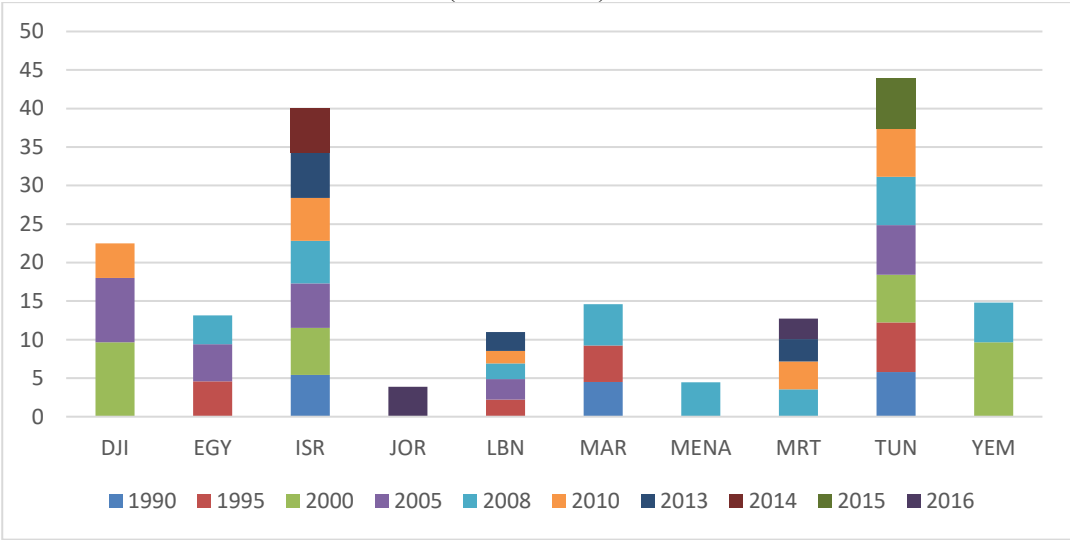
Ever since countries like Egypt and Tunisia have suffered from dramatic reputational damage and opportunity losses in the tourism sector, on which they had relied heavily as a major contributor to growth over several decades. This setback was mainly a result of both countries' experience with the Arab uprisings in addition to the different type of destabilisation that occurred in their neighbouring oil-rich state of Libya where the experience was different in all aspects.

At the beginning of the 2000s, the region was in dire need of a potential catalyst for growth and development especially with the increase of oil prices after the mid-2000s which offered a stimulus for more government spending on infrastructure and human capital investment. However, the 1980s and 1990s left an economic legacy of inadequately-designed fiscal and monetary policies which were expected to throttle growth, subdue the private sector and restrain its expansion.

Governments' expenditure on education as a percentage of GDP has seen considerable improvement, but varied noticeably in terms of the results and the impact across nations in the Middle East and North Africa.

In some MENA countries the spending on education as a ratio of GDP was comparatively higher than in several nations in ECA throughout the period from 1990 to 2016. This expansion in education resulted in better access to schooling for large percentage of the society, but despite the quantitative achievements in this field, the worrying issue remains the quality of the outcome, and the mismatch between the capacities of graduates and the market demand in this region.

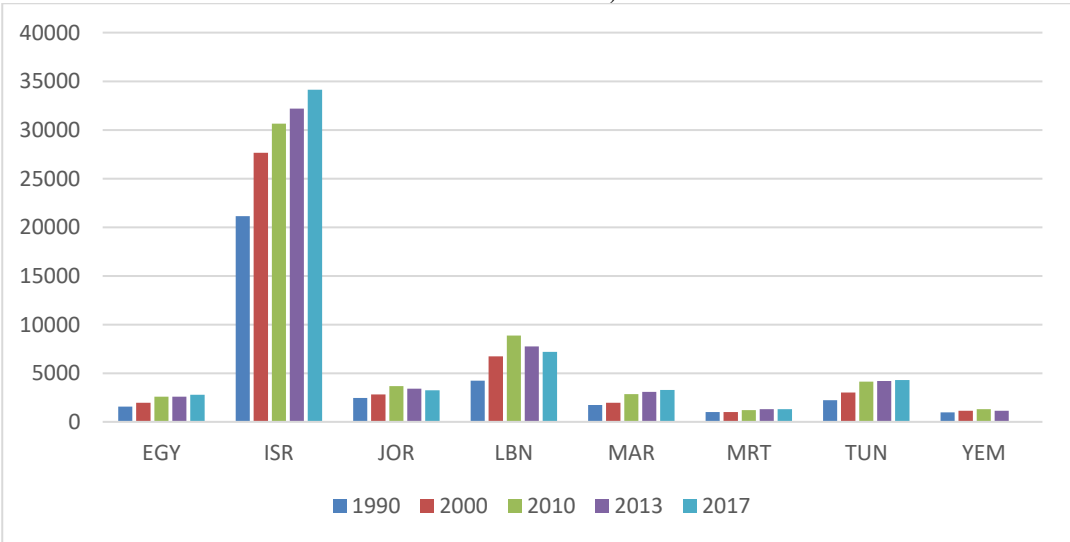
Figure 1.1 Government Expenditure on Education, Total (% of GDP) in MENA from 1990 to 2016 (Selected Years).



Source: The World Bank Group, World Bank Open Data 2018.

Based on some macroeconomic indicators such as real GDP per capita measured in constant terms, the MENA region has been comparatively underperforming since 1990. Apart from Israel, all the other selected countries experienced low rates of growth in this respect.

Figure 1.2 The Changes in GDP Per Capita in The MENA Region (Constant U.S Dollars 2010)



Source: The World Bank Group, World Bank Open Data 2018.

From the human capital perspective, and according to the global human capital report 2017, unemployment rates among university graduates in MENA

increased continuously over the decade prior to the great recession in 2008 and the Arab Spring in 2011 in countries like; Egypt, Tunisia, and Morocco at levels like 24.8%, 21.9%, and 17.8% respectively.

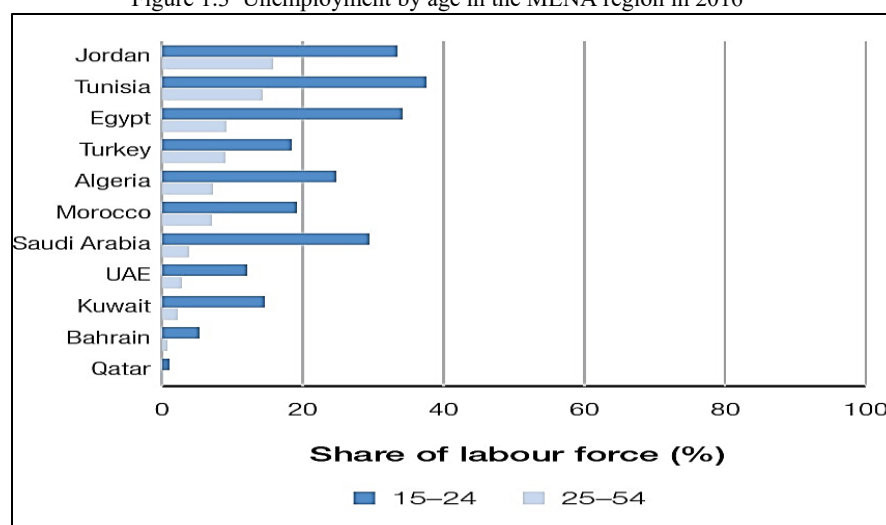
The youth unemployment continues to be widespread in most MENA countries in 2016, which is risking and causing a lasting effect on the labour force of the next generation in this region.

In North Africa in particular, unemployment rates among the youth were higher than any other region in the world in 2006 at 25% of the total, whereas, in the Middle East, the unemployment rates in the same age group were at 21%.

The scarcity of adequate jobs for university graduates in MENA is a major and worrisome economic dilemma which gives rise to more leakages of highly-skilled workers towards the informal sector in pursuit of job opportunities to broaden their experience.

The occupational movement of workers from the formal sector to the informal poses an alarming and imperative question about the level of human capital utilisation in MENA and the possible loss for the economy resulting from the withdrawal of an important segment of human capital from the formal labour force via leakages into the informal sector.

Figure 1.3 Unemployment by age in the MENA region in 2016



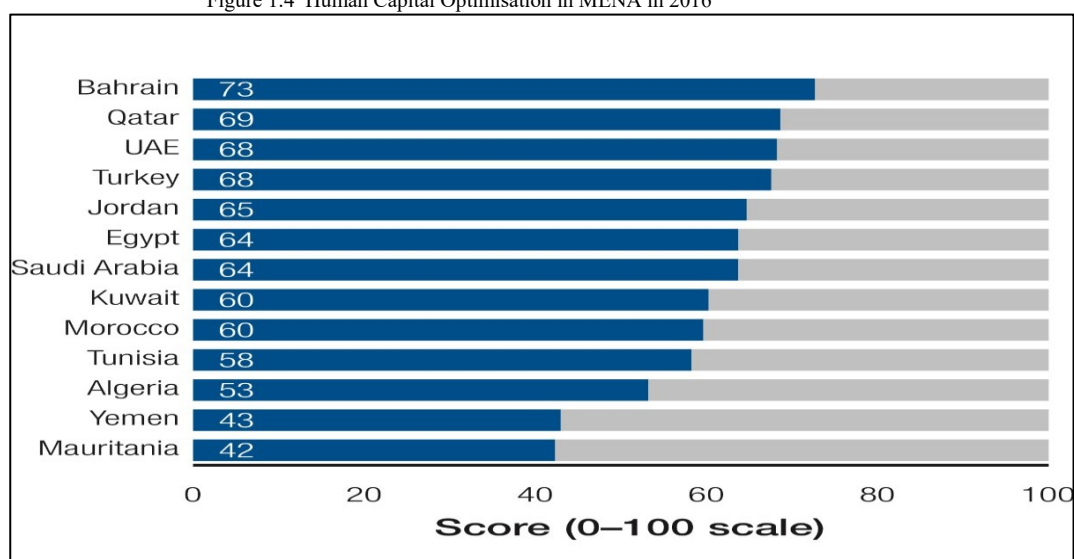
Source: World Economic Forum, Human Capital Index 2016.

Human capital optimisation measures how much of the country's human capital is represented in the active workforce. The remaining proportion of the country's human capital stock includes children, university students, non-working housewives, pensioners, and the unemployed. The difference between human capital optimisation and conventional employment rates is that the former considers the different human capital endowments for each age groups.

Figure 1.4 shows the divergent rates of human capital optimisation in MENA. It ranges from 42% in Mauritania to 73% in Bahrain in 2016. It is in general above 60% in most countries as shown in the figures below. This is where the average global human capital optimisation is 65%. Whereas currently the MENA region as a whole captures only 62% of its full human capital potential. In the post-Arab spring economies such as Egypt and Tunisia it stands at 64% and 58% respectively.

Given the significance of the endowments of human capital and accumulation of financial capital for adopting the appropriate level of technology, the underutilisation of human capital and the leakages in educated labour from the formal sector spell serious troubles for the MENA economies and their ability to bridge the technological gap with the rest of the world in the future.

Figure 1.4 Human Capital Optimisation in MENA in 2016



Source: World Economic Forum, Human Capital Index 2016.

Moreover, the transition process from partly manned jobs which are executed by a high percentage of low skilled labour under the supervision of a lower percentage of highly skilled labour into highly computerised and automated jobs mainly monitored by highly-skilled workers is largely dependent at the macroeconomic level on the abundance in each segment of low and high skilled workers.

This implies that in more developed economies which are skilled-worker abundant a firm's decision to switch to more mechanised and skilled-biased technology seems to be both plausible and necessary. However, in less developed economies – the unskilled-labour abundant – MENA and ECA included – if firms decided to maintain the low-skilled jobs by not adopting highly-sophisticated technologies on production lines, their choice can be regarded as economically reasonable and rational and could be attributed to the scarcity of the skilled labour necessary to operate and run the computerised firms efficiently in these regions.

The main idea is that each firm in an economy has a choice to make relating to the combination of high and low skilled workers and the level of technology which suits this combination of labour.

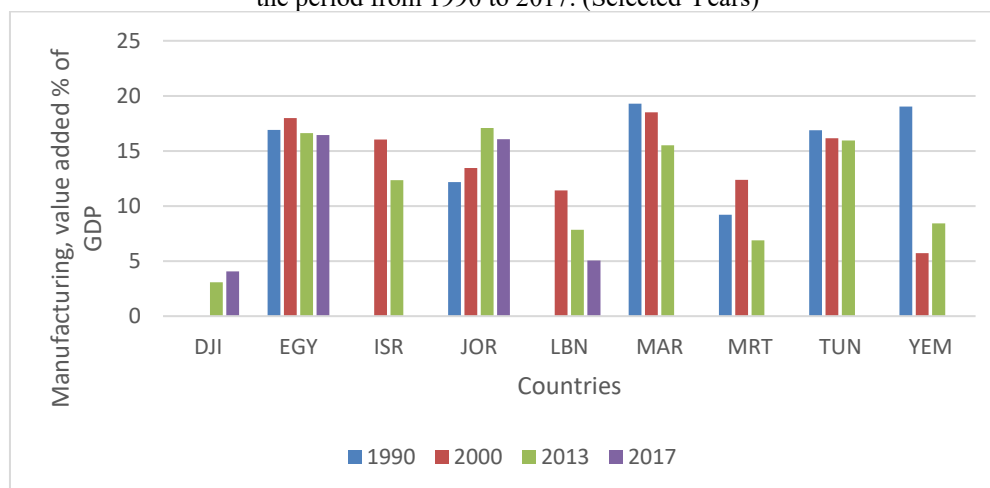
According to the World Economic Forum's Human Capital Index, the pool of talent in MENA is less diversified in comparison with other regions. This can be put down to a different pattern of specialisations selection.

The Engineering, Manufacturing, and Construction specialisations represented about 29% of the talent pool in MENA. This is where 13% of the pool is covered by ICT professionals, whereas just 8% of the pool is represented by the Natural Sciences, Mathematics and Statistics.

From a macroeconomic point of view, the change in the contribution of the manufacturing sector to the value-added GDP across the Middle East and North Africa economies varied significantly from one nation to another. Countries like Egypt, Tunisia, and Jordan have experienced stable share of the manufacturing sector to GDP over the period from 1990 to 2017. On the other

hand, other countries such as Lebanon, Morocco, and Yemen have faced fluctuation in the share of this sector over the same period.

Figure 1.5 The share of Manufacturing Sector, value added as (%) of GDP in MENA during the period from 1990 to 2017. (Selected Years)

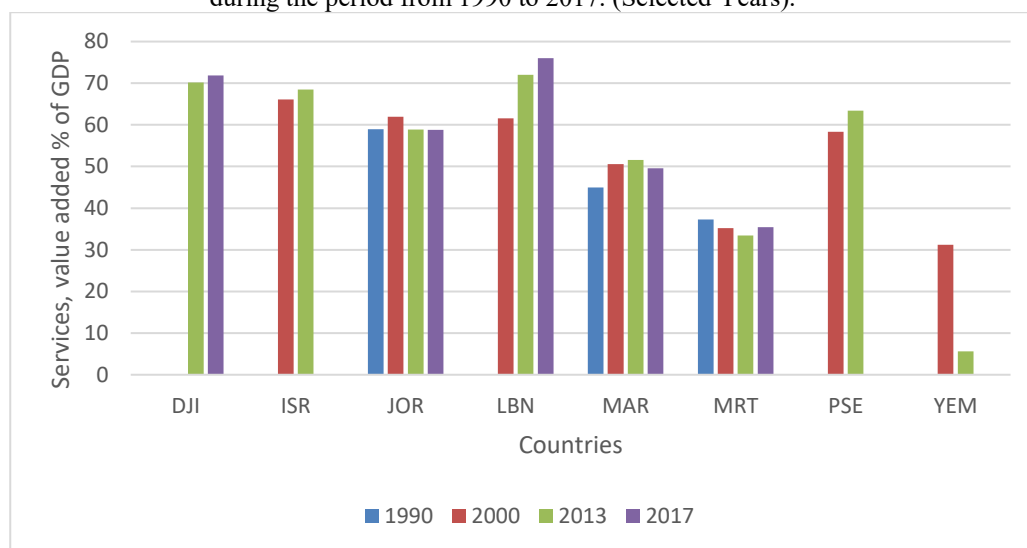


Source: The World Bank Group, World Bank Open Data 2018.

Some more diversified countries had seen progress in the manufactured goods, like Egypt, Tunisia, Israel, and Morocco after being acceded to the WTO in 1995 as full partners in cases like Tunisia and Morocco. Most countries in MENA are concerned about the reduction – or at some stage – the elimination of trade barriers including tariffs.

Building on that, the manufacturing sector may be exposed to strong competition from the global markets and may not withstand and resist competition from the cheap Asian manufactured goods. This could explain the reason why some policymakers in this region are not yet persuaded that the free trade benefits which their countries could reap outweigh the burden of protectionism.

Figure 1.6 The share of Services Sector, value added as (%) of GDP in MENA during the period from 1990 to 2017. (Selected Years).



Source: The World Bank Group, World Bank Open Data 2018.

On the other hand, the contribution of the services sector to the value-added GDP increased steadily since 1990 in the majority of the MENA economies.

1.3 The Eastern Europe and Central Asia Region (ECA)

Despite the differences between the Eastern Europe and Central Asia economies, they broadly share similar growth model hugely driven by the foreign inflows of capital. The foreign direct investment dominated the inflows of foreign capital during the first period of the transition from the centrally planned economy to the market economy.

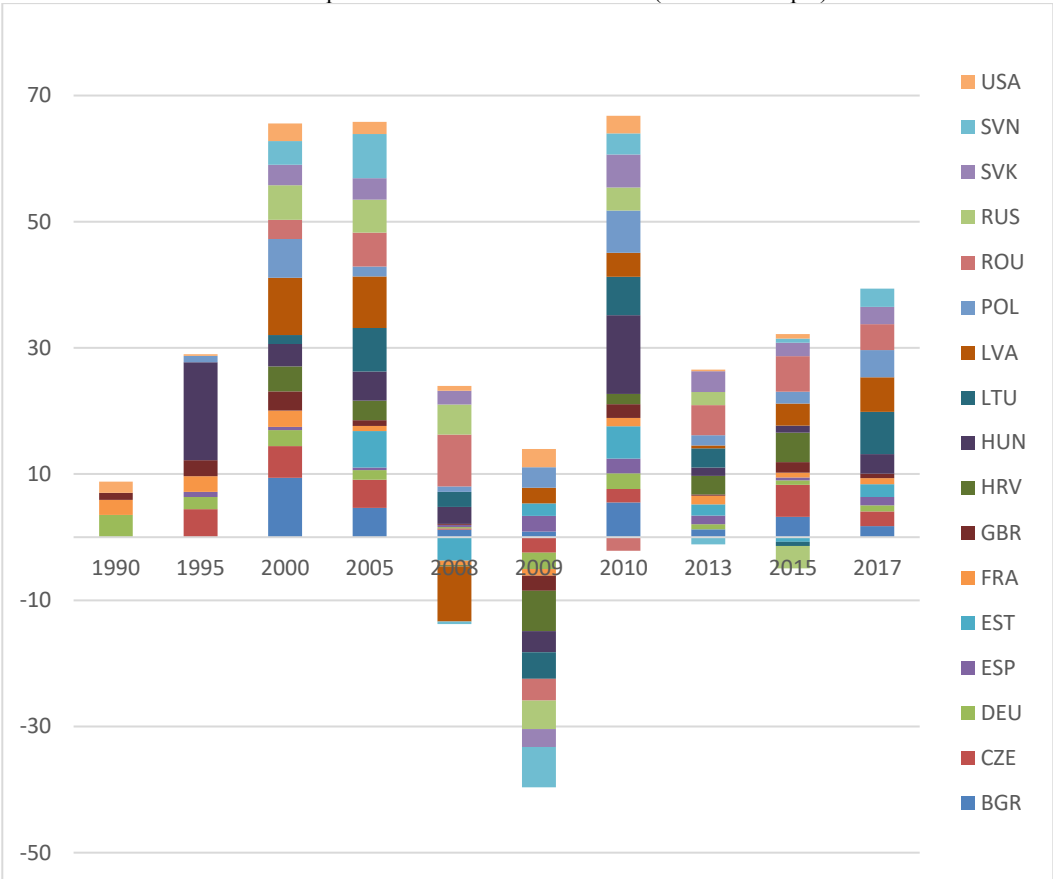
Geographical proximity and the integration with the EU both politically and economically paved the way to these capital inflows into these countries.

After the second world war ended, the entire region of ECA came under the Soviets rule, and the industrialisation in this region followed the Soviet-style communism during the 1950s: companies were nationalised, the industrial enterprises owners were deprived of their pre-war advantages as an industrial elite.

Isolation from global capital markets, led the Soviets to pursue capital accumulation through internal resources. This is where they relied on the agricultural sector products which were purchased at low prices to secure and allocate the fund towards the mining and steel production sector, and the military industry.

At the macro level, productivity appeared to be high, but at sectoral level, productivity was only increasing in the manufacturing sector, whereas overall labour productivity annual growth was comparatively higher than it was in the Western economies during the period from 1990 to 2017. This might be put down to the fact that the Western economies are close to the frontier and therefore they are close to their potential capacity, so the growth will not be expected to be high as in the transition economies.

Figure 1.7 The Change (Annual Growth %) in Labour Productivity in The Eastern and Western Europe Economies from 1990 to 2017 (Selected Sample).



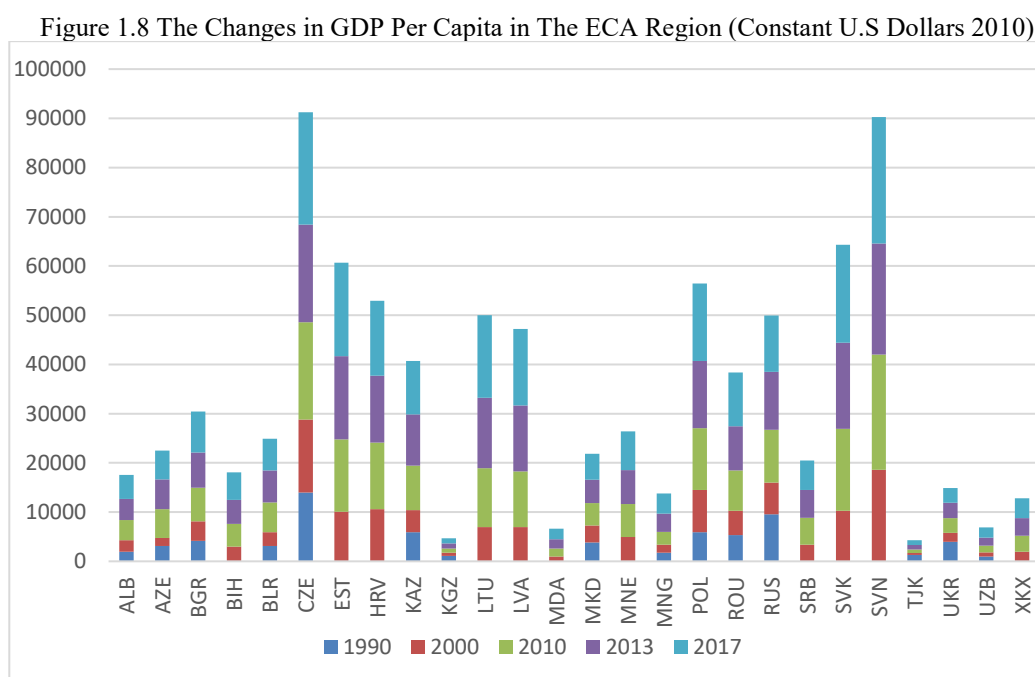
Source: GDP per capita and productivity growth, 2018 Organisation for Economic Co-operation and Development.

The dissolution of the Soviet Union (SU) during the turn of the 1990s, and the demolition of the Berlin Wall have dramatically changed the lives of millions across the two continents in Europe and Asia.

The Eastern Europe region in modern terms is best understood not as a geographical term but as a political term, representing those countries which used to be under Soviet Union bloc rule between 1945 and 1989 as well as those that were not part of the Soviet Union. Many of these countries are now member states in the European Union but were once part of the Warsaw Pact.

In 1989, many of these satellite states, including Poland, the Czech Republic, Slovenia, Hungary, and Slovakia started to make a sequence of intense reforms and changes. As a result of these changes, this region of Eastern and Central Europe was re-integrated with the Western Europe and the world economy.

Over the course of the transition period, some countries stand out as being the best performers in several aspects. As such, the developments in GDP per capita over the period from 1990 to 2017. Slovenia, the Czech Republic, the Slovak Republic, Estonia, and Poland tower the group of nations which significantly improved the level of their GDP per capita measured in constant U.S dollar in 2010.



Source: The World Bank Group, World Bank Open Data 2018.

The transformation and evolution mission which was initiated to catch up with the capitalist economies was expected to be difficult, especially with the outbreak of economic recession in the early 1990s, but the transferred assets inherited from that period were good drivers to optimism. The human capital accumulation and the manufacturing sector infrastructure were in a comparatively good condition to drive these countries towards the market economy.

Nations such as Poland, Hungary, the Czech Republic and Slovakia in East Central Europe have been the most successful in reforming their economic and political systems. One of the main factors in ensuring the transition from the Communist economic and political philosophy to market Capitalism was the alternative elite of economists that formed its own networks and started to think of the transition process of the centrally planned economy into a market economy in the late 1970s and early 1980s, maybe even before the signs of the SU collapse emerged.

As the transition process progressed, along with the simultaneous expansion of the banking sector and the large inflows of capital to the ECA economies, this region became more integrated with the neighbouring economies of Western Europe and the rest of world, which resulted in more vulnerability to external economic shocks.

The development and reforms which took place in the financial system in the ECA countries, helped to spur the domestic demand, but in the same time made this region more susceptible to exogenous shocks.

The deactivation of the price system was one of the main features of the communist economic philosophy. The importance of the price system usually emanates from the fact that it organises economic activities and coordinates the productive resources owners' and producers' decisions in terms of the resource allocation in the light of preferences and scarcity. The price system deactivation resulted in the considerable waste of resources, but in addition, during the first years of the freed price system, economic conditions worsened, inflation rose significantly and the scale of the losses in output resulted in budget deficits as

revenues slowed down, government expenditure obligations inflated, and the timescale needed to recover and grow varied markedly across countries.

The international trade scale grew noticeably in this region during the period 1993-98 due to the good infrastructure built before the collapse, which connected these countries with most of the neighbouring regions in Europe and Asia and, also because of significant foreign investments from Western European countries given that many of the former Soviet Union countries were expected to be members of the EU.

The flow of foreign direct investments into this region was crucially important in the transition process, encouraged and emboldened by the new investment policies introduced by the newly elected governments to attract more businesses into their countries in the mid-1990s that adopted a wide range of institutional reforms accompanied by real exchange rate appreciation and interest rate depreciation strategies.

FDI flows have contributed considerably and positively to the domestic investment and to the quality of goods and services produced in ECA nations and can be regarded as a major source of advanced technology adaptation, managerial expertise and know-how, along with job creation and access to international markets. FDI also contributed to closing the gap between the ECA countries' saving in investment rates, shaping the structure of the ECA economies, and enhancing the role of the manufacturing sector.

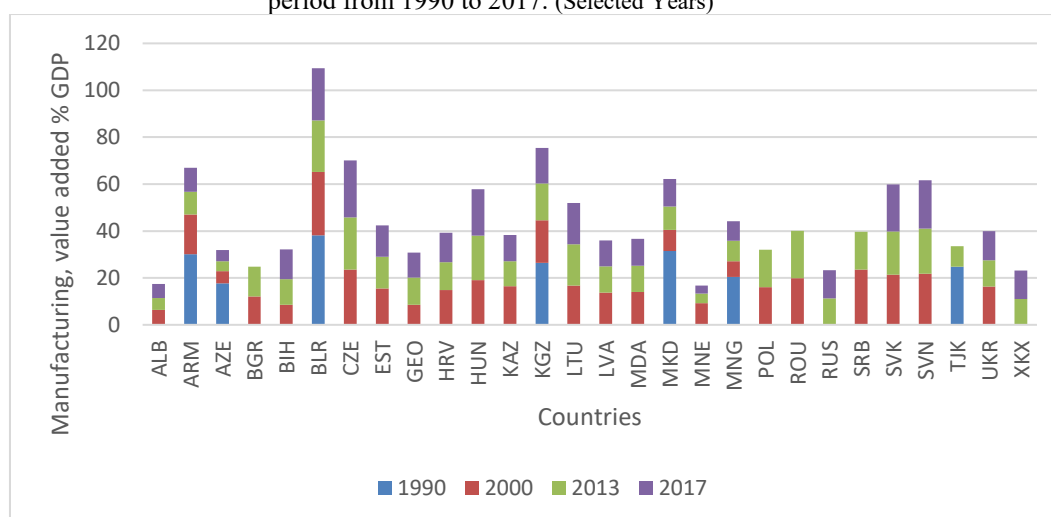
Individual performance in each country in terms of GDP growth rates was high in general, but the volatility of each economy's GDP per capita growth differed substantially.

Overall, these countries have experience three different stages in their way to be transitioned from the planned economy to the market economy. These patterns of convergence with the EU can be summarised as follows: (a) moderate catching up during the late 1990s. (b) expansion during the period from 2000 to 2008. (c) a slowdown in the process of convergence from 2008 to 2017.

The importance of the manufacturing sector in the total volume of GDP in almost all the ECA region, has decreased over time since 1990. This sector faced a deep crisis, because it was exposed to strong international competition from cheaper and good quality goods imported from overseas during the 1990s, which led to the closure of several production units, and in the same this resulted in more privatisation in the stragglers and those firms which fell behind.

The scale of this crisis varied widely across this region's economies. This is where the fast-reforming economies such as Poland, the Czech Republic, Slovakia, and Slovenia experienced relatively shorter periods of stagnation and soon returned to their development levels before the start of the transition process.

Figure 1.9 The share of the Manufacturing Sector, Value Added (% of GDP) in ECA during the period from 1990 to 2017. (Selected Years)



Source: The World Bank Group, World Bank Open Data 2018.

On the other hand, the share of the services sector in the GDP value added, grew steadily in most ECA economies since the turn of the 1990s.

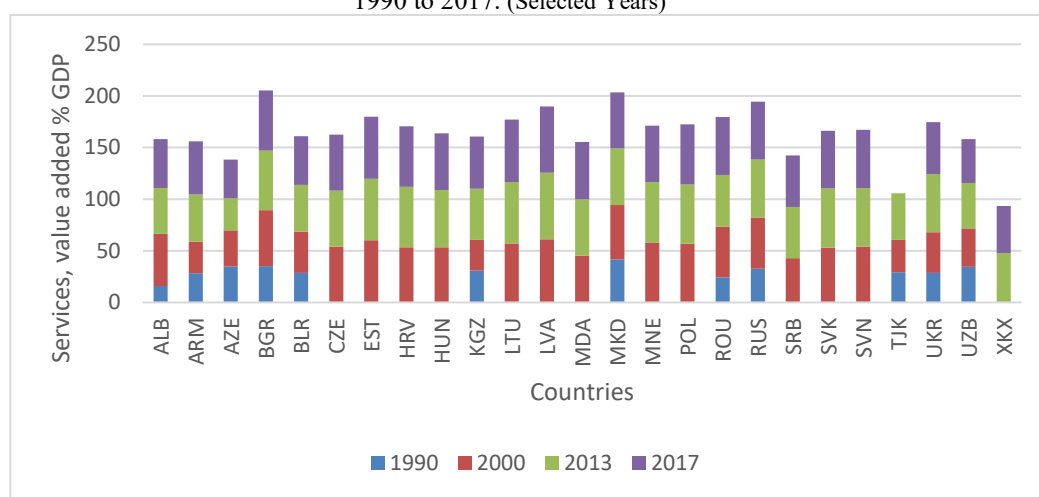
The growth in the services sector is one of the main features of the economic development. In the ECA economies, the contribution of the services sector to the economic activity represents more than 50% in several nations.

The improvement in the efficiency and quality in the services in the ECA economies such as, telecommunications, and transportation have positive effects on the production costs, and hence increase the competitiveness of the

manufacturing sector and the economy at large. This is also worthwhile when it comes to the degree and pace with which the firms operating in these economies are integrating into the global markets.

High quality services in ECA play significant role in attracting and fostering the flow of FDI's, which was reflected in faster growth in the GDP per capita in several countries in this region as mentioned above.

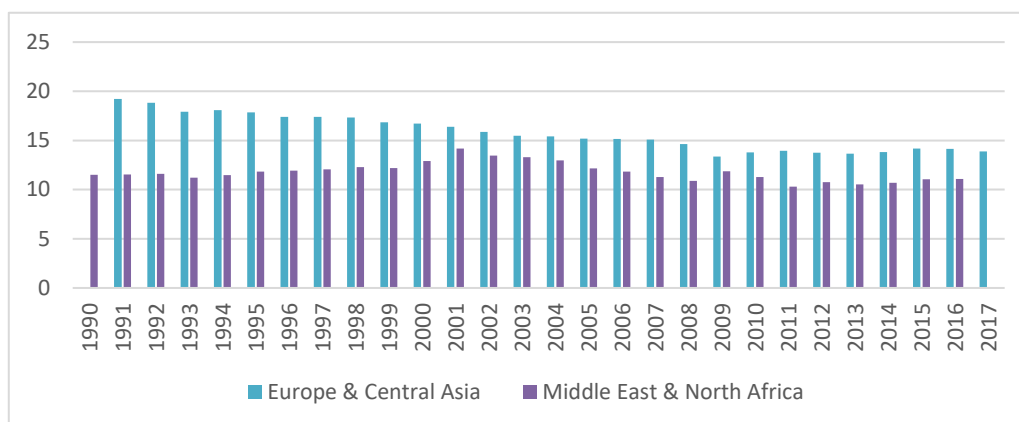
Figure 1.10 The share of the Services Sector, Value Added (% of GDP) in ECA during the period from 1990 to 2017. (Selected Years)



Source: The World Bank Group, World Bank Open Data 2018.

Overall, the pattern of change in the contribution of the manufacturing sector to the value-added GDP – on average – in both regions MENA and ECA, since 1990, varied considerably. This dissimilarity between the two regions can be partly ascribed to the differences in the economic and political structures, and the degree, nature, and pace with which these economies integrated with the global markets over the few past decades.

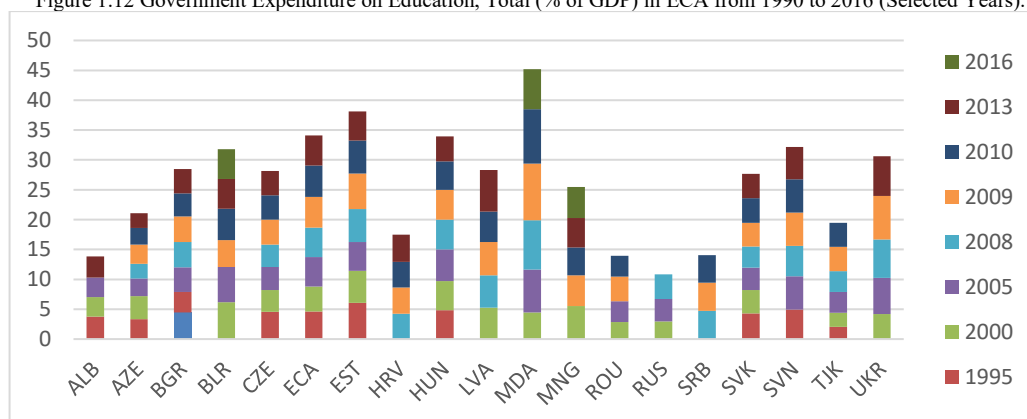
Figure 1.11 The share of the Manufacturing Sector, Value Added (% of GDP) in MENA and ECA during the period from 1990 to 2017.



Source: The World Bank Group, World Bank Open Data 2018.

Government spending on schooling as a ratio of GDP in ECA diverges significantly since the start of the transition in 1990. In 2000 for instance, it ranged from 3.3% of GDP in Albania to 6.2% of GDP in Bulgaria. In 2005, it ranged from 3.2% of GDP in Albania to 7.2% of GDP in Moldova. Whereas in 2013, it ranged from 2.4% of GDP in Azerbaijan to 7% of GDP in Latvia. As for each country in this sample individually, the change in the percentage of GDP which is allocated to education did not appear to be of a dramatic nature.

Figure 1.12 Government Expenditure on Education, Total (% of GDP) in ECA from 1990 to 2016 (Selected Years).

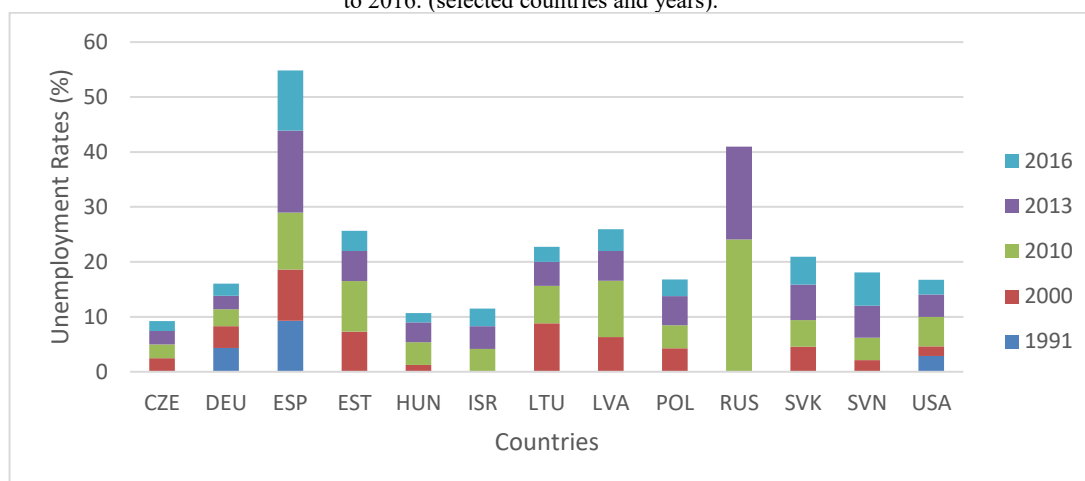


Source: The World Bank Group, World Bank Open Data 2018.

Regarding the unemployment rates among the highly educated labour in Eastern Europe compared to the Western economies, some countries in this region such as, the Czech Republic, Lithuania, Latvia, Estonia, and Poland, had decreased the share of their unemployed tertiary education workers in recent years. As was mentioned earlier, most

countries in ECA had experienced high rates of unemployment due to substantial job losses during the early years of the transition, but since the early 2000s some of these countries began to recover and raised their highly-skilled workers employment rates noticeably.

Figure 1.13 Unemployment rates among the tertiary education labour (25-64 years) from 1991 to 2016. (selected countries and years).



Source: Education at a glance: Educational attainment and labour-force status. 2018 Organisation for Economic Co-operation and Development.

1.4 Aim and Objectives

This research aims to:

1. Investigate the impact of human capital stock on productive efficiency using stochastic frontier analysis to examine the different effects of different education levels on efficiency, considering the differences in distance to the global technology frontier.

The focus of this thesis is specifically on the developing – MENA – and transition – ECA – economies, and the aim of the analysis is to find out which component of human capital composition across these two regions is most important in explaining the cross-country differences in efficiency.

This study attempts to analyse the role of human capital investment in productivity gains, mainly through efficiency and labour productivity in the three aforementioned regions – especially in MENA and ECA – at a micro-level

by testing Vandebussche, Aghion, & Meghir (2006) assumptions in relation to the different relationship between human capital and technological progress through imitation and innovation activities.

2. Examine the impact of formal training – as a treatment variable – provided by firms to their permanent full-time workers on productivity – as an outcome variable – in the formal private manufacturing sector in MENA and ECA.

This study seeks to fill the gap in the literature of growth with a comparative analysis of human capital's role as a determinant of firms' efficiency across three different regions including the Middle East and North Africa, and Eastern Europe and Central Asia.

It will explore the effects of education compositions on productive efficiency in the private manufacturing sector in these economies, along with other crucial factors for productivity improvement such as FDI and international trade.

The main aim is to examine the importance of the three levels of education and the different roles they play in promoting efficiency in manufacturing plants.

The investigation is undertaken using a stochastic frontier analysis methodology – which is a parametric approach – it tries to identify the extent to which the human capital stock available for manufacturing plants has the capacity to affect and interpret the variations of cross-country and cross-region productivity given the differences in distance (proximity/remoteness) to the world's technological frontier.

The idea is that countries are expected to perform and operate either on or below the frontier of production, and thereby an improvement in performance is likely to stem either from a decrease in inefficiency (gains in technical efficiency) or from sharing the increase in the production possibilities as a result

of the outward shift in the frontier per se, which mainly results from technological progress by means of innovation and imitation, Miguel, Afonso, Aubyn (2010), Kathuria, Raj, & Sen (2013).

This thesis is also designed to examine whether there are any disparities or convergence in the way in which human capital affects productive efficiency across the regions subject to study, and to explore the pattern they follow in terms of the relationship between productivity and efficiency and the three different levels of education in the above mentioned three regions.

The cross-sectional and cross-country firm-level data sourced from the World Bank Enterprise Survey (2013) have been utilised in order to reach this objective, which only a few studies – if any to the researcher’s best knowledge – have used to analyse and investigate the role of human capital different components in efficiency and productivity in the MENA and ECA economies, using the Stochastic Frontier, and Matching methodologies which are explained in detail in chapter 3 in the methodology section.

1.5 Key Research Questions

1. Given the cross-country differences in terms of the abundance of skilled and unskilled human capital and the disparities between economies regarding the distance to the global technological frontier, this thesis seeks to answer the question; What impact do highly-educated and low educated labour forces have on firm-level productive efficiency and on micro-level performance in the developing, transition and developed economies?

2. Does formal training – as a strategy to enhance workers’ skill sets – affect the level of labour productivity of the private manufacturing enterprises in MENA and ECA?

In other words, does training improve competitiveness through better productivity in the private manufacturing firms in MENA and ECA?

Given that economic growth is achieved when countries improve their productivity, it is important to identify which channels can help to stimulate productivity.

1.6 Motivation and Contribution to Knowledge

This study fills the gap in the growth literature and contributes with empirical investigation of the human capital role as a determinant of efficiency across lower-middle income, upper-middle income, and high-income economies. The investigation is performed to explore the effects of education composition on the private manufacturing sector’s productive efficiency considering the existing heterogeneity across these economies.

One of the major differences between this study and other research; such as Christopoulos & McAdam (2015) is that human capital stock in the Middle East and North Africa region Christopoulos & McAdam (2015) is represented by the average number of years of schooling indicator, which is sourced from Barro & Lee (2013) dataset and observed over a 5-year period. Whereas, this study uses firm-level data from the World Bank Enterprise Survey conducted in this region in (2013).

The WBES dataset contains different and more detailed indicators representing human capital stock at the firm-level in MENA and ECA, such as; the percentage of full-time permanent workers with high levels of education (mainly university degree), the percentage of full-time permanent workers with intermediate skills (acquired from technical and vocational training schools and

colleges), and the percentage of workers with secondary school level education (low skilled labour).

In addition, the effect of the average number of years of schooling embodied in a permanent full-time production worker on firms' technical efficiency will be examined in the stochastic frontier model.

The model of Vandebussche Aghion and Meghir (2006) (VAM 2006) on growth, distance to frontier and composition of human capital remains untested in large parts of the world's low- and medium-income transition and developing economies, essentially in the Middle East and North Africa. However, due to data constraints – mainly the lack of panel data availability – the literature on growth and empirical research on human capital's role in MENA is rather limited. Hence, against this limitation, one of this study's chief contributions to the growth literature lies in testing the hypotheses of Vandebussche, Aghion, and Meghir (2006) in 9 of the middle-income economies in the MENA area, and 28 high and middle-income economies in the ECA region.

This thesis presents firm-level evidence from MENA and ECA, by examining the disparities between different income-level regions in terms of education as an efficiency-enhancer based on each region's distance from the global technological frontier.

This research is mainly motivated by the findings of Krueger & Lindahl (2001a) and the assumptions of Vandebussche Aghion and Meghir – VAM (2006) – in their survey and empirical analysis of the effects of education on economic growth considering the distance of each country from the world's technological frontier.

They – Krueger & Lindahl (2001a) – argue that education is positively and statistically significant as a determinant of economic growth only for low-income economies with initial levels of education in contrast with the non-positive impact of low levels of schooling on growth in high-income countries – OECD members included – which is a surprising discovery.

The possible justification for this phenomenon lies in the different roles which human capital may play at different technological progress stages, something which is yet to be addressed and explored thoroughly throughout the empirical literature of growth, Vandenbussche, Aghion, & Meghir (2006).

However, fewer studies – if any – focused on investigating the relationship between human capital and efficiency – in the light of Vandenbussche, Aghion, & Meghir (2006) theory – across MENA and ECA regions at firm-level irrespective of the dissimilarities between economies and the developmental stage they had reached.

This thesis is among the first to examine the exogenous cross-country heterogenous effects not only on the technological frontier, but also on inefficiency and random noise terms, using firm-level data from the Middle East and North Africa, along with the Eastern European and Central Asia regions. The exogenous effects on the composed error term are modelled by the addition of environmental variables that reflect the cross-country heterogeneities as additional explanatory variables to the mean of inefficiency term, or they enter the model as a measure of controlling heteroscedasticity into the variance of inefficiency and random error terms.

This study provides important evidence that the average number of years of schooling cannot always be viewed as a valid proxy for human capital in terms of its impact on firms' performance, and its importance and credibility in explaining the cross-country disparities in productivity and growth. To the researcher's knowledge, this has not been addressed thoroughly in the literature and previous research, especially in the Middle East and North Africa, and the Eastern European and Central Asia countries and across the firm-level research.

The insignificance of this proxy on efficiency is obvious in the obtained results, both in the case of the Middle East and North Africa, and Eastern Europe and Central Asia manufacturing firms, especially when the composition of human capital is broken down into specific categories including; high, intermediate, low skilled workers. It is found that the number of years of education is not a significant proxy for human capital when low-skilled and semi-skilled labour are separated and their impact on technical efficiency is estimated independently.

The interaction between the skills' level embodied in the workers, and the average number of years of education for a typical full-time worker, explains more about the relationship between the number of years spent in education, and technical efficiency. This is where the effect of number of years in education on technical efficiency is only found to be significant when associated with a higher level of skills.

This study contributes to the growth and development literature in the following specific respects:

- 1- This study provides important empirical evidence on whether there are differences in the impact of human capital compositions on technical efficiency, and performance, across the selected sample of economies, in the presence of heteroscedasticity in both error terms and heterogeneity in the stochastic frontier production functions, across the two regions. These regions include 9 middle-income economies from the Middle East and North Africa (MENA), 28 middle and high-income transition economies from the Eastern Europe and Central Asia area (ECA).

The investigation is principally concentrated on the contribution of the shares of skilled and unskilled workers in the total labour force – distinguished via the three education stages – to efficiency.

2- This thesis demonstrates that the reallocation of labour – high-skilled and low-skilled – yields complementarity between human capital and a country's proximity to the technological frontier using the SFA methodology, with the correction for heteroscedasticity in the two error terms.

The rationale for assuming the presence of heteroscedasticity in the stochastic frontier model, is that correcting for heteroscedasticity yields more accurate and robust measures of technical inefficiency.

The three education levels in this investigation are: the secondary school levels (unskilled/low skilled labour), the college or upper secondary school level (intermediate-skilled labour), and the university level (highly-skilled labour). The stochastic frontier models included in this research are designed to deal with the three levels independently to examine their different effects on efficiency. The addition of the average number of years of schooling of a full-time permanent worker – as an extra proxy for human capital stock – serves as another dimension to explore whether it has significant effects on efficiency in the private manufacturing firms.

3- The novelty of this thesis is that it provides firm-level empirical evidence from the formal private manufacturing sector in order to investigate the aggregate conclusions drawn from the macro-level analysis concerning the human capital effects on efficiency. The thesis also tries to reconcile the macro-level evidence presented in previous research and the micro-level evidence obtained in this study.

The study differs from previous macroeconomic analysis frameworks in the way that it attempts to provide a persuasive analysis of the association between

human capital and efficiency. The analysis is executed by using different human capital components which are endogenously deployed at the firm-level within the manufacturing sector.

In contrast, in most previous studies reviewed in the literature so far, human capital indicators at macroeconomic level, such as; the average number of years of schooling in the country, the average enrolment rates in education, government expenditure on education as a percentage of GDP, and teacher-student ratios (student-teacher), are the most commonly used proxies when examining the effects of educational attainment on efficiency and productivity, as well as GDP growth across the different nations.

There are several reasons for choosing these two regions, besides the panel firm-level data unavailability and inaccessibility for researchers in the human capital field in some regions.

The main reason for this choice is the different organisational structures and the dissimilarities between production functions across economies in different developmental phases, which can be a suitable platform for analysing the distinctive effects of human capital composition in each region in comparison with the others.

4- Another important contribution of this thesis concerns the additional crucial channel in forming human capital stock. This channel is related to the impact of formal training – as a process of skills development – on the manufacturing firms' output per worker in MENA and ECA.

This impact of training programs is examined across the MENA and ECA economies, so as to uncover the story of whether the formal training offered in some enterprises had a significantly positive impact on the productivity of full-time permanent employees. In addition, the investigation involves addressing the other explanatory factors which might had played considerable roles in driving and motivating manufacturing firms decisions in MENA and ECA to provide training programs to their permanent full-time workers.

1.7 Structure of this Thesis

The thesis is organised as follows;

Chapter 2 provides a detailed literature review in the context of both economic growth models and the concept as well as measurement of productivity. It also provides discussions of the differences between the different growth models, starting with the growth accounting model – Solow’s model as a prime example – the Neoclassical model, and the endogenous growth models. The literature includes an explanation of Vandebussche, Aghion, and Meghir’s views on growth, human capital composition, and distance from the frontier.

Some strands of methodological developments in measuring productivity are also revisited in this chapter along with a historical overview of how productivity growth and its determinants differ across countries and regions of the world. This chapter concludes by discussing the importance of human capital, training, and research and development spending for efficiency, productivity and growth.

Chapter 3 provides an extended discussion of the methodology used in this thesis, mainly stochastic frontier analysis and matching methods. It also discusses the datasets that are used to address the aims and questions of this research.

Chapter 4 studies the effects of human capital on three components of firm-level efficiency in MENA in section 4.2. Section 4.3 presents an empirical examination of the role of formal training in firms’ performance and productivity.

Chapter 5 provides in section 5.1 an investigation into the impact of the skilled and unskilled labour of firm-level efficiency in the ECA region using stochastic frontier analysis methodology. Section 5.2 studies the relationship between formal training and firm-level performance measured by labour productivity.

Chapter 6 contains in its first section 6.1 a comparison between the different effects of permanent full-time workers' education levels on technical efficiency in MENA and ECA. Section 6.2 provides an analytical comparison of the impact of formal training on firms' performance both in MENA and ECA.

Chapter 7 concludes this thesis with conclusions and discussion of possible policy implications in the MENA and ECA regions.

Chapter 2: Literature Review

2.1 Introduction

Productivity has been widely acknowledged as a pivotal factor to long-run economic growth; “*productivity isn't everything, but, in the long run, it is almost everything.*” (Krugman, 1994b), P.11). Hence, improvements and increases in productivity will allow firms, and at a larger scale the economy, to generate more output with the same quantity of inputs or less, where several influential elements can play a role in driving productivity, such as technological advancement and the skill-enhancing activities for human capital formation, not to mention that the spillovers of competition between firms and international trade have their direct and indirect significant influences on productivity too, (Krugman, 1990), (Balakrishnan and Pushpangadan, 1998).

Over the years, both theoretical and empirical research on total factor productivity (TFP henceforth) experienced an important and continuous ascent, where the analysis on the origins of TFP, according to some authors, dates back to the pioneering work of Solow 1957, (Van Beveren, 2012).

As a matter of fact, when defining TFP as the ratio between real product and real factor inputs, this leads back to (1942) when Tinbergen first introduced this concept in his original article in German, which was presented in English in 1959. In the meantime, several other scholars developed and measured this concept some years before 1959, (Chen, 1997).

Total factor productivity is usually named as the Solow's residual, (Goodridge, 2007). This mainly stands for the per capita economic growth above the rate of per capita growth in capital stock, and it is a residual because it comprises the part of output growth that cannot be accounted for in the growth of the primary factors of production (the capital accumulation or labour increase) (Hulten, 2001). The Solow residual can be

calculated by subtracting the growth of primary inputs (weighted by their respective shares of nominal output) from the output growth, and this can be shown as:

$$z = y - s_k k - s_l L \quad \text{Equation 2.1}$$

Where y denotes the growth rate of output; K is the growth rate of capital input, and L is the growth rate of labour input. s_k and s_l are the shares of capital and labour in nominal output, respectively, (Goodridge, 2007).

Over the course of the historical context of growth in the United States, namely, during the 19th century, economic growth had mainly occurred as an outcome of the growth in population, the expansion of land, and the increase in capital, but not as a result of neither the growth in TFP nor the developments in labour productivity. In fact, the relating data demonstrate that TFP, on the whole, suffered from a decline on account of the disruption resulting from the war (Shackleton, 2013).

2.2 Growth Accounting Models

Numerous studies, (Solow, 1957) included favouring productivity as the centrepiece in explaining output growth, and this is observed steadily as a core factor in driving economic growth knowing that the Bureau of Labour Statistics supported this view and put it into use in their releases of data and analyses on productivity, (Hulten, 2001).

Notwithstanding, (Jorgenson and Griliches, 1967) were opposed to this perspective offering their own view, which was supported later by (Young, 1995), in what has been named later as the new growth literature. Their view, in summary, lies in the impact of the errors associated with the measurement of total factor productivity when compiling data on the growth of real output, and the growth of real input, drawing on the economic theory of production with the assumption of constant returns to scale CRS coupled with the necessary conditions to reach the producer's equilibrium. According to them these errors result in bias in the TFP measurement. Thus, it is suggested that the allocation of changes in real output, and changes in real input, between their movements along the production function and its shifts need to be corrected for this bias that has been attributed to conceptual and measurement errors, (Jorgenson, 1991).

In consistency with this, it has been claimed that the economy's reliance, merely on the accumulation of capital without technological advancements, needs to be addressed sufficiently by valid economic reasoning, given that the diminishing returns to capital accumulation is very likely to work as a hindrance to the economic growth process and might even lower it to zero at some point, (Le Van and Nguyen, 2008).

It should be noted that the proponents of Solow's assumptions on growth imputed the rapid post-war growth in the NIEs to the employment of cutting-edge technologies that were first invented in the advanced economies. In his work on Taiwan, Pack (1992) suggested that the degree of success, which a small number of the Asian economies have achieved in the post-war period, in effect, largely comes down to their mastery in utilising the technological knowledge from the more developed economies in order to practically accommodate them and disseminate them inside their domestic economies, (Pack, 1992).

However, strands of empirical research discovered that the economic growth in the Newly Industrialised Economies (NIEs) was mainly accounted to the growth in input factors; namely, the physical capital, and labour coupled with an upturn in TFP, where it needs to be borne in mind that the effect of the technological progress cannot be dismissed from being a paramount driver in stimulating and promoting growth (Young, 1994), (Young, 1995), (Kim and Lau, 1994).

On the other hand, it is worth pointing out that the high rates of growth can also be attributed to the forced savings and investment, (Krugman, 1994a). As a corollary, it can be stated that the lack of technological advancements in conjunction with the existence of the diminishing returns, and the pace of the economic growth in the NIEs, is prone to being constrained or might be flatlined at some point over the course of time, (Krugman, 1994a).

All in all, the topic of how much of the output growth can be attributed to total factor productivity, and how much of it needs to be ascribed to capital formation, has been a highly argumentative one, and it tended to spark a great deal of debate and discussion among economists and observers over the years.

2.3 Neoclassical Growth Models

Despite the usefulness of the applications of growth accounting models for examining the relationship between human capital and growth, their basic assumptions caused them some limitations. One prime example, to cite, is the debate that took place between Denison (1972) and (Jorgenson and Griliches, 1967) where in fact, the work of the latter has been regarded as a milestone in the evolution of productivity theory where they, and based on a strict application of the neoclassical theory, have introduced a number of measurements into Solow's framework, (Hulten, 2001).

In their findings, they point out that the residual had all but disappeared, which seemed to be inconsistent with contemporary empirical outcomes, namely, by Denison (1972) who indicated in his work that the residual has a considerable contribution to the economic growth, (Jorgenson et al., 1972) . He compared the steps he followed with those of Jorgenson and Griliches and discovered that the cause of the divergent results between the two studies was in part owing to the different time periods covered by both studies. Whereas, the other reason for this divergence was the 'capacity-utilisation adjustment' based on the use of electricity, which demonstrated a long term increase between the equivalent years in the business cycle, and when this was taken out, Denison concluded that the Jorgenson and Griliches residual was not zero as they already had estimated, (Jorgenson et al., 1972).

Within the debate between Denison, on the one side, and Jorgenson and Griliches on the other, there were several issues that overshadowed the discussion. Solow considered the aggregate production function as the cornerstone to measure TFP, while Jorgenson and Griliches came up with important innovations, which gave rise to improvements in the model of TFP. One of their suggestions was to integrate the neoclassical theory of investment into the productivity analysis. This was according to the fundamental GDP identity equation which can be expressed as follows:

$$P_t Q_t = w_t L_t + r_t K_t \quad \text{Equation 2.2}$$

Where P_t , Q_t denotes the price and the quantity of goods and services, respectively, which are determined by the product market. $P_t Q_t$ represents the total value of goods, which in turn, represents the expenditures of consumers and the revenues of producers (Hulten, 2001).

On the other hand, the amount L_t, K_t and the corresponding prices w_t, r_t of inputs are determined by the factor market. While the total outlay of inputs $w_t L_t + r_t K_t$ is regarded as the producer's total cost and the consumer's gross income. In a nutshell, the two markets (the product market and the factor market) are associated to each other through the revenue and cost from the producer's standpoint, and the expenditure and gross income from the consumer's perspective, (Kendrick, 1961).

For the sake of blending the neoclassical theory of investment into the productivity analysis, Jorgenson and Griliches had to first perceive that the output value in the GDP identity equation is the outcome of the two combined fractions (the value of the produced consumption goods + the value of the produced investment goods), (Jorgenson and Griliches, 1967). Or to put it in a mathematical form as this:

$$PQ = P^c C + P^I I = wL + rK \quad \text{Equation 2.3}$$

The investment goods price was assumed to be equivalent to the rents present value which sprung from the investment (the depreciation of capital adjusted). Now the user's capital cost - it is usually referred to as the 'capital good's rental price' or 'the price of a capital service', which in effect is indicating the unit of cost for the use of a capital asset for one period, or the price of obtaining or employing one unit of capital – needs to be estimated, (Hulten and Wykoff, 1981).

It can be expressed as follows:

$$r = (i + \delta)P^I - \Delta P^I \quad \text{Equation 2.4}$$

There are a number of approaches in which the r or any of its components can be measured, and one of which is to obtain the investment good price P^I from the national accounts data, while the depreciation rate δ can be deduced based on the depreciation study of (Hulten and Wykoff, 1981).

Jorgenson and Griliches suggested a way in which the rate of return i can be estimated; it lies in imposing constant returns to scale in order to find the i that causes some sort of disruption to the equation of accounting $PQ = wL + rK$, and it is worth mentioning that only in this situation are the constant returns to scale a pre-requisite so as to measure TFP, (Jorgenson and Griliches, 1967).

2.4 Endogenous Growth Models

Contrary to neoclassical models, and in the research in the late Eighties, the endogenous growth models clearly integrated the technological progress in the production function, along with capital, labour, intermediate inputs, and human capital, to outline that the technical change is determined by the economic decisions by a similar way such as capital accumulation.

The key advances in the theory of economic growth, especially the developments in endogenous growth models, lie in the assumption that the long-run growth is determined within the model. The main element in these models is the technological progress, which means that a purposeful research and application would certainly result in new and cutting-edge products and modern methods of production, and would pave a way so as to adopt the superior technologies that have been contrived and originated, as well as those developed in other countries or sectors, (Barro, 2013).

In Romer's model (1990) human capital plays a special role, and it has been considered as the key input to the research sector that produces new ideas and commodities which underlie technological progress, (Barro and Lee, 1994).

According to Barro, the recent endogenous growth models are very beneficial for understanding why advanced economies, and the world at large, can carry on growing in the long-run in spite of the workings of the diminishing returns in the accumulation of physical and human capital, Barro (2013). In line with this, Nelson and Phelps (1966) proposed that, a larger stock of human capital makes it much easier for any country to absorb the ideas created somewhere else, and this will strengthen this country's capacity to utilise the innovated technologies and to grow more rapidly over time, (Nelson and Phelps, 1966).

That is to say that human capital overcomes the limitations imposed on growth due to the diminishing returns to other inputs (labour and capital), and it promotes growth and development through the important externalities of knowledge stock through raising the productivity of both labour and capital, and providing the appropriate environment for the emergence of entrepreneurs, who implement and benefit from diffusing innovations in order to encourage quality over the quantity of children when fertility rates gradually fall down worldwide, (Mathur, 1999).

In 1988, Lucas assumed that, in addition to the stock of physical capital, there is a meta-physical variable called Human Capital, a small part of it is devoted to production, whilst the remainder is devoted to the accumulation of human capital, (Lucas, 1988). Thereby, the level of human capital in the economy will determine the level of Total Factor Productivity TFP (Stevens and Weale, 2004). However, recent years have witnessed a surge in both the theoretical and empirical studies on TFP, and an increasing interest has been driven by the firm-level data, due to the fact that it has now become more available than at any other time before. This gives researchers the opportunity to estimate the TFP at the firm level, applying the new methodologies that have become available since the nineties, (Van Beveren, 2012).

Bearing in mind that much of the theoretical analysis for the leading role of human capital in the growth process, and the relationship between both sides, is all-inclusively understood and agreed upon. Despite that, it turned out that the evidence on the causality of this relationship has a tendency to be a highly controversial one. It had sparked vigorous discussions when it comes to the empirical outcomes about the direction of this relationship, which became more sophisticated and is not sufficiently evident.

In this respect, there are three main types of conclusions to be considered: (a) studies that consider human capital as a fundamental factor of economic growth; (b) studies that stand for the assumption that human capital accumulation cannot clarify the difference in income distribution when using these findings at an international scale; and (c) studies that consider human capital as a result of economic growth, (Loening, 2002). However, the difficult question that seems to face economic policy makers is how to generate and stimulate a sustainable unintermittent growth using scarce, irreproducible, and exhaustible resources.

The answer appears to be that technological progress can answer a considerable part of this question, but it could be the case that technological progress will involve the greater use of depletable resources, unless there are new ways, yet to be invented, to economise the use of those inputs – which are not regeneratable – of production, to allow for per capital income levels and standards of living to rise in the long run, (Grossman and Helpman, 1994).

2.5 Vandebussche, Aghion, and Meghir: 2006 Model

In line with the endogenous growth models, the contribution of human capital to growth, via innovating new ideas and imitating those existing ones, was further examined by Vandebussche, Aghion, Meghir in their (2006) model.

They developed a theoretical model where the effects of skilled and unskilled labour on growth have been investigated in the light of the economy's proximity and remoteness to the technological frontier. In their theoretical framework they suggest that higher education needs to be given, increasingly, a higher priority than the lower levels of education to enhance growth, as the economy shifts closer to the technological frontier.

The assumption is that relatively skilled workers are better suited to innovation activities, while imitation, which is a more unskilled-intensive activity, is fundamental in this model. This is while bearing in mind that the absolute intensity of skilled labour in innovation, and unskilled labour in imitation, is not specifically required in the argument of Vandebussche, Aghion, and Meghir (2006). Thus, the allocation of endogenous skilled and unskilled labour between innovation and imitation, and the impact of the two components of human capital, largely relies on the technological progress in the economy, (Vandebussche et al., 2006).

The argument also involves exploring the effect of the interaction between human capital, and the economy's distance to the frontier, where the model proposes that the effects of the interaction for higher education and the proximity to the frontier is positive, whereas for primary and secondary education it is negative, (Ang et al., 2011). In addition, given the more basic and the less technologically advanced technology that is in use in the less developed economies, there might be a weaker demand for high skilled labour and stronger demand for the basic level of skills embodied in workers, (Hanushek, 2013).

Moreover, the effect of the interaction between primary and secondary education, in an economy that is far from the frontier, is positive, owing to the reliance on imitating technologies and innovations produced in economies at the frontier, which could be put down to the low cost of imitation in comparison with the cost of innovation in less developed countries.

In their model, Vandenbussche, Aghion, Meghir (2006), share this specification with both Benhabib and Spiegel (1994) and with Acemoglu, Aghion, and Zilibotti (2002), this is where they assumed that technological progress is a combination of innovation – by skilled human capital – and imitation by unskilled human capital.

2.6 The Concept of Productivity

Historically, changes in the output value per unit of input is the way in which productivity has been defined, (Levinsohn and Petrin, 2003b), (Hulten, 2001). Simply put, it can be said that productivity is defined as the efficiency in production, (Syverson, 2010). It is in other words, the amount/value of the output of a firm or an industry obtained by using a given set/amount of inputs, (Apostolides, 2008). It is, however, also known as a ratio of the volume measure of output to a volume measure of input use.

Krugman defines productivity as, *“productivity isn’t everything, but in the long run it is almost everything. A country’s ability to improve its standards of living over time depends almost entirely on its ability to raise its output per worker”*, (Krugman, 1994b), P. 11)

Blinder and Baumol set their concept for why productivity matters *“...nothing contributes more to material well-being, to the reduction of poverty, to increase in leisure, and to the country’s ability to finance education, public health, environment improvement, and the arts than its productivity growth rate.”*, ((Blinder and Baumol, 1993), P. 491).

Total factor productivity has been long regarded as the productivity standard measure, and it is seen as the difference or the discrepancy between the logged actual output and the logged predicted output given the logged inputs for a Cobb Douglas production function, (Levinsohn and Petrin, 2003b).

It is worth mentioning that the difference between labour productivity and total factor productivity is that the former represents the ratio of the output (production) of goods and services to the labour hours worked, in order to produce that amount of output.

Whilst the latter (TFP) implies the relation of output in real terms to a combination of an inputs mixture that are utilised so as to generate that output.

These inputs encompass, labour, capital, energy, materials, and purchased business services (K capital, L labour, E energy, M materials, S services), (Apostolides, 2008). Thereby, it can be said that total factor productivity is an index of which reflects the output per unit for a set of mixed and combined inputs, and any changes in this index elucidate that any changes in output are not due to the changes in combination of these inputs, which means that TFP is the part of the output that cannot be explained by changes in the capital, labour, and other inputs.

However, and on top of all that has already been taken into account, the point that can be made is that of any of the output variations caused by any unmeasured changes in input, as a result of, for instance, quality differences or/and intangible capital, can be looked at as productivity, (Syverson, 2010).

Drawing on that, total factor productivity is designed to measure the contribution of technology, advances in knowledge, improvements and management, and the techniques of production that enhance and increase outputs, compared with the previous year using the same amount of inputs.

It should be noted here that the manufacturing total factor productivity measure excludes intermediate inputs between manufacturing corporations from both output and input.

In relation to this, and according to (Eberhardt and Teal, 2010), total factor productivity is defined in both a narrower and wider sense. In the narrower vision, TFP can be referred to as the output growth owing to both technological progression and efficiency improvements. But in the wider vision it can be seen as the growth of output caused by all kinds of factors, which include better operative and effective institutions, better climate, and less corruption.

2.7 Measures of Productivity

Contrary to its concept, which at a quick glimpse appears to be straightforward, measuring productivity entails the researcher to seriously consider and investigate a number of issues when constructing productivity measures from actual production data.

Generally speaking, total factor productivity is the measure of productivity that is mostly accepted by economists, and there are a number of different approaches to measure TFP, (Waters II and Tretheway, 1999).

The choice of the best way of measurement largely hinges on the purpose that productivity is measured for, along with the availability of data. All in all, productivity measures can be categorised into single factor productivity measures (relating a measure of output to a single measure of input), and into total factor productivity measures (relating a measure of output to a bundle of inputs).

Another issue that needs to be taken into account is in relation to the distinct measures used to estimate productivity, whether at the industry level or at the firm level; this is where some relate the gross output value to a single or a bundle of inputs, while others deploy the real value-added concept as a means to trace the fluctuations in output.

Three main issues are equally important and need to be taken into account when measuring productivity; (a) How the relationship between input and output is specified; (b) How good is the measuring of the factor inputs; (c) The weights that are given to each category of input when aggregating the sub-inputs, (Chen, 1997).

Labour productivity estimates reflect the amount of output produced by each unit of labour employed. In essence, labour productivity seems to be relatively straight forward to estimate with a reasonable reliability and to compare across countries after the differences in purchasing power parity PPP has been adjusted, (Conway and Meehan, 2013).

Given the fact that labour productivity measurements disregard and deny the centrepiece contribution of capital accumulation and its cost along with the other productive factors in promoting output; then Subsequently, this will cause labour productivity estimates to differ across countries and industries, as well as over time, due to the divergence in other productive factors, (Matheson and Oxley, 2007).

It is worthy to state that there are two components in which labour productivity is associated with and largely impacted by. The first is the capital deepening, which is referred to as the intensity of capital, which in turn reflects the amount of capital available per unit of labour, (Mason and Osborne, 2007).

In theory, it is widely agreed upon that the higher the capital intensity level is, the higher the labour productivity is expected to be, where workers will have more capital to deploy in the production process, (Conway and Meehan, 2013). The second factor that influences labour productivity is TFP, which accounts for a “unit bundle” of both capital and labour, and thereby, reflects the changes in the capital stock, not to mention that TFP estimating necessitates capital services to be aggregated and combined with the hours worked.

In corroboration for that, empirical research found that capital deepening and total factor productivity have been pivotal factors of economic growth, particularly since the 1990s, (Wölfl and Hajkova, 2007). However, the magnitude of their contribution can be largely affected by the ways of measurement, where it can differ from one approach of measurement to another, (Jorgenson and Griliches, 1967).

2.8 Methodology for Measuring Productivity

Since the early attempts undertaken by economists, to measure the source of productivity growth and the change in productivity, a number of examples of measurement procedures have been introduced for this purpose. One of which is (Malmquist, 1953), who presented his TFP index, which is designed to measure the change in productivity.

Solow (1957) utilised an aggregate production function so as to measure the growth in productivity in the U.S economy, (Sharma et al., 2007). He decomposes the growth in output into two parts; the first part is due to the input growth, and the other could be attributed to the aggregate productivity changes. The latter is usually referred to as the Solow residual as mentioned before, (Sharifabadi and Boshraubadi, 2011). One of the procedure’s shortcomings is that it does not identify the source of the growth in TFP, and whether it stems from the technological advancement or from the gains from technical efficiency.

By that, the issue becomes how to decompose TFP growth into its factors, where the researcher tends to use two main techniques, so as to meet this objective, which are non-parametric approaches to obtain productivity indices, and the other is the stochastic frontier models mentioned in greater detail in chapter 3, (Sharma et al., 2007).

Apparently, there are a number of studies that have estimated and assessed the TFP with a variety of techniques, (Jung et al., 2008), (Van Biesebroeck, 2008, Van Biesebroeck, 2007) observed and reviewed these methods and categorised them based on the more commonly-used approaches. These are (1) the index number by Tinbergen (1941), Kendrick (1955), Solow (1957), Diewert (1976), Caves *et al* (1982), and lastly, Good *et al* (1999). (2) Data Envelopment Analysis or the so-called Non-parametric frontier estimation DEA by Farwell (1957), and Charnes *et al* (1978). (3) Parametric estimation or instrumental variables estimation GMM by, (Blundell and Bond, 2000), and (Blundell et al., 2001). (4) Stochastic Frontier Analysis SFA by Farwell (1957), Aigner and Chu (1968), Aigner *et al* (1977), Meeusen and van den Broeck (1977), Cornwell *et al* (1990). (5) Semi-parametric estimation by (Olley and Pakes, 1992), (Jung et al., 2008, Levinsohn and Petrin, 2003a), and (Wooldridge, 2009).

2.8.1 The Solow Model

In Solow's paper "*technological change and the aggregate production function*" published in 1957, the growth rate was demonstrated as a combination of the growth rates in the production factors (physical capital, labour, and technical progress),(Solow, 1957), (Ganev, 2005), and (Le Van and Nguyen, 2008). He used the Hicks-neutral technology production function for the accounting growth which as can be shown;

$$Y(t) = A(t). [F|K(t). L(t)] \quad \text{Equation 2.5}$$

Where; $Y(t)$ is the aggregate production or income. $A(t)$ is the level of common technology at a certain time. $K(t)$ is the stock of physical capital utilised in the production process and $L(t)$ is the labour inputs, (Hulten, 2001).

The above function can be transformed to the differentiated form with respect to time as follows;

$$\frac{\dot{Y}(t)}{Y(t)} = \frac{\dot{A}(t)}{A(t)} + a(t). \frac{\dot{K}(t)}{K(t)} + b(t). \frac{\dot{L}(t)}{L(t)} \quad \text{Equation 2.6}$$

$$a(t) + b(t) = 1$$

Where; $a(t)$ is the share of capital cost in the total production costs, and $b(t)$ is the share of labour costs in the aggregate production costs as well.

Data are available regarding $Y(t)$, $K(t)$, and $L(t)$. And they can be calculated, but as regards $A(t)$, (Barro, 1999). It can be calculated as a residual through the following formula;

$$\frac{\dot{A}(t)}{A(t)} = \frac{\dot{Y}(t)}{Y(t)} - a(t) \cdot \frac{\dot{K}(t)}{K(t)} - b(t) \cdot \frac{\dot{L}(t)}{L(t)} \quad \text{Equation 2.7}$$

The discrete model that has been used over the years, in order to calculate TFP when working on real data, can be written as below;

$$\frac{\Delta A(t)}{A(t-1)} = \frac{\Delta Y(t)}{Y(t-1)} - a(t) \cdot \frac{\Delta K(t)}{K(t-1)} - b(t) \cdot \frac{\Delta L(t)}{L(t-1)} \quad \text{Equation 2.8}$$

2.8.2 Output, Inputs, Productivity, and Efficiency at the Micro-Level

There is rich history of the coefficient of resource utilisation applications, which was first envisioned by (Debreu, 1951) to measure the efficiency of economic systems. Efficiency measurement is sometimes understood as a problem of comparing efficiency between different sets of production possibility, and economists are so often encountered with the question of how efficient one firm is in comparison with the others? The answer to this question lies in two main factors. First, the production technology. Second, the inputs choices. Therefore, the issue is more related to how efficient the selected combination of (input, output) relative to the available technology to the firm, (Chambers and Miller, 2012).

Efficiency setting in (Debreu, 1951) is usually understood in the Pareto logic. In this sense efficiency is determined in the social welfare context.

In the Pareto sense and the modern welfare economics, efficiency concerns the best possible allocation of resources that makes some individuals better off without making an individual worse off. In the marketplace, the competitive equilibrium is one of

potential outcomes of Pareto's efficiency which is included in the problem of economic allocation of resources, (Martorana. M, 2007).

The implementation of the growth accounting framework to assess the contribution of numerous inputs in the economic growth, is established on the production frontiers where the gross product of any industry is determined by a combination of capital, labour, intermediate inputs and technology in a period of time, (O'Mahony and Timmer, 2009). This approach of growth accounting has been developed by (Jorgenson and Griliches, 1967). It is customary in this method to add up inputs into broad categories.

When the output is measured as value-added, the broad categories are capital and labour. However, if the output is an aggregate production, it is necessary that it should comprise of energy, materials, and services, which are known as KLEMS. This style of grouping permits the researcher to specify the contribution of capital, labour, energy, materials, and services to the output growth.

However, it is important to highlight that this classification involves a great deal of heterogeneity issues of these inputs, which are consequently causing several common problems in the measurement that become even worse when measuring the growth of capital. This is assuming that industry j can generate a group of products in time T , and is able to purchase different inputs including capital, labour, and intermediate inputs. Thereupon, the production function can be expressed as:

$$Y_j = A_j F(K_j, L_j, M_j) \quad \text{Equation 2.9}$$

Where;

Y_j denotes output, K_j is capital service flows, L_j indicates labour services flow, M_j represents the intermediate inputs (either purchased from domestic industries or imported from international markets). A_j is the factor-neutral shifter or TFP, which captures the variations in output, which are not explained by shifts in the observable inputs that perform through the function $F(\cdot)$, (Syverson, 2010).

Under the circumstances of full competition in the production factors' markets, as well as the high efficiency in utilising inputs with the assumption of the CRS constant

returns to scale, the growth in output can be computed using the translog form of production function as below;

$$\Delta \ln Y_{jt} = \bar{v}_{jt}^X \Delta \ln X_{jt} + \bar{v}_{jt}^K \Delta \ln K_{jt} + \bar{v}_{jt}^L \Delta \ln L_{jt} + \Delta \ln A_{jt}^Y \quad \text{Equation 2.10}$$

Every factor on the right-hand side of the equation represents the growth of output attributed to the growth in each element (intermediate inputs, capital services, labour services, and technological change), consecutively, as measured by total factor productivity, (Timmer et al., 2007).

Where; A^Y represents the technological change, \bar{v}^i denotes for the two-period average share of inputs in the nominal output. Where it can be mathematically expressed as follows:

$$v_{jt}^X = \frac{P_{jt}^X X_{jt}}{P_{jt}^Y Y_{jt}} \quad v_{jt}^L = \frac{P_{jt}^L L_{jt}}{P_{jt}^Y Y_{jt}} \quad v_{jt}^K = \frac{P_{jt}^K K_{jt}}{P_{jt}^Y Y_{jt}} \quad \text{Equation 2.11}$$

Taking into consideration that $\bar{v}^L + \bar{v}^K + \bar{v}^X = 1$

Perfect competition reduces inefficiency, since it means that many firms co-exist in the same marketplace in the same time approximately, utilising almost the same level of technology, producing a large number of homogenous goods and services. In that sense, the existence of competitors will increase the pace of information and technical knowledge diffusion, which in turn will enhance the experience for the producers and consumers alike. This will result in higher levels of efficiency both at the micro and macro level in the economy, (Carlsson, 1972), (Caves and Barton, 1990).

The dominance of the powerful firms on the local market can be reduced in the case that these firms are export-oriented ones. This can be measured by the degree of openness and the share of their exports to the international markets. This implies that these firms will be faced by strong competition in the global market, and they will be forced to decrease their inefficiency in order to be able to compete with the foreign firms, and the probable effect of this external competition is to have better efficiency in this business environment, (Gumbau-Albert and Maudos, 2002).

Having discussed the mechanism of the neoclassical growth models, (Romer, 1990c, Romer, 1986, Romer, 1990d, Romer, 1990a). In that he argues that the decreasing returns to capital, perfect competition, and exogenous technology do not fully define the differences in per capita incomes and national growth rates across nations, where it is justified by the conflict between the model's predictions and the historical evidence, (Grossman and Helpman, 1994). To make his case, Romer assumes that the growth rate of the world's technological leader has been rising over time, and not declining, which according to the neoclassical model could only happen if the pace of the acceleration of the exogenous technical advancement is steady.

In addition, the neoclassical model assumes that countries do not enjoy the same common level of per capita income due to the lack of sharing a similar behaviour in savings and the same level of technology. However, (Mankiw et al., 1992) refute this view, and suggest that the evidence, on the variations in the international per capita income between countries, is in line with the standard model of (Solow, 1956). This is once it has been augmented to comprise human capital as an accumulable input and it allows for the cross-country disparities in savings rates to reflect the varying tastes and cultures.

By inefficiency, and under specific conditions, plants which operate in the market economy could lack the ability and skills to perform effectively, and may produce inefficiently, which indicates the inefficient use of the scarce resources available to these production units, and by extension, this means that the economy is producing less than the optimal level of output of goods and services from these resources.

According to Pareto efficiency or Pareto optimality, resources are assumed to be allocated in the most efficient manner considering the possible inequality and unfairness that could occur. Inefficiency is simply the difference between the observed values of production and the maximum values obtainable given the technology used (Gumbau-Albert and Maudos, 2002)

Inefficiency presence depends on a multitude of factors; (Nelson and Phelps, 1966) suggested that education is important when explaining the countries failure to use the best-practice technology, and by reason, this can apply to firms' failure to benefit from their resources in the best possible way to reach the highest level possible of output due to their lack of adequately educated workers (Stevens and Weale, 2003).

Several studies have developed their strategies to identify the determinants of efficiency. (Lovell, 1993) suggested that "the identification of the factors that explain differences in efficiency is essential for improving the results of firms although, unfortunately, economic theory does not supply a theoretical model of the determinants of efficiency".

However, the efficiency determinants can be outlined as follows:

- 1- Exogenous factors to firms, including the competition degree in the market in which these firms operate.
- 2- Firms characteristics, including firm size, firm location, the intensity of investment. etc
- 3- Firms ownership, whether it is private, public or a combination of both.
- 4- The dynamic deviations from the firm's equilibrium situation in the long run due to evolution in the market demand for the firm's production, or as a consequence of some change in the production scheme or the level of technology used in the production process (Gumbau-Albert and Maudos, 2002).

2.9 Human Capital and Productivity

In some strands of the empirical literature, however, the evidence on human capital impact on productivity is rather mixed; some of the research reports a significant and positive impact of human capital on TFP growth, (Fleisher and Chen, 1997), (Vandenbussche et al., 2006), (Fleisher et al., 2010). While other studies present the negative and significant role for human capital in the growth of productivity, (Pritchett, 2001).

There can be all manner of reason behind this mixed evidence on the role of human capital in productivity. It can be put down to the endogeneity of human capital as some argue (Bils and Klenow, 2000), (Krueger and Lindahl, 2001b), or it can be because of the inadequacy in measuring human capital quality, which is a difficult task, as well as an argumentative issue, (Hanushek and Kimko, 2000, Bosworth and Collins, 2003), or it can be the result of the various methods used to measure TFP including growth accounting, Olley and Pakes (1996), Levinsohn and Petrin (2003), Malmquist TP index, frontier methods, and time trends, (Wei and Hao, 2011). However, the concept of human capital goes back at least to Adam Smith, where he noted:

“....., of the acquired and useful abilities of all inhabitants or members of the society. The acquisition of such talents, by the maintenance of the acquirer during his education, study, or apprenticeship, always costs a real expense, which is capital fixed and realized, as it were, in his person. Those talents, as they make a part of his fortune, so do they likewise of that of the society to which he belongs. The improved dexterity of a workman may be considered in the same light as a machine or instrument of trade which facilitates and abridges labour, and which, though it costs a certain expense, repays that expense with a profit” ((Smith, 1776), P. 217).

Human capital, according to Oxford English Dictionary, is defined as *“The skills the labour force possesses and is regarded as a resource or asset”*, and therefore, it extends to the idea of investing in people via education, training, and health to increase the productivity of individuals, (Goldin, 2016). The OECD (2001) sets a concept of human capital as *“the knowledge, skills, competencies, and attributes embodied in individuals that facilitates the creation of personal, social, and economic well-being.”* (Kavanagh and Doyle, 2006, Organisation for Economic Co-operation and, 2001).

According to (Gillman, 2011a) human capital, denoted by h_t , is defined as that which turns raw labour time into time that yields a higher marginal productivity. The simplest way to think of it, is an index that starts at one, $h_t = 1$, and that rises through investment in human capital. Then the wages rate is not just w_t per unit of raw labour time, but rather $w_t h_t$ per unit of raw labour. To put it another way, the human capital increases the ‘effective wage rate’ of $w_t h_t$ and as the human capital rises, the effective

wage rate rises along the balanced growth path, and the time that now enters the production function, which in raw terms is l_t the amount of labour time, which now becomes $l_t h_t$, which is the ‘effective labour time’.

The time is in effect augmented by the degree of human capital. Meanwhile w_t reverts back to the wage rate of raw labour and this is now stable along the balanced growth path (instead of rising as when there is exogenous growth), so that per capita income rises only because human capital and the effective wage rise, (Gillman, 2011b).

It is thought that Irving Fisher was one of those early users of the term “human capital”, used as a formal term in economics, (Fisher, 1897). However, the term was later embraced and used by several writers, and it did not become common use until the seminal works of (Mincer, 1958), (Schultz, 1961), and (Becker, 1964), respectively.

There is a widely held belief that the knowledge and skills, embodied in human beings, directly boost productivity and also stimulate an economy’s ability to grow and develop, as well as to adopt and absorb modern technologies, (Khan, 2005), (Ali et al., 2008).

It is also assumed that the effect of human capital on the growth rate of output, through the total factor productivity and technical progress, comprises a large externalities component due to the difficulty in estimating separately the full economic value of cutting-edge notions, (de La Fuente, 2011). Moreover, it is recognised that the key to long-run economic growth is productivity, where high productivity is thought to strengthen a firm’s ability to generate and produce more goods and services using the same available amount of production factors, (Singh and Trieu, 1999).

In spite of the consensus on the relationship between human capital, technology and productivity, the number of firm-level studies, which have been carried out to evaluate the progress in productivity through these two factors, have been considered to be modest, (Turcotte and Rennison, 2004). Some studies in the United States ascribed the improvement in labour productivity to the gains in efficiency accomplished through the augmented production and the utilisation of Information and Communication Technologies, (Turcotte and Rennison, 2004), while others went to the point to conclude that half of the acceleration in the productivity growth in the United States, between the first and the second half of the 1990s, comes down to the wide use of the

ICTS, (Oliner and Sichel, 2002).

The evidence on the correlation between education and growth through different channels, such as innovation and imitation, is still indefinite. For instance, and concerning the link between education and innovation, one could compare the pace of growth in Europe with its equal in the U.S. which seemed to be slower in the former.

Some argue that this can be attributed to the low investments in higher education in Europe compared to the U.S., (Sapir, 2003). Spending more money on research and development is another important channel to generate innovations particularly in firms whose top managers are well equipped with a higher level of technical education, (Scherer and Huh, 1992).

On the other hand, and regarding the nexus between education and imitation, the anecdote is different. European growth, over the three decades, during the aftermath of the second World War, was at a faster rate than in the U.S., even though the investment in education in Europe was principally in the initial levels, such as primary and secondary schooling, and the same seems to be true in the case of East Asian economies namely in Korea. That is why it is not a straightforward task to predict growth using a proxy, such as average years of education for human capital stock in a country and compare its growth rates with another country, even though the two countries are at the same distance from the frontier. Therefore, without considering the difference in their human capital compositions and the scale of investment in education, the causes and determinants of growth will not be easy to pinpoint, (Aghion et al., 2009).

In a similar vein, and despite the consensus among the advocates of endogenous growth theories on human capital being an important factor in growth, (Romer, 1990b), (Aghion and Howitt, 1990), (Aghion et al., 1998), (Acemoglu, 1996), and (Acemoglu et al., 2006), the empirical research has provided rather mixed and ample evidence on its importance, (Ang et al., 2011).

There is a great deal of follow-up research to (Nelson and Phelps, 1966) involving the importance of human capital (educated labour) as a facilitator to advanced technology adoption and diffusion, and recent research has emphasised that human capital, along with its role to increase a country's ability to develop its own innovation efforts, can

also be a decisive driver to raise the level of capacity for more readiness and preparedness for absorbing ideas and technologies developed elsewhere, and thereby they pave the way for the economy to catch-up and converge, (Benhabib and Spiegel, 2005), (Griffith et al., 2004), (Kneller and Stevens, 2006) and (Madsen et al., 2010).

There is a proliferation of literature on the investigation of the role of human capital in growth, which is still to some degree opaque and of a contradictory nature, where the understanding and interpretation of this role appeared to be obtuse at times.

Providing that more recent attention has focused on this role across different countries from different regions, it is found that human capital plays a greater role in promoting growth in economies with low levels of education and low-skilled labour, (Krueger and Lindahl, 2001a). Whereas, some contend and suggest granting the creative role, played by highly educated human capital, as a driver to the innovation of state-of-the-art technology, it is also believed, for that matter, that unskilled human capital can also have the capacity to assist imitation and ease technologies diffusion. This suggests that the closer the economy is to the technology frontier, the more important the higher levels of education would be, compared to the primary and secondary levels of education, (Vandenbussche et al., 2006).

On the other hand, highly-skilled human capital can encourage and promote the innovation and production of new advanced technology, (Ang et al., 2011).

2.9.1 Human Capital, Efficiency, and Productivity in the Transition and Developing Economies

It might be worth pointing out that during the times of growth and transformation, the output of agriculture and employment falls in absolute terms relative to the growth in the industry output linked with the growth in the population magnitude, which in turn will be absorbed in the growing industrial sector. This is what has been referred to – in the literature – as the turning point, (Piesse and Thirtle, 1997).

In 1989, at the beginning of what is known as the Transition in the Eastern and Central European economies such as the Czech Republic, Slovakia, Slovenia, Poland and the Baltic states, and the re-integration with the global economy, the manufacturing sector

was required to adapt to this new reality in order to improve its efficiency to face the international competitiveness.

Due to several shortcomings of the planned socialist economic system, a considerable number of firms and production units used to employ large numbers of low-skilled and poorly managed labour across these countries. At the time of the transition process, large numbers of workers were laid off and left outside the job market, and the unemployment rates rose markedly during the 1990s especially in the heavy industry sector because it lacked some economic, technical, and environmental criteria to be able to compete in the market economy, (Bukowski and Śniegocki, 2017).

The industry structure in ECA in broad terms, and in central Europe in particular has changed. The scale of employment in the manufacturing sector went down by 20 to 30%, mirrored by – to a great extent – the higher levels of labour productivity and goods quality.

Like physical capital (machinery and buildings), human capital is durable and it is formed of skills and knowledge that accumulated over time in individuals, but it also suffers from depreciation as in the case of physical capital, (Miles and Scott, 2008). Educational attainment growth – as part of the human capital accumulation process – was rapid in the developing economies since the 1960s. The interesting point is that the education contribution to growth in the developing countries was below the anticipated level based on the applications of Solow's augmented model using cross-country data, (Pritchett, 2001).

The contribution of education to growth certainly varies across the world's nations. This can be imputed to a number of issues. First, the educated labour force is not assigned to the right jobs to do the right thing in some regions such as MENA and ECA. This suggests a mismatch between skills profile and the available set of jobs, which also means that the quantity of skilled workers has increased but their contribution to productivity and growth at large did not. Second, the changes in economic policies, sectoral transformations, and the pace of technical advancements have differed substantially across nations, which gave rise to different rates of growth in the demand for the educated workers. Therefore, it can be extrapolated that in economies with the same level of returns of education, and the same scale of expansion in educational

attainment, can see dramatic falls, rises or stagnation in the marginal returns of schooling. Third, the inadequacy of the education environment in some countries was not appropriately qualified and schools were not conveniently established to provide individuals with the sufficient stock of knowledge to create and develop certain level of skills, (Pritchett, 2001).

In developing countries, it appears that a firm's productivity tends to be extremely low. The evident reason for this is that firms in these countries are often badly managed; it is important to have a high level of coordination and motivation through formalised management practice especially in large firms, (Bloom et al., 2010).

One of the suggested causes for the slowdown in productivity is that countries do not invest sufficiently in human capital, particularly in secondary and tertiary education, and in some nations the innovation's pace slows down dramatically, which could also hold back the productivity growth due to institutional failures, low quality of governance and high levels of corruption, and underdeveloped financial systems, which may restrict the country's ability to maintain the rate of growth, (The Middle Income Trap, 2016).

According to some research, developing economies invest more than \$100 billion on education and other human capital investment activities. Hence, it is quite important to understand the expected effects of these investments and how they contribute to growth when exploring the trends and differences of growth in the international context, (Petraakis and Stamatakis, 2002, Alderman et al., 1996).

In addition, recent research underscored that developing countries have been less successful in reducing the technology gap than the more developed countries, and this is where improving their quality of schooling and school attainment can ease these difficulties to enhance their economic performance for better long run growth prospects, (Hanushek, 2013).

Since improving the standards of living is one of the important goals at the macroeconomic level. Therefore, the growth in productivity is thought to be a crucial driver that helps in raising the quality of living in an economy, (Kavanagh and Doyle, 2006).

Productivity is a relevant concept in this context where it can vary between production units and across the years for many reasons. It varies on account of the different technologies used in production, and the different levels of efficiency in production operations, and it could have differed due to dissimilar environments in which goods and services were generated. Abramovits distinguished the variation of productivity as the “the measure of our ignorance”, (Abramovitz, 1956), and to dispel this “ignorance” a great deal of effort has been dedicated to pare the residual by minimising the measurement error when establishing the output and input quantity indices, and in doing so, the residual would be appropriate for analysis, (Fried et al., 1993).

Productivity growth, in effect, can be imputed to many factors. One of which is human capital, and in the core of it stands the skilled workers who acquired skills mainly through education and training, (Leitch, 2005, Bergheim, 2005). During the 1960s most developing economies achieved considerable education attainment as the cross-national data demonstrate. Yet the contribution of this improvement in education was less than expected based on the Solow growth accounting model, (Pritchett, 2001). The impact of the quantitative achievements in education on growth and competitiveness in the developing economies fell short of expectations. Simply due to the lack of certain level of quality in the outcome of the educational process, and the lack of better allocation and utilisation of the financial resources which were poured into the education systems by governments in some of these economies.

Regarding the MENA economies, they seem to be underperforming in terms of several aspects of the global competitiveness indexes, and even though the degree of openness is not a problem per se, firms in this region are still able to trade (export and import) with the rest of the world more than many of their counterparts in other developing countries. This can be attributable to the fact that most of the trading firms are small and medium enterprises.

Moreover, it is also found that the average size and the productivity differences between the exporters and non-exporters are smaller in comparison with other areas. Another

major feature of the MENA economies is that the formal private sector is not sizeable, yet, it still plays an important role in the economic development.

In relation to labour productivity growth in MENA, it is found to be higher than that in other peer economies in a similar level of income, and the gains in labour productivity that can be ascribed to innovation are found to be in line sometimes with those in the developed economies, but on the down side, private sector firms in this region are lagging behind those in other developing economies with regard to the growth in total factor productivity, (Pedro de Lima, 2016).

However, in the case of the Middle East and North Africa, and according to the human capital index, (Report, 2016), merely one country, Israel 23, makes it into the top 30 on the index list, yet it improved in (2017) to climb up to 18. Whereas, some of the gulf states (Bahrain 46, Qatar 66, and UAE 69) are ranked in the mid-range of the total number of the countries included in the sample, but the UAE and Qatar achieved a better score in (2017) by being ranked 45 and 55, respectively, whereas Bahrain has dropped one step down to 47.

Given the relatively high levels of income that these countries already enjoy, there can be an additional advantage to raise the level of human capital performance in the years to come by admitting that the quality of education, relative to the rest of the world, is an issue of concern in this region even when controlling for the income and development levels, (Heyneman, 1993). It can also be observed that Jordan came in at 81st place in (2016) and has fallen to 86 in (2017).

In North African countries Egypt was 86 in (2016) and dropped to 97 in (2017), Morocco was 98 in (2016) and plummeted to 118 in (2017), Tunisia was 101 in (2016) and declined to 115 in (2017), Algeria was 117 in (2016) and went up to 112 in (2017), and Mauritania was 130 in (2016) along with Yemen at 129 in (2016), where they switched places in 2017. The performance in this index, as can be observed, is much lower than in other economies in the sample spanned across the region, (Report, 2017, Report, 2016).

Additional factors to human capital could lead to these higher levels of labour productivity in MENA. Essentially, these are the intensiveness degree in which the complementary inputs (capital, materials) are used, or the use of unrivalled technology. This explanation seems reasonable to some extent, assuming that TFP per se involves measuring the efficiency in which production factors are used, comprising not only of labour inputs but also capital, and intermediate inputs.

The empirical research suggests that the over-dependence on capital and intermediate inputs is a widespread phenomenon more than the more advanced and elaborate technology, which can be accessible amongst the MENA economies, (Pedro de Lima, 2016). In this particular situation, Morocco stands out as being, comparatively, the most coherent and efficient structure in the matter of the relatively high levels of labour productivity inherent in relatively higher TFP, (Pedro de Lima, 2016).

Historically, and since the time of Adam Smith, a considerable volume of literature and several debates have emerged on whether the more open economies can grow faster and benefit from the technology transfer across the borders via international trade, which in turn will imply a greater degree of openness and a higher degree of flexibility and adaptability in favour of the more efficient approaches in production, (Grossman and Helpman, 1991, Barro and Sala-i-Martin, 1995, Mastromarco and Ghosh, 2009).

The interconnection between human capital and efficiency has become a central issue and it largely pivots on several factors, such as the degree of openness of an economy, and foreign direct investments flows and externalities, along with the appropriateness and quality of the skills embodied in the stock of human capital to absorb new technologies. This helps to deploy more efficient production techniques in order to satisfy the criteria that will allow an economy to catch up with the technological frontier, by diversifying outputs and exports, motivating individuals for possessing better skills, performing with higher levels of productivity, and receiving higher payoffs and wages, which in the end will raise the levels of per capita income in the economy as a whole, Romer (1990), Grossman & Helpman (1993) (Grossman and Helpman, 1993, Benhabib and Spiegel, 2005, McAdam, 2015, Romer, 1990c, Barro, 1998).

This is to a large extent true in the case of developing countries and in the Middle East and the North Africa region in particular. This is where the effects of utilising the imported technologies from developed economies can be significant on growth in total factor productivity, and this has been in one way or another reliant on the level of human capital in these economies, (Benhabib and Spiegel, 1994), which is notwithstanding the subject of the low level of returns from basic education, (Pritchett, 1999) in these countries, as opposed to higher returns from university education, (Salehi-Isfahani et al., 2009), which poses one of the interesting questions in the income inequality debates.

Furthermore, the significant wage premia in the public sector in MENA tends to contribute in a negative way to the development of labour-intensive manufacturing process, very much so in the labour-abundant economies in MENA, where the abundance of low skilled labour presents a common phenomenon that is yet to be explained in the manufacturing sector, (Christopoulos and McAdam, 2015). Nonetheless, (Acemoglu et al., 2006) argue that despite the MENA nations lagging behind the world's technology frontier, importing modern education systems from the more developed countries, could be unsuited to the production environment and the setting of the production relationships in MENA, (Acemoglu et al., 2006).

In a similar vein, previous studies noted that only a small number of research and development intensive economies is in the leading role for generating the world's assets of capital goods, and highly-sophisticated and state-of-the-art equipment and machinery, whereas the rest of the world import what has been produced, and adapt to it in the more affluent economies, (Eaton and Kortum, 2001).

The conspicuous shifts that economies in Eastern Europe, East Asia, and Latin America have been experiencing, throughout the last three decades, have altered their portion in the world gross production of goods and services, as well as their share of world trade in a marked and pronounced manner, whereas, and by a stark contrast, the Middle East and North Africa economies encountered a cease in developing and increasing their share in the world's economy, and became stagnant in the most optimistic evaluations during the same period, (McAdam, 2015).

2.10 Human Capital and Efficiency

The contemporary literature of efficiency analysis began with (Farrell, 1957) who was enormously influenced by the ideas of measuring “technical efficiency” posited in (Koopmans, 1951), and the “coefficient of resources utilization” by (Debreu, 1951), (Nguyen, 2010). This where according to (Koopmans, 1951), a producer is said to be technically efficient if, and only if, the goal of producing more of at least one output without the need of producing less of another output, or using more inputs, is achieved. Thereby, technical efficiency in the stochastic frontier analysis can be determined by the ratio of the realised output to the potential output.

The concept of “Technical Efficiency” TE refers to the ability to maximise outputs from a given vector of inputs, or put the other way around, it is the firm’s ability to minimise input utilisation in the production function of a given vector of outputs, (Coelli et al., 2005), (Arazmuradov et al., 2014).

Producer’s efficiency (technical, allocative) principally concerns the comparison between the optimum (maximum production possibilities, behavioural targets of producers; optimum cost, profit, revenue) and the observed levels of the producer’s outputs and inputs. In other words, the comparison involves the ratio of the observed to the maximum potential output attainable given the available input. Conversely, it includes the ratio of the minimum potential to the observed level of input needed to produce the given output or a combination of the two.

There are two constituents of economic efficiency, technical and allocative efficiency. According to Koopmans (1951), technical efficiency can be observed as; a production unit that is technically efficient if an increase in any output necessitates a reduction in at least one other output, or an increase in at least one input, and if a reduction in any input involves an increase in at least in one other input or a reduction in at least one output, (Koopmans, 1951).

By way of contrast, (Debreu, 1951) and (Farrell, 1957) introduced a different view on how to define technical efficiency, which was designated with the term the Debreu-Farrell Measure; this is “one minus the maximum equiproportionate reduction in all inputs that still allows the production of a given output, a value of one indicates technical efficiency whereas a score less than the unity indicates the severity of technical inefficiency”.

On the other hand, allocative efficiency or price efficiency refers to the production unit’s ability to combine the inputs and outputs in the optimal shares in the light of the prevailing market prices.

The behavioural goals of the production unit are the relative measures of the allocative efficiency, such as the comparison between the observed level of cost versus the optimum level of cost, and the observed level of profit vis-à-vis the optimum level of profit. Thereby, both technical and allocative efficiency can be measured via two methodologies: (i) the input approach; the aim of it is to evaluate the ability of avoiding waste by means of producing as much output as the use of the input allows. Hence, it is relevant to the question: Can input usage be minimised by keeping output constant? (ii) the output approach; the rationale of this approach is to assess the ability to avoid waste through minimising the use of input as little as the production of output allows. Accordingly, it has to do with the question: Can production be maximised by holding inputs fixed? (Porcelli, 2009).

From a technical point of view, the composite error term consists of a noise v , and an inefficiency term u . Where the former v is intended to capture the statistical noise, or what is known as the exogenous random shocks which are beyond the production unit’s grasp.

Whereas, the latter u is the reflection of the inefficiency presence and assumed to be $u \geq 0$. To estimate the firms’ technical efficiency, distributional assumptions for both v and u are specified. According to (Meeusen and van Den Broeck, 1977) and (Aigner et al., 1977), v is intended to be normally distributed and with a zero mean and σ_v^2 variance.

The difference though is that (Meeusen and van Den Broeck, 1977) assume that u is exponentially distributed. Whereas, (Aigner et al., 1977) suggest u to be both, with an exponential and half-normal distribution. With these distributional assumptions, a maximum likelihood method can be utilised to estimate all the parameters of the model.

The literature on regional growth draws on the endogenous growth theory when examining the effects of human capital on economic growth, (Ang et al., 2011). The integration between human capital and physical capital through the reciprocal relationship that links them together, by means of externalities related to human capital investment, is believed to be the core of the positive impact of human capital on economic growth, (Sanromá and Ramos, 2007).

The reviewed literature suggests that higher levels of education are assumed to lead to higher levels of innovation, and therefore, higher growth rates, (Lucas, 1988), (Romer, 1990b), (Gregory et al., 1992), (Hansen and Knowles, 1998), (Vandenbussche et al., 2006); this is in despite (Bils and Klenow, 2000) of the argument on the reverse causality between education and growth, where they state that the richer and faster growing countries find it easier than less developed countries to increase their spending on education because they have better institutions to improve the quality of the education system output, (Aghion et al., 2009).

Some recent studies on human capital provide compelling evidence that primary and secondary levels of schooling tend to play a crucial role in promoting growth throughout developing countries, (Krueger and Lindahl, 2001b), while on the other hand, higher education plays a more decisive role in more developed economies, (Petraakis and Stamatakis, 2002). Other studies showed ample evidence at best, on the positive impact of human capital in boosting growth, where with using a regional dataset, it was found that primary education, in Spain for instance, is positively associated with higher growth in poorer regions, whereas secondary levels of education seemed to be more significant in strengthening and supporting growth in more affluent areas, (Di Liberto, 2007).

Several theoretical frameworks, including the neo-classical models and endogenous growth models, have integrated human capital as a pivotal determinant of long-term growth and economic success, (Maudos et al., 2003). Human capital can also foster technical change via stimulating both innovation and imitation, which in turn acts as a stimulus to the economic growth rate, which is named as the rate effect of human capital, (Benhabib and Spiegel, 1994).

In addition, considerable attention has been paid to examine the relationship between human capital and efficiency across the years, and sizeable empirical research has established a positive quantifiable impact of human capital on efficiency, productivity and therefore growth, (Dimelis and Papaioannou, 2014). Some of them argued that human capital can provoke productivity growth through the spillovers of technology absorption and diffusion, (Nelson and Phelps, 1966).

Others suggested that by the means of intensifying domestic technical innovations, productivity can be spurred on (Romer, 1990b) & (Romer, 1990d), (Aghion et al., 1998). By way of contrast, some empirical evidence, resulting from examining the interaction between human capital and productivity, has shown some ambiguity that has emanated from the divergent and contrastive outcomes of the human capital effect on productivity (Wei and Hao, 2011). (Pritchett, 2001) contended that, during the last four decades starting from 1960s leading up to the 2000s, educational attainment has grown at a rapid pace, especially throughout developing countries, and yet, he argued that on average, education did not contribute markedly to growth based on Solow's standard augmented model.

The proposed rationalisation for the differences in the impact of education on growth across countries includes: (i) the significant skills underutilisation in some countries is caused by an improper institutional environment, and by devoting the available skills in the wrong economic activities. (ii) The variations of the marginal returns of education are due to changes in the growth rates of demand for educated labour caused by different structural shifts, and by the policies in some countries, which are exposed to various technical developments derived externally. (iii) The distinct approaches and strategies followed in transferring knowledge have widely

varied across countries, which gave rise to variant and diverse impacts on growth throughout nations, (Pritchett, 2001).

(Huffman, 2001) also suggested a major research gap in the human capital relevant literature, and he referred to the puzzle of why schooling does not demonstrate a straight and all-inclusive effect in the agricultural products, and he points out that the workers' level of education does not contribute to productivity growth in this sector.

Furthermore, the misinterpretations of the impacts, when using school attainment as a proxy of education, ignores the changes in the general achievements of school graduates over time, representing another major impediment in assessing the realistic contribution of human capital, (Huffman, 2001).

Cörvers (1997) distinguished between two factors of human capital: intermediate and highly-skilled workers and their effects on labour productivity. The estimates indicated the positive impacts of both factors on productivity, and just the highly-skilled labour alone is proved to be the statistically significant component of human capital that positively affects productivity, (Corvers, 1997).

The economic performance of a producer is normally assessed and described using two terms: efficient or productive. Productivity mainly refers to the ratio of a producer's output to the same producer's input. Given the fact that producers, in the more likely event, would use several inputs to generate many outputs; therefore, productivity calculations would require the aggregation of these outputs and inputs in a valid economic manner, so that productivity stays the same, as being the ratio of the output to the input, (Lovell, 1993).

The literature contains various definitions of what human capital exactly means, and it is commonly defined as “ knowledge, skills, competencies, and attributes embodied in individuals which facilitate the creation of personal, social, and

economic well-being” (Healy and Côté, 2001). The theme of the human capital role in enhancing the prospects of economic growth is a long-standing one, and despite the strong empirical proof of this crucial role, the controversy remains over the exact weight of human capital in economic development.

In the early 1960s, the attention paid to the quality of labour has increased significantly, and the focus was principally on the education and training that the labour force receives. This stage can be seen as the onset that crystallised the concept of human capital, (Healy and Côté, 2001).

Over the period between 1960 and 2000, noteworthy and compelling evidence had come to light indicating the significance of investment in education in increasing growth and productivity. More precisely, some have suggested that the third level of education, after primary, and secondary education, is more important for growth specifically in the OECD countries from 1960 to 1990, (Gemmell, 1996). Other studies, argued that human capital can provide indirect channels to appreciate and elevate the rate of growth through its positive effect on physical capital, which is based on the competences embodied in individuals via education, which helps in employing physical capital in a more efficient manner, (Barro, 1989), (BARRO, 1991), and (Benhabib and Spiegel, 1994).

The perfect information assumption in the standard competitive theory connotes that the return to a factor is proportional to its marginal contribution to a physical product. But, for education and other intangibles, it is not yet crystal clear that the direct contribution to a physical product can clarify and interpret the total contribution to revenue, (Welch, 1970).

In the economic literature there can be four distinct effects of human capital on labour productivity: worker’s, allocative, diffusion, and research, (Cörvers, 1994) and (Corvers, 1997). Welch (1970) points out that the productive value of education stems from two different episodes: the “worker’s effect” or “own productivity”, which refers to the worker’s ability to be more efficient in using the resources available on account of receiving more education.

This effect represents the marginal product of education. The outcome of this is that these efficient workers are assumed to produce more physical output, and switch the production possibility curve outward. Hence, the higher the proportion of intermediate or highly skilled workers, as opposed to low-skilled workers, in the whole combination of labour, the higher the efficiency and productivity levels. The second phenomenon is called the “allocative effect”, which implies the worker’s ability to acquire and decrypt information about other production inputs’ costs and features, which in turn would change the use of specific inputs and consider the use of new inputs that would not be used before, as well as developing alternative uses of them, that is if a certain change in the worker’s education has not occurred, (Welch, 1970).

The third impact is known as the “diffusion effect”, which incorporates the adaptability of a better-educated worker to absorb and assimilate technological advancements and generate new production approaches in a faster manner, (Nelson and Phelps, 1966); thereby, higher education levels facilitate the dispersion of technology, and provide a worker with the quality of being able to successfully opt for the more remunerative inventions that are to be quickly adopted, accommodated and employed, (Bartel and Lichtenberg, 1987).

Empirical evidence confirms that a well-educated and highly-trained labour force is fundamental in attracting and adapting technology investment; whereby, it leads to more technical change, and therefore, long-term economic growth, (Bresnahan et al., 1999). (Bassanini and Scarpetta, 2001) also examined the impact of human capital on growth and observed a significant positive role of human capital across a selected group of OECD countries.

The fourth impact is believed to be “the research effect”, which involves the crucial role of higher education, as an essential and vital factor in research, and the development of complex activities, which in turn entails intermediate and highly skilled workers to reach higher levels of technological knowledge in order to be able to increase the growth levels of productivity, (Englander and Gurney, 1994).

With reference to some of the literature on production functions identification, incorporating human capital as an explicit input has been regarded as a contentious issue, (Miller and Upadhyay, 2000). The advocates of integrating human capital as a direct input argue that their approach generated better estimates, (Gregory et al., 1992). However, others contend and present human capital as an insignificant contributor when explaining the change in output directly; in fact, its impact can be traced and discovered in total factor productivity, (Islam, 1995). Benhabib and Spiegel (1994) included human capital into their estimations of a growth rate production function, and found it insignificant, and its coefficients rather negative, which led them to think of its role in growth from an interaction perspective, by which it (human capital) can influence growth through its impact on TFP, and not via direct inclusion in the production function, (Benhabib and Spiegel, 1994), (Miller and Upadhyay, 2000).

With respect to the effect of human capital on technical inefficiency, some studies implemented SFA, (Kneller and Stevens, 2006), and they found out that technical inefficiency was negatively linked to the levels of human capital in 9 industries across 12 OECD countries over the years 1973-1991.

Other empirical studies, (Maudos et al., 2003) applied SFA and Data Envelopment Analysis DEA to quantify the relationship between human capital and growth in the OECD organisation during the period 1965-1990. The findings supported the positive impact of human capital on growth through the improvements in labour productivity and by a technical shift, (Dimelis and Papaioannou, 2014).

2.11 The Importance of Human Capital

There are three main policy domains for which education is considered to be crucial: (i) the stock of skills in the economy, which is of a central importance for the prospects of economic growth; (ii) the distribution of the skilled people in an economy, which is a fundamental determinant for income inequality, especially with the high wage premium for skills; and (iii) the relationship between an individual's stock of skills and

knowledge and their background, which is also a key factor of social mobility and societal progress, (Burgess, 2016).

Concerning growth, higher levels of education, presumably, will lead to higher labour productivity; thereby, higher aggregate levels of education in a country will support faster economic growth on the national level, (Goldin and Katz, 2008).

Recent cross-country research by (Hanushek and Woessmann, 2012) had found that measures of cognitive skills are associated with economic growth; albeit, some economists were concerned about this, and contended that the evidence on this relationship between skills and growth is rather mixed. Hanushek & Woessmann argue that previous research used unsuitable proxies for educational attainment. More precisely, they emphasise that neither the completed years of education nor the national rates of enrolment in schools can capture the skills of educated individuals; Alternatively, there are direct measures of cognitive skills that are being sourced from the international tests of maths and science abilities in 50 nations, (Hanushek and Woessmann, 2012).

From an inequality point of view, when the education system generates highly skilled people at a rapid rate, and at a rate that allows an economy to keep up with the increasingly growing demand for skills due to technological advancements, then the results will be a rise in the average income and a fall in income inequality, and this has been named as ‘the race between education and technology’, (Goldin and Katz, 2008), (Burgess, 2016).

In recent decades, a great importance has been given to the role of human capital in any economy. Especially, with the emergence of the knowledge economy, which has been derived from the revolution in information technology, innovation, and communication, in which human capital was regarded as the foundation of this new economy, (Gogan, 2014).

It is theorised that human capital is a key driver of output growth at the macroeconomic level (Solow, 1988), (Romer, 1990d), (Romer, 1994), (Bowlus et al., 2005). However, having said that, empirical research indicate that the direction and the causality of this relationship was not robustly backed up, owing to a variety of issues,

such as the limitations of data, and other factors' impacts on growth, which are not to be easily separately determined, controlled or mastered, (Barro and Lee, 1993), (Barro and Lee, 1996).

Over the past decade, several authors (Barro and Sala-i-Martin, 2004), (Durlauf et al., 2005) devoted great effort, and placed their focus on, in providing new evidence on the relationship between human capital and growth, where it has been documented that countries acquiring a higher level of human capital accumulation have a higher likelihood to grow in the future, and faster than others, assuming that other things are equal across countries. This is despite the reported finding of a highly heterogeneous impact of low education levels on growth between the more advanced and less developed economies, where the impact was found not to be positive in the developed countries. This suggests the possible different roles that human capital can play in different development stages, (Krueger and Lindahl, 2001a), (Vandenbussche et al., 2006). On the other hand, human capital has its influences on an individual's value-added and earnings, opportunity of employment, and productivity, as well as their social status from a microeconomic perspective, (Bowlus et al., 2005).

Moreover, the role of human capital can be both direct and indirect at the same time. It can be direct due to the fact that it (in terms of quantity) enters the production process, and hence, it can contribute to the growth of output.

On the other side, it plays a centrepiece role in paving a way, and facilitates for more innovations and creativity in the final output of goods and services through the skills and expertise that are embodied in the human capital.

Similar to this, some economists associate some of the innovative characteristics of human capital to the R&D activities, and the role they have in stimulating and spurring productivity and economic growth, (Gehring et al., 2012).

A great deal of studies have been conducted in the literature on human capital, with particular attention being paid to investigate, in more depth, the link between human capital, on the one side, and productivity and earnings, on the other side, (Denison, 1962), (Jorgenson and Griliches, 1967) and (Kendrick, 1976).

Based on these studies results, it has been concluded that human capital positively affects productivity, and those who are more educated are more driven to work and are highly likely to earn more than others. In consistency with this, it is argued that acquiring a higher qualification indicates the individuals' ability and motivation rather than their high productivity. Simply put, more genius and well-off individuals find it less costly, regarding effort and time, to obtain a high level of education than those who are not capable of being able to afford to pay for such levels of education, (Spence, 1973).

Despite the controversy on the direction of the causality between education and training on the one hand, and productivity, earnings, as well as economic growth, on the other hand, the general agreement appears to be that the effects of education and training result in higher productivity and earnings, coupled with a higher organisational performance. This suggests a positive and a strong causal link between the investment in education, and general training on the one side, and earnings, as well as the performance in firms at the microeconomic level, on the other side.

The implications seem to have the same outcomes at the macroeconomic level where the social returns would increase as the private benefits do. This emphasises that what could be beneficial for an individual would also be useful for a society, (Wilson and Briscoe, 2004).

In the late 1950s, namely in 1958, and in his pioneering work, which is mentioned earlier, J. Mincer came up with a new concept concerning the relationship between the years of schooling and earnings, which became later known as "The human-capital-earnings function". In it, there is a recognition of earnings, as a dependent variable, and as a function of the accumulation in human capital stock and skills that are acquired through education and training by individuals, but it is also worth mentioning that this accumulation is brought about by a series of positive net investments in order to increase earnings over a worker's life, (Mincer and Polachek, 1974).

Mincer also sought to perceive how earnings are distributed across the population where some important questions arose in this respect, such as why do males earn more than females? Why do occupational distributions differ by gender? Why is earnings

growth smaller for those who do not permanently participate in the labour force? (Polachek, 2008).

A great deal of research and studies highlighted, and investigated, the impact of human capital on wages and earning – which was regarded by (Lebedinski and Vandenberghe, 2014) as a proof that education and training can raise labour productivity – and this research was equipped with a variety of methods and approaches in the related strands of literature, which were utilised, so as to estimate human capital and its various impacts, (Tchernis, 2010).

In labour economics and the economics of education, it is vastly agreed upon that earnings' functions are regarded as the cornerstone, and the most commonly applied and widely utilised empirical equations. It is even further thought, and claimed, that almost every day there were new estimates of the rates of returns to education, but, for many reasons, few of these can be considered as being realistic, (Heckman et al., 2006).

In 1974, Mincer had published his prominent work of *Schooling, Experience, and Earnings* in the labour economics. He modelled the natural logarithm of earnings as a function of the years of education and the years of potential labour market experience (age – years of schooling – 6). Mincer has pointed out that the schooling part of the equation was an equilibrium condition in the model, where the main objective of investing in people is to maximise the present value of the future earnings, (Lemieux, 2006).

With regard to Mincer's model, it has been stated that the levels and the differences in individual log-earnings, in a competitive labour market, depend to a large extent on the differences in human capital, (Söderbom and Teal, 2001).

In his formulation, Mincer assumes that at any point of an individual's lifetime t , the observed earnings [the potential earnings $wK(t)$ – human capital investment $(1 - s(t))K(t)$] can be represented as a concave function of the worker's labour market experience, (Polachek, 2008). On the assumption that the schooling investment would last for S years, and on-the-job training is expected to decrease over time, the most widely used quadratic function of log-earnings, or what is often referred to as the Mincer earnings function (regression), can be expressed as:

$$\ln Y_i(t) = a_0 + a_1 S_i + a_2 t_i + a_3 t_i^2 + \varepsilon_i \quad \text{Equation 2.12}$$

Or can be written as;

$$\ln[Y(s, x)] = \alpha + \rho_s s + \beta_0 x + \beta_1 x^2 + \varepsilon \quad \text{Equation 2.13}$$

Where:

$$Y(t) = wK(t) - s(t)K(t)$$

$Y(s, x)$ is the wage at schooling level s and work experience x .

a_0 or α is the initial earnings capacity.

a_1 or ρ_s is the return rate on education, which is assumed to be the same for all the levels of schooling.

a_2 and a_3 are related to the amount and the financial returns to on-the-job training.

ε_i is a mean zero residual with $E(\varepsilon|s, x) = 0$.

It should be noted, in this section, that the log-earnings quadratic form of Mincer's function has been criticised by some scholars, (Murphy and Welch, 1990), (Heckman et al., 2003).

It is argued that the quartic function is more appropriate than the quadratic one, because the increase in earnings that can be attributed to the schooling needs is not independent of the accumulated schooling and experience that a worker already acquires. In other words, using Current Population Survey data from 1964 to 1987, they found that a quadratic function is not flexible enough so as to capture the main features of the experience-earnings profile.

The key aspect of this argument is that the quadratic function understates the growth in earnings over the first 10 to 15 years of a career, while by way of contrast, they reached a conclusion that the quadratic function in the years of experience captures, very well, the fundamental constituents of the empirical experience-earnings profile, (Lemieux, 2006).

In order to make the function more comprehensive, Mincer inserts some specifications into it. For instance, he assumes that the earnings of a worker in the initial period can be calculated based on the following formula:

$$E_1 = E_0 + rC_0 \quad \text{Equation 2.14}$$

Where; C_t in general, represents the amount of dollars that the worker pours into investing in human capital in time t .

Regarding the above formula elements;

E_1 depicts the earnings in the period one.

E_0 demonstrates the potential earnings of an individual based on the innate ability, which is denoted by $wK(0)$.

Equivalently;

$$E_2 = E_1 + rC_1 = E_0 + rC_0 + rC_1 \quad \text{Equation 2.15}$$

By way of a summary, it can be rewritten as;

$$E_t = E_0 + r \sum_{i=0}^{t-1} C_i \quad \text{Equation 2.16}$$

Since, it is not empirically straightforward to collect data on the amount of money one may invest in human capital, Mincer attempted to use the $k_t = \frac{C_t}{E_t}$ so as to express the proportion of worker's earnings that he decides to channel in human capital investment. Using this proportion, the percent of time that a worker spends on investing in human capital can be estimated.

In the Ben-Porath model (1967), $Y(t) = [1 - s(t)]wK(t)$, where $s(t)$ (which also represents the time spent on investing in human capital) is equivalent to k_t .

If we substitute k_t for C_t we obtain;

$$E_t = E_0 \prod_{i=0}^{t-1} (1 + rk_t) \quad \text{Equation 2.17}$$

And with the logarithmic form, it would look like this;

$$\ln E_t = \ln E_0 + \sum_{i=0}^{t-1} \ln(1 + rk_t) \quad \text{Equation 2.18}$$

Where $\ln(1 + rk_t)$ is approximately equal to $\approx rk_t$.

And if rk_t is tiny, the above equation can be expressed as;

$$\ln E_t = \ln E_0 + r \sum_{i=0}^{t-1} k_t \quad \text{Equation 2.19}$$

On the whole, much of the current literature on growth and human capital confirms two major routes: (1) that countries with a larger stock of human capital have more capacity to grow faster, and (2) investing in schooling is a prerequisite and the foundation for human capital, which in turn, is the principal generator of ideas and new technology, (Romer, 1990c).

In the main, there appears to be some accord on the above two points. However, (Aghion et al., 2009) suggest that researchers, mostly, have no choice but to apply their methodologies on crude proxies for human capital stock, such as average years of schooling or enrolment rates in formal education in a nation. They, therefore, argue that the average years of education, as an indicator, is the result of individuals' decisions to have more education, while considering the future returns of that education, thus, it is endogeneity that could be the main driver for this decision, and not the nation's investment policy, in it being persuasive, to lead these individuals to decide to have more education.

Above all, the average years of schooling proxy counts for the average number of years of attending a primary or a secondary school, just the same way as it deals with the average number of years in a university, or in a doctoral program, irrespective of the differences in quality and schooling mechanisms. Putting it another way, it does not sound reasonably convincing that if a child (or a group of children) is attaining one additional year in a primary school that it would positively affect the technological innovation, (Aghion et al., 2009).

Moreover, another caveat, included in the literature of education and growth, is that, besides the problem in the average years of education concerning the quality aspect being overlooked and unnoticed across educational stages, it also ignores the qualitative differences in the knowledge offered to students across nations when compared with each other.

It is then, a reasonable assumption to consider that the amount and quality of knowledge taught, and delivered in schools in a developing country, will differ considerably from that offered in a developed nation. Still, the use of the years of education, as a raw measure of educational attainment, neglects that fact.

Another major flaw, which years of education has, is that it unconditionally assumes that the main source of all the cognitive skills of human capital is formal education, ignoring the evidence that other factors – such as family, peers, and so on – can play key roles in inculcating and forming values and skills needed for higher levels of performance; the negligence of these none school sources adds another issue of measurement error into the analysis of growth, (Eric A. Hanushek and Wößmann, 2007).

Investment in education is fundamental to empower individuals, in order to improve and enhance their skills, so as to meet their needs and aspirations hand in hand with the firms and industry criteria within markets. It is then to some degree obvious that the effectiveness of the human capital utilisation is what, to a large extent, determines its contribution to productivity.

Neoclassical theory suggests that the return of an additional working hour (the hourly wage), for an individual employed by a firm that works within a perfectly competitive labour market, is supposed to be equal to the value of the output that have been produced in that additional hour. This means that the more productive an individual is, the higher wage is that they would supposedly receive.

The production function for the goods output then has the simple extension from the baseline dynamic model with capital and effective labour as inputs and the productivity factor not rising over time:

$$y_t^s = A_G (l_t^d h_t)^\gamma (k_t)^{1-\gamma} \quad \text{Equation 2.20}$$

If human capital rises over time, so that h_t is growing, then the effective labour $l_t^d h_t$ is growing also. This allows for a continuous growth.

The question then becomes; how does human capital increase over time? Is it exogenous to the model? or is it a part of the decision-making process of consumers on how to allocate resources?

2.12 Training and Productivity

There are many skills which newly hired workers need to acquire, and many technical procedures and software packages they are required to be acquainted with, when entering a firm to become fully productive. Many of the skills and the relevant training programs might be of lower value in other firms, because they are highly firm-specific. As a corollary, employees might decide not to invest in these skills by not participating in the training schemes designed for them unless they had been motivated by their employers to improve their skill profile in order to receive higher wage and promotion over time, (Hartog and Van den Brink, 2007, Sloof et al., 2007)

A promotion policy known as *up-or-out* is commonly adopted in some firms and organisations. Basically this strategy involves either promotion or dismissal of newly appointed employees after a trial period in the institution.

This policy might incentivise workers to collect more firms-specific skills in order to be upgraded rather than be laid off. But this strategy might be counterproductive rather than beneficial to the firm, because dismissing a number of employees who received training and improved their skills to some degree could be costly for the firm from an economic point of view. It could also add to the mismatch problem between jobs and skills in the job market in the economy as whole due to the firm-specific knowledge which had resided in the employees and it does not have a market in the gap of the available job opportunities, (Milgrom and Roberts, 1992).

Promotions can be useful to the firm via two major routes. First, assigning individuals in the position which are best suited for them and the role in which they can better contribute to the firm's aggregate performance. Second, promotions are proper platforms for workers to be incentivised and motivated to perform at their highest levels, (Sloof et al., 2007).

Another choice of recruitment policy is *up-or-stay*. In this case the non-promoted and least performers have a second chance to stay in the firm, but they will be assigned to do

low-level duties. The drawback of this strategy is that the lack of motivation and incentive is likely to result in lower performance from the employees both in the process of upgrading their skills throughout the training period, and lower performance after being assigned to their new roles, (Milgrom and Roberts, 1992).

The theory of human capital is the most adopted model for explaining the so called (school-to-work) transition process, and the reliance on the theory is owing to the two-side decision that is expected to be made by individuals; this is when they choose whether to continue their study at college, and spend on more education and training to acquire better skills beyond the current level (consumption), or to halt investing in formal schooling and find a proper occupation in the labour market (Investment), (Johnes and Johnes, 2007, Nguyen, 2007).

Hence, students will select to stay in college, merely, if they think that the present value of the benefits, expected from education, surpasses in scope the costs that are expected to be paid for more schooling, including tuition fees, books, accommodation, and any other intangible costs (Becker, 1993, Becker, 1964). All these costs, in effect, will be compensated for by the benefits resulting from education, such as higher financial returns, lower risks to job loss, a more pleasant and rewarding occupation, along with some other non-pecuniary returns, (Bradley. S and Nguyen. A, 2007). In this respect, Schultz (1961) points out that the estimation of the conventional costs associated with education, comprising of the costs of the services and teachers, and administrator to maintain and operate the educational institution, is not a difficult task.

The problematic task then is the estimation of the other components of the aggregate costs of education, such as the forgone earnings by students, given that in some cases, as in the United States in particular, the foregone income represents more than half of the higher education costs, which in practice, represented one-fourth ($\frac{1}{4}$) of the total costs of elementary, secondary, and higher education, and by 1956, the forgone earnings by students represented more than two-fifths $\frac{2}{5}$ of all college costs, (Schultz, 1961).

The concept of human capital has been broadened in (1964) by Becker to include the quantity and quality of formal and informal education, different types of training, and the health of the labour force (Becker, 1964). Moreover, it has been referred that, human capital investment has its significance for growth, and reflections on wages structure, health, vocational training, and other kinds of income, such as property income,, which in turn, will be reflected at a larger scale at a macroeconomic level in better standards of living and prosperity, (Schultz, 1962). According to (Hartog and Van den Brink, 2007) “..the wealth of a nation is to a large extent determined by the educational attainment and health status of their population”.

In 2010, the world population, aged 15 and above, is estimated to have 7.9 years of education on average, with a steady increase from 3.1 years in 1950 and 5.3 in 1980. The estimated years of education, for the population aged 15 and above in the high-income economies, are found to be around 11.3 years. This is in comparison with 7.2 years of education in the developing economies with a significant increase from 2.0 years of education on average in 1950, and in South Asia, Middle East, and North Africa, the average years of schooling have more than doubled since 1980s. While in developed countries these achievements were centred in the higher secondary and tertiary completion as well as enrollment ratios, it is found that higher primary and secondary completion and enrollment ratios account for most of the achievements in developing countries during the period from 1950 to 2010, (Barro and Lee, 2013).

Chapter 3: Methodology and Data

This chapter provides an explanation about the used methodologies in this thesis, comprising of the stochastic frontier analysis, and the propensity score matching, along with the Mahalanobis metric matching method.

The application of Solow residual neoclassical approach (1957) assumes that all countries in the sample operate efficiently on the frontier, and under the assumption of constant returns to scale. This appears to be too restrictive.

3.1 Stochastic Frontier Analysis

In 1977 and in two independent papers, a stochastic frontier function for Cobb-Douglas case was specified and introduced by (Aigner et al., 1977) and (Meeusen and van Den Broeck, 1977).

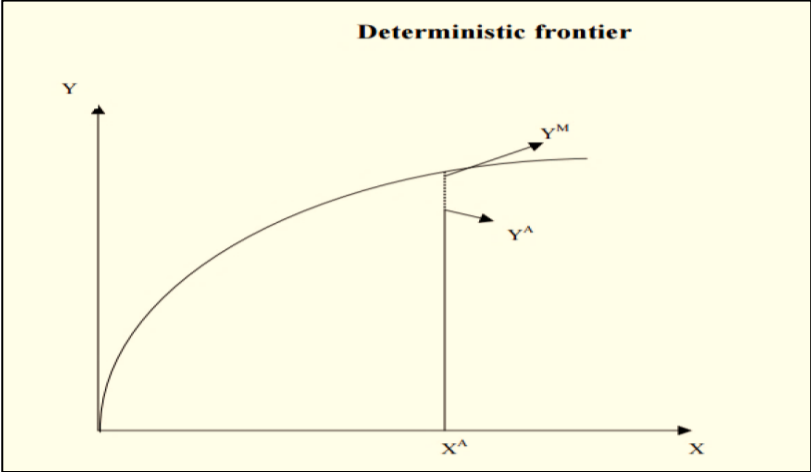
This specification assumes that inefficiency represents a component of the error term in the orthodox production function (Maudos et al., 2003). Thus, the error term contains inefficiency effect along with other factors effects which are uncontrollable by the production unit such as; natural disasters, strikes, sickness, and so forth.

The core idea is that all production units are expected to perform either below or exactly on the frontier line, this is where none of the production units is expected to perform at any level above the frontier, simply because they do have the capacity to do so, due to several factors, including technological limitations.

The most widely used frontier analysis is the output-oriented stochastic frontier approach, where the basic idea involves the existence of an unobserved best-practice production frontier corresponding to the set of maximum attainable output levels for a

given combination of inputs. However, most of the time actual production comes about below the best-practice of production frontier because of technical inefficiency. See figures 3.1, 3.2, and 3.3.

Figure 3.1 The Deterministic Frontier of Production



Source: William Greene, Stern School of Business, NYU, 2005.

Where

The potential maximum output is Y^M
 The observed output is $Y^A \leq f(x; \beta) \equiv Y^M$

Technical efficiency is

$$TE = \frac{\text{The observed output}}{\text{The potential maximum output}} = \frac{Y^A}{Y^M}$$

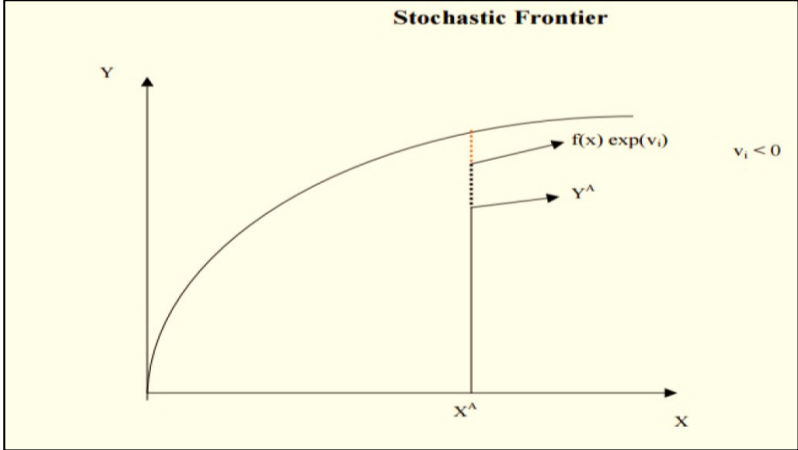
Where

$$0 \leq TE_{it} \leq 1$$

Therefore

$$\therefore Y^A = Y^M \cdot TE = f(x; \beta) \cdot TE$$

Figure 3.2 The Stochastic Frontier of Production



Source: William Greene, Stern School of Business, NYU, 2005.

The observed output is $Y^A = f(x; \beta) \cdot \exp(v) \cdot \exp(-u)$

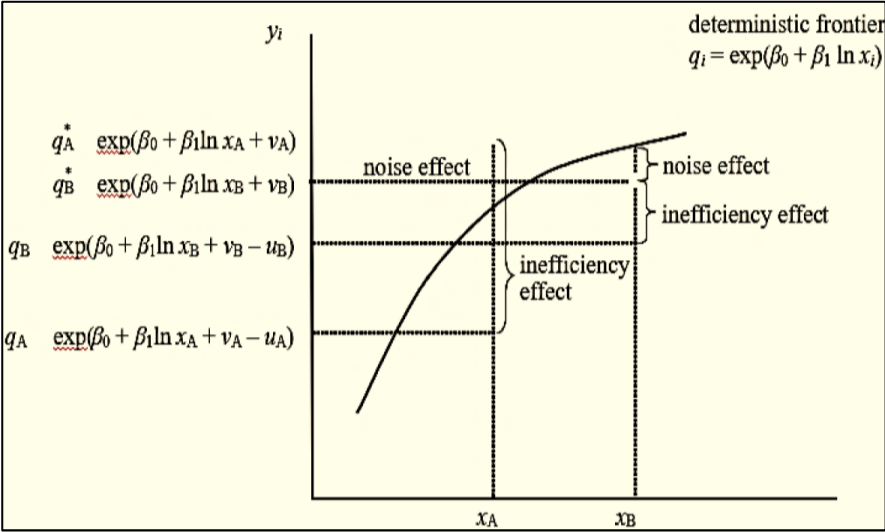
Where

- $v \leq 0$ “noise” error term, (normal distribution).
- $u \geq 0$ “inefficiency error term”, (half-normal distribution).

- and
- $f(x; \beta) \rightarrow$ deterministic kernel
 - $\exp(v) \rightarrow$ the effect of exogenous shocks on output
 - $\exp(-u) \rightarrow$ inefficiency
 - $f(x; \beta) \cdot \exp(v) \rightarrow$ stochastic frontier

It is worth noting that the statistical noise (v) arises from the inadvertent omission of relevant variables from the vector (x) as well as from measurement error and approximation error associated with the choice of functional form. Moreover, the term “statistical noise” is used to refer to the effects of weather, strikes, the risky environment in which production operations takes place and other effects that are exogenous to the production unit.

Figure 3.3 Deterministic Frontier and Stochastic Frontier



Source: Coelli, Rao, O'Donnell, & Battese (2005), School of Economics, the University of Queensland, Australia.

The figure 3.3 illustrates the basic idea of deterministic frontier and stochastic frontier.

Where:

OLS: $q_i = \beta_0 + \beta_1 x_i + v_i$

Deterministic: $q_i = \beta_0 + \beta_1 x_i - u_i$

SFA: $q_i = \beta_0 + \beta_1 x_i + v_i - u_i$

Where:

$$q_i = \exp(\beta_0 + \beta_1 \ln x_i) \times \exp(v_i) \times \exp(-u_i) \quad \text{Equation 3.1}$$

\uparrow
 deterministic
component

\uparrow
 noise

\uparrow
 inefficiency

The distance by which a firm lies below its production frontier is the measure of its inefficiency. However, (Farrell, 1957) proposed a decomposition of economic efficiency into technical efficiency and allocative efficiency where the former is meant to measure the firm’s ability to reach the maximum level of output given a vector of inputs, whereas the latter refers to the firm’s ability to use the inputs available with optimal shares given their market prices. That is to say:

$$Economic\ Efficiency = Technical\ Efficiency + Allocative\ Efficiency$$

Measuring technical efficiency can be achieved through two frontier methods. The first approach is named as the Data Envelopment Analysis (DEA) which is a non-parametric method, while the other is referred to as the Stochastic Frontier Analysis (SFA) which is regarded as a fully parameterized model, and both are categorized as frontier approaches, yet no excogitated formulation has been introduced to merge these two in one single analytical framework.

The rationale of these techniques is that efficiency of production is determined by the distance between the actual production and the best practice production frontier (Dimelis and Papaioannou, 2014).

However, the question is; which one is better for measuring technical efficiency?

Arguably, the advantage of using both DEA and SFA is that technical efficiency and technical change both can be derived and combined into the Malmquist index (1953) (Wei and Hao, 2011).

The main strength of DEA is that it does not require assumptions about the form of technology because it simply lacks parametrization. However, DEA falls short of considering the statistical noise and it is too sensitive to outliers. The main flaw of DEA along with other deterministic frontier estimators is that the deviation of an observation from the frontier must be attributed to inefficiency because there is no provision of measurement error or noise in the model. The setting of DEA is problematic because the statistical properties are definable.

Per contra, the SFA can tackle the errors that exist in statistical data particularly in developing countries (MENA included). To put it another way, it considers the influence of noise that affects the shape and the positioning of the frontier.

Technically speaking, the two-component error term are; the symmetric term (V_{it}) which demonstrates the noise, and the asymmetric term (U_{it}) that explains technical inefficiency.

In addition, the SFA provides a technique where panel data can be applied and encompasses other external environmental factors which could affect technical inefficiency related to the decision making unit (Arazmuradov et al., 2014). Another advantage of SFA is that it considers the effect of the random shocks on GDP.

However, the downside of this approach is that it requires an exact functional form (which is not given much of attention) of production function and the distribution assumption on the error term (Greene, 2008).

Following (Aigner et al., 1977) approach and (Meeusen and van Den Broeck, 1977) methodology, in particular the (Battese and Coelli, 1995b) specification, technical inefficiency can be estimated from the stochastic frontier and simultaneously interpreted by a group of a firm's specific characteristic variables. The benefit of this

methodology is that it escapes the problem of inconsistency which results from applying the two-stage method when investigating determinants of inefficiency (Diaz and Sánchez, 2008).

The frontier approach provides a measure of firm's inefficiency compared with the sample's best observations. The values of the estimates explain the differences in the effects of inefficiency across firms. Given that technical conditions and market circumstances can differ from one country to another, country dummy variables are considered and allowed in the production function to reflect the unobservable influences on technical efficiency.

They are also – country dummies – included in order to represent the idea that different technologies can be appropriate to different countries (Stevens and Weale, 2003).

The traditional ways of measuring and analyzing productivity growth through non-frontier models including the growth accounting approach prominently introduced by (Solow, 1957), and (Denison and Poullick, 1968, Denison, 1967), and the index number approach such as: Divisia, and Tornqvist indices (Jorgenson and Griliches, 1971) (Hulten, 1973) and (Christensen, 1975) all imply the assumption of all workers and all units of production are efficient.

Thus, growth in productivity will be mainly attributed to technical change or in other words, TFP growth is interpreted as the movement of the frontier function (Maudos et al., 2000). Still, the estimates would be regarded as biased owing to the presence of technical inefficiency.

On top of that, and despite the nonoccurrence of technical inefficiency, the estimates of the accounting growth of TFP would be affected by the allocative inefficiency which causes them to be biased again, and therefore it will affect the measurement of human capital impact on growth.

On the other hand, non-parametric approaches (e.g. Data Envelopment Analysis) do not impose any restrictions on the production function. However, they are not flawless,

because they cannot segregate the inefficiency effects from the white noise, (Dimelis and Papaioannou, 2014).

To avoid the prejudice problem, and considering the existence of inefficiency, the frontier techniques are more efficient tools to use.

One of the pros of SFA is that it allows for the estimation of firm-specific inefficiency according to the methodology proposed by (Jondrow et al., 1982) based on the conditional expected value of u_i given e_i , (Hadri et al., 2003).

The general form of Cobb Douglas stochastic frontier production function can be observed as follows:

$$Y_{it} = \hat{\beta}x_{it} + E_{it} \quad \text{Equation 3.2}$$

$$E_{it} = V_{it} - U_{it} \quad \text{Equation 3.3}$$

Where, Y_{it} denotes the appropriate function (logarithm) of the production for the i^{th} sample firm, ($i = 1, 2, \dots, N$) in the t^{th} time period ($t = 1, 2, \dots, T$)

x_{it} , represents the $(1 \times k)$ vectors of appropriate function of the explanatory variables associated with the i^{th} sample firm in the t^{th} time period (the first element would generally be one)

$\hat{\beta}$, represents the $(k \times 1)$ vector of the coefficients for the associated independent variables in the production function which need to be estimated.

The term $(V_{it} - U_{it})$ is the composed error term. V_{it} , represents the random variables which are assumed to be independently, identically and normally distributed with zero mean and constant variance. $N(0, \sigma_v^2)$, and it is independent of the U_{it} .

U_{it} , represents non-negative random variable that are assumed to be identically, independently and normally distributed with zero mean $N(m_{it}, \sigma_u^2)$ and it is used to capture technical inefficiency.

According to (Coelli et al., 2005) the above Cobb-Douglas stochastic frontier function can also take the following form:

$$Y_i = \exp(\beta_0 + \beta_1 \ln x_i) \times \exp(v_i) \times \exp(u_i) \quad \text{Equation 3.4}$$

Where,

$\exp(\beta_0 + \beta_1 \ln x_i)$ = deterministic component

$\exp(v_i)$ = noise

$\exp(u_i)$ = inefficiency

and according to (Kokkinou, 2009) the forenamed function can be rewritten as:

$$y_i = F(x_i\beta) \times \exp(v_i - u_i), u_i \geq 0 \quad \text{Equation 3.5}$$

Where

u_i denotes for the shortfall of output from the frontier as previously defined.

Since v_i is the random statistical noise, a symmetric distribution is usually assumed for v_i . In the same time, u_i which represents technical inefficiency term is assumed to be one-sided, it is also non-negative for the production frontier, and non-positive for the cost frontier. In most of the cases of production frontier, the distribution of [$e_i = (v_i - u_i)$] will be skewed, keeping in mind that the composed error (e_i) will be $(v_i + u_i)$ in the case of cost frontier.

(Bauer, 1990), (Greene, 1993) and (Kumbhakar and Lovell, 2000) provided detailed overviews of the developments in the parametric stochastic frontier models in different levels and applications, and in this case, a model for technical inefficiency effects in the stochastic frontier production function for cross section data was applied, and it considers

$$u_i = z_i\delta + w_i \quad \text{Equation 3.6}$$

z_i is a $(1 \times m)$ vector of explanatory variables associated with technical inefficiency of production of firms. δ is an $(m \times 1)$ vector of unknown parameters.

The stochastic frontier implications and the econometric inefficiency estimations are overwhelmingly dominated by the Cobb-Douglas and translog models in the literature. It also could be written in the logarithm form like this;

$$\ln y_{it} = f(l_{it}, k_{it}) + v_{it} - u_{it} \quad \text{Equation 3.7}$$

Where, y_{it} denotes the observed output in logarithmic form at time t in firm i . L_{it} represents the log of labour inputs, and K_{it} is the log of capital inputs and both are observed at time t in firm i .

The density function for U_{it} is defined by

$$f_{U_i}(u) = \frac{\exp[-\frac{1}{2}(\frac{u-\mu}{\sigma})^2]}{(2\pi)^{\frac{1}{2}} \sigma [1 - \Phi(\frac{-\mu}{\sigma})]} \quad \text{Equation 3.8}$$

Where

$$u > 0$$

$\Phi(x)$, denotes the distribution function of the standard normal random variable.

The translog frontier function is a highly flexible functional form, and it nests the Cobb Douglas in terms of it does not restrict the elasticity of factor substitution to be constant, nor does it restrict technical change to be neutral (given that technical advancement pre-multiplies all three factors (McAdam, 2015).

With respect to technical efficiency of a given firm (i), TE_i , it can be defined as the ratio of its mean production (in original units), given its realized firm effect, to the corresponding mean production if the firm effect was zero (Battese and Coelli, 1988). In that, it measures the difference in the observed output of the firm relative to the output produced by a fully efficient firm using the same amount of inputs.

The value of TE_{it} can be defined and estimated through the following form;

$$TE_i = \frac{E(Y_{it}^*|U_i, x_{it}, t=1,2,\dots)}{E(Y_{it}^*|U_i=0, x_{it}, t=1,2,\dots)} \quad \text{Equation 3.9}$$

$$TE_{it} = \frac{y_{it}}{\exp(x_{it}\beta + v_{it})} = \frac{\exp(x_{it}\hat{\beta} + v_{it} - u_{it})}{\exp(x_{it}\hat{\beta} + v_{it})} = \exp(-u_{it}) \quad \text{Equation 3.10}$$

The value TE_{it} is necessarily expected to be between one and zero. Thereby, the closer the observed point is to the frontier, the higher is the technical efficiency of a firm. If, for instance, a firm's technical efficiency is 0.85, then it implies that the firm realizes, on average 85% of the production possible for a fully efficient firm having comparable input values (Battese and Coelli, 1988).

The analysis of production function in the stochastic frontier framework concerns two steps. The first step requires the use of the maximum likelihood in order to estimate the frontier model. In the second, measures of inefficiency or efficiency are constructed using the estimated frontier model.

3.1.1 Modelling of Frontier Production Function

Given that Cobb-Douglas technology is a restrictive form of production function, there can be some commonsense in estimating a more flexible version of production function (transcendental logarithmic production function) known in short as (Translog production function) which has its advantages and disadvantages likewise.

On the plus side, it is less restrictive on production elasticities and substitution elasticities than the CD version. On the minus side, it is more difficult to interpret and requires estimation of many parameters especially in the case of many independent variables.

Translog production function takes the following formula;

$$\ln Y_{it} = \beta_0 + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \left(\frac{1}{2}\right) \beta_{LL} \ln L_{it}^2 + \left(\frac{1}{2}\right) \beta_{KK} \ln K_{it}^2 + \beta_{LK} \ln L_{it} \ln K_{it} + \sum_{t=1}^{t=n} \lambda_t TE_t + v_{it} - u_{it} \quad \text{Equation 3.11}$$

The translog stochastic production function for the ECA region is set as follows:

$$\ln \text{Gross Sales}_i = \beta_0 + \beta_1 \ln (\text{Capital}_i) + \beta_2 \ln (\text{Labour}_i) + \beta_3 \ln (\text{Squared Capital}_i) + \beta_4 \ln (\text{Squared Labour}_i) + \beta_5 \ln (\text{Capital} \times \text{Labour})_i + (v_i - u_i) \quad \text{Equation 3.12}$$

Whereas the technical inefficiency function is defined as follows:

$$\begin{aligned} \text{Technical Inefficiency} = & \delta_0 + \delta_1 (\text{Low skilled}_i) + \delta_2 (\text{Highly skilled}_i) + \\ & \delta_3 (\text{Intermediate skilled}_i) + \delta_4 (\text{Yrs of Shooling}_i) + \\ & \delta_5 (\text{GDP per Capita}_i) + \delta_6 (\text{Formal Training}_i) + \delta_7 (\text{Internet Users}_i) + \\ & \delta_8 (\text{Distance to Frontier}_i) + \delta_9 (\text{Country Dummies}_i) + \\ & \delta_{10} (\text{Active Population}_i) + \delta_{11} (\text{Legal Rights Index}_i) + \delta_{12} (\text{Bribery}_i) + \\ & \delta_{13} (\text{Tax Rate}_i) + \delta_{14} (\text{Rural Population}_i) + \delta_{13} (\text{Foreign Shareholders}_i) + \\ & + \delta_{15} (\text{Life Expectancy Rate}_i) + \delta_{16} (\text{Firm Age}_i) + W_i \quad \text{Equation 3.13} \end{aligned}$$

It should be noted that the marginal product of a translog production function is a Cobb-Douglas production function. In other words, the restricted form of the translog production function can be represented by an orthodox Cobb-Douglas production function with two inputs (labour and capital), this is where these restrictions will be tested statistically. However, the function takes the following shape;

$$Y_{it} = Ae^{\lambda} (L_{it})^{\alpha} (K_{it})^{\beta} e^{(v_{it}-u_{it})} \quad \text{Equation 3.14}$$

After taking logarithmic transformation, CD production function can be shown as;

$$\ln Y_{it} = c + \lambda_t + \alpha \ln L_{it} + \beta \ln K_{it} + V_{it} - U_{it} \quad \text{Equation 3.15}$$

In the case of MENA and ECA cross sectional firm level data:

Y = Gross sales in US dollars as a unified monetary measurement unit of value across firms from different countries.

L = Full time equivalent workers numbers.

K = Net book value of land and buildings + net book value of machinery and equipment.

The Cobb Douglas stochastic production function for the MENA region is set as follows:

$$\ln \text{Gross Sales}_i = \beta_0 + \beta_1 \ln (\text{Capital}_i) + \beta_2 \ln (\text{Labour}_i) + (v_i - u_i) \quad \text{Equation 3.16}$$

Whereas the technical inefficiency function is defined as follows:

$$\begin{aligned} \text{Technical Inefficiency} = & \delta_0 + \delta_1 (\text{Low skilled}_i) + \delta_2 (\text{Highly skilled}_i) + \\ & \delta_3 (\text{Intermediate skilled}_i) + \delta_4 (\text{Yrs of Schooling}_i) + \\ & \delta_5 (\text{GDP per Capita}_i) + \delta_6 (\text{Formal Training}_i) + \delta_7 (\text{Loan}_i) + \\ & \delta_8 (\text{International Exports Share}_i) + \delta_9 (\text{Country Dummies}_i) + \\ & \delta_{10} (\text{Sector Dummies}_i) + \delta_{11} (\text{Firm Size}_i) + \\ & \delta_{12} (\text{Licensed Technology in Use}_i) + \delta_{13} (\text{Foreign Shareholders}_i) + \\ & + \delta_{14} (\text{Distance to Frontier}_i) + \delta_{15} (\text{R\&D Spending}_i) + W_i \quad \text{Equation 3.17} \end{aligned}$$

No consensus yet on what is the best frontier model, but the stochastic frontier is preferred over other models because of its advantage for allowing random noise which is out of the firms' control and comprising measurement error including specification error and sample error despite some claims that stochastic frontier approach imposes strict functional forms that could lead to an unascertained shape of the frontier.

(Battese and Coelli, 1995a) noted that provided the inefficiency effects are stochastic, the explanatory variables in the inefficiency model may include some of inputs variables in the stochastic frontier.

The key point is that the misspecification of the true frontier – which in fact can be put under control by the econometric tests of the functional form – is less risky than neglecting it.

Following Caudill, Ford, and Gropper methodology, CFG (1995), a multiplicative heteroscedasticity is assumed in the one-sided error term u_i and the density function

corresponding to this model HU (Heteroscedasticity only in u) can be observed in what follows:

$$f_i(e_i) = \left(\frac{2}{\sigma_i}\right) f^* \left(\frac{e_i}{\sigma_i}\right) \left(1 - F^* \left(\frac{\lambda_i e_i}{\sigma_i}\right)\right), \quad -\infty < e_i < +\infty \quad \text{Equation 3.18}$$

Where

$$\sigma_i^2 = \sigma_v^2 + \sigma_{ui}^2, \quad \lambda_i = \frac{\sigma_{ui}}{\sigma_v}$$

f^* is the standard normal density, and F^* is the distribution function.

The loglikelihood function takes the following form:

$$\log L(\beta, \alpha, \gamma) = \sum_{i=1}^N \log(f_i(e_i)) \quad \text{Equation 3.19}$$

Note that we could include $\sum_{t=1}^T \log(f_{it}(e_{it}))$ in the panel data case.

As argued by (Hadri, 1999), in the cross sectional data, the two-sided symmetric error term can also be affected by size-related heteroscedasticity. Ignoring this assumption is likely to lead to a misspecified maximum likelihood function due to heteroscedasticity being not integrated in the estimation which yields inconsistent estimated parameters, (White, 1982).

To integrate heteroscedasticity in the symmetric noise term v_i , at the same time with the one-sided inefficiency term u_i , the model HUV (Heteroscedasticity in u and v) is specified where we now have a vector of non-stochastic regressors related to the firm size characteristics to be included in the v_i side along with a vector of unknown parameters to be estimated. Also, the values of both σ_i^2 and λ_i will be determined as $\sigma_i^2 = \sigma_{vi}^2 + \sigma_{ui}^2$ and $\lambda_i = \frac{\sigma_{ui}}{\sigma_{vi}}$. where each of σ_{vi} and σ_{ui} comprise a set of explanatory variables that affect both v_i and u_i , respectively.

The stochastic frontier analysis, which is a fully parameterised model, was applied to estimate production inefficiencies following the CFG (1995) and Hadri (1999) methodologies, which suggests a one-step procedure where the inefficiency effects are defined as a function of firm-specific factors – as in the two-stage approach – but in the

one-step estimation they are incorporated directly into the maximum likelihood estimation MLE to avoid the inconsistency problem in the two-stage approach.

The SFA methodology enables the assessment of different variables' effects on efficiency and the extent of their importance in firms' performance. In this field, unlike other areas, the model's parameters estimation is not the ultimate intent per se. Instead, estimating and analysing the firms' and industries' inefficiencies are objectives of a greater interest (Greene, 1990).

The rationale for choosing the SFA is because of estimating average production functions by conventional regression methods rather than frontiers hinges upon the assumption that all units of production are efficient, which means that if this assumption does not hold, the parameters estimated would be affected, and consequently the importance of human capital as well.

Moreover, estimating TFP through the growth accounting approach (Solow's approach) implies all individuals are efficient, therefore, any estimated growth in TFP would be interpreted as a shift of the frontier function (technical change), but in the existence of technical or allocative inefficiency, the estimated TFP would be biased, and accordingly, the assessment of human capital contribution to efficiency will lack accuracy (Maudos et al., 2003).

The use of SFA is necessary to take into account any possible presence of inefficiency and to avoid the bias resulting from the estimation by conventional methods (Färe et al., 1997), (Taskin and Zaim, 1997).

3.1.2 Heteroscedasticity in the Stochastic Frontier Models

(Caudill et al., 1995) noted that the measures of inefficiency are based on the residuals derived from the stochastic frontier estimation, and they noticed that these residuals tend to be sensitive to errors of specification, and to a higher degree in the stochastic frontier models. They argue that this problem of sensitivity will affect the accuracy of the inefficiency measures. To tackle this issue, they proposed that

researchers might need to test for heteroscedasticity presence, and if present, they can correct for heteroscedasticity in the one-sided error term (inefficiency).

Furthermore, (Hadri, 1999) suggested that the two-sided error term might also suffer from heteroscedasticity, and if that was to be ignored, then the maximum likelihood estimates will be inconsistent and inaccurate. Therefore, he advises to test for heteroscedasticity in both error terms, and if present, the appropriate corrective procedures must be applied on both terms to obtain the correct and robust estimators.

In the homogenous and homoscedastic stochastic frontier models, the random error term is assumed to be normally distributed with a zero mean and a constant variance, $v_{it} \sim N(0, \sigma_v^2)$, and the inefficiency error term is assumed to have a one-sided distribution with a constant mean and a constant variance σ_u^2 .

These assumptions imply the homogeneity of technology and inefficiency distribution over time as well as across production units. However, some other variables can be added to the original inputs X 's which could affect the shape and the position of the frontier or the inefficiency distribution, causing what is known as heterogeneity and heteroscedasticity issues. (Caudill and Ford, 1993) examined the effects of heterogeneity and heteroscedasticity and the bias in the inefficiency term in the frontier estimation resulting from heteroscedasticity in firm size, in their examination, they detected an overestimation in the intercept, underestimation in the slope and variance of the error term, and imprecise inefficiency effects, (Zhang, 2012).

In addition, (Caudill et al., 1995) noted that the inefficiency measures are based on the residuals yielded from the stochastic frontier, and they found that these residuals are sensitive to the stochastic frontier specification errors, therefore the inefficiency term derived from the residuals will be affected by the specification errors as well. Therefore they suggested a correction for heteroscedasticity and test for its presence in the one-sided error term, where they reported a marked change in the estimated cost frontier and in the inefficiency measures when accounting for heteroscedasticity in the estimation procedure, (Zhang, 2012).

Moreover, (Hadri, 1999) argued that heteroscedasticity could also have an effect on the two-sided error term, and it is ignored in the same time, which might result in inconsistent maximum likelihood estimates, therefore he introduced a double

heteroscedasticity in both error terms into a cross-sectional stochastic cost function, (Hadri et al., 2003).

The results suggest the high sensitivity of the measures of firm specific inefficiency to the correction for heteroscedasticity, and the introduction of the double heteroscedasticity refers to the existence of heteroscedasticity in both the one-sided error term, and the two-sided error term as well. Both in $v_{it} \sim N(0, \sigma_v^2)$ and $u_{it} \sim N^+(0, \sigma_u^2)$.

In the case of the cross section stochastic frontier model, the variances only change across production units, while, in a panel data model, variances could change over time and across production units. (Hadri et al., 2003) contend that introducing the heteroscedasticity term into the inefficiency error term u in panel data models, would result in highly sensitive stochastic production frontiers to heteroscedasticity, whereas (Coelli et al., 1999) examine the heterogeneity in the stochastic production function in comparison with the heteroscedasticity in the inefficiency term, and found that the degrees of technical inefficiency generated by the two methods are different despite the similarity in rankings of efficiency scores, (Zhang, 2012).

The inclusion of heterogeneity and heteroscedasticity involves extra variables to be added into the function, where those extra variables can be either time-invariant especially in the case of cross section data, or time-varying as in the case of panel data.

Heterogeneity is divided into two categories, the observed heterogeneity and the unobserved heterogeneity. This is where the former is related to the variables that can be measured, while the latter is incorporated into the model in the form of effects into the variance of error term causing conditional heteroscedasticity. Where heteroscedasticity can be either integrated in u or v or in both u and v , (Kumbhakar and Lovell, 2000).

In the panel data models, and when v is heteroscedastic, the estimates of the parameters in the frontier function and those of technical inefficiency function are consistent under both the time-invariant fixed-effects and the random-effects methods. Whereas, in both the maximum likelihood approach, the estimates consistency is preserved only if the time trend observed (T) (in the panel) is relatively large in comparison with individuals (N).

In the time-varying panel data models, and when v is heteroscedastic, with the correction of (Kumbhakar, 1990), (Cornwell et al., 1990), and (Lee and Schmidt, 1993) methods, the imprecision in the estimates can be solved and the MLE can be considered even if the (N) is large (Zhang, 2012). According to (Hadri, 1999, Caudill and Ford, 1993, Caudill et al., 1995) a term of multiplicative heteroscedasticity is incorporated into the one-sided error term with the variance $\sigma_u^2 = \exp(\gamma'Z_{it})$.

Furthermore, (Wang, 2002) proposed heterogeneity and heteroscedasticity both to be included into the technical inefficiency term u , and the efficiency effects of the stochastic frontier model to be non-monotonic. That is, the impact of the exogenous variables on production can have two directions (positive or negative). To put it another way, the sign of the effect of a single exogenous factor does not always remain positive or negative. The suggested property of non-monotonicity by (Wang, 2002) connotes that the influence of the external factors may encourage or discourage efficiency in the observed sample.

3.1.3 The Truncated Normal Stochastic Frontier Model

The truncated normal model is adopted for generality purposes. The benefit of this additional level of generality is the relaxation of the possible erroneous restriction in the normal-half normal model that the mean of the underlying inefficiency term is zero. The extended model is obtained by allowing μ , the mean of U_i to be nonzero;

$$y_i = \beta'x_i + v_i - u_i, \quad u_i = |U_i| \quad \text{Equation 3.20}$$

Where

$$U_i \sim N[\mu, \sigma_{u_i}^2] \quad \& \quad V_i \sim N[0, \sigma_{v_i}^2]$$

(With a constant term in the model, no similar parameter can be introduced into the distribution of v_i).

(Stevenson, 1980) argues that the zero mean assumption in (Aigner et al., 1977) is an extra restrictive condition which might be unnecessary. However, he generated results for a truncated as opposed to half-normal distribution where the one-sided error term u_i is obtained by truncation at zero the distribution of the variable with the possibility of nonzero mean. The advantage of this extra degree of generality is to relax possible

erroneous restriction, but at cost of ill-behaved log-likelihood at times due to unrestricted μ . In addition, the estimation of the nonzero μ usually yields inflated values of standard errors of the other parameter, and it quite often hinders or blocks out iterations' convergence, (Greene, 2007).

By way of descriptive exposition, the individual term in the log likelihood for the normal-truncated normal model (NTN) can be defined as follows

$$\log L_i = -\frac{1}{2}\log 2\pi - \log \sigma - \frac{1}{2}\left[\frac{S_{\varepsilon_i} + \mu}{\sigma}\right]^2 - \log \Phi\left(\frac{\mu}{\sigma_u}\right) + \log \Phi\left[\left(\frac{\mu}{\lambda} - S_{\varepsilon_i}\right)/\sigma\right] \quad \text{Equation 3.21}$$

Where the above definitions suggest that:

$$\sigma_u = \sigma\lambda\sqrt{1 + \lambda^2} \quad \text{Equation 3.22}$$

To generate the log likelihood for this normal-truncated normal model, we can use the formula in *Equation 3.22* with the following reparameterization

$$\alpha = \mu(\lambda\sigma) \quad \text{Equation 3.23}$$

The NTN function will be maximised with respect to α , β , λ , and after optimisation, the structural parameter μ will be recovered from $\mu = (\alpha\sigma\lambda)$ and the model will be as follows

$$\log L_i = -\frac{1}{2}\log 2\pi - \log \sigma - \frac{1}{2}\left(\frac{d_{\varepsilon_i}}{\sigma} + \alpha\lambda\right)^2 - \log \Phi(\sigma\sqrt{1 + \lambda^2}) + \log \Phi[(\alpha - d_{\varepsilon_i}\lambda)/\sigma] \quad \text{Equation 3.24}$$

3.2 Matching Methods

The matching methodology is integrated into this research and is intended to provide a broader understanding of what kind of effects can treatment variables such as formal training and research and development expenditures – as two other channels of human capital formation and accretion – have on labour productivity.

The rationale for the matching methods choice is that matching can be used as a tool for pre-processing data to improve causal inference in observational data, (Ho et al., 2007), (Morgan and Winship, 2014) by pruning observations from the sample selectively,

(King et al., 2011) to tackle imbalance in the empirical distribution of the prior-treatment confounders between the treated and control groups (Stuart, 2010) which lowers the degree of model dependence in the statistical estimation of causal effect (Ho et al., 2007), (Imai et al., 2008, Iacus et al., 2011) and therefore reduces the estimates inefficiency and bias.

Propensity score matching, in particular, is used as a method to address selection bias in the estimates of treatment effects to move towards more causal estimates. That is to say, selection bias – omitted variable bias – is simply those systematic differences between individuals who experience a specific treatment and those who do not. If those differences are not accounted for then the estimates of the treatment effects will be biased.

Matching approaches can be used to fix the matched sample size and attempt to reduce the imbalance issue such as the completely randomised experiment procedures by propensity score matching, or the fully blocked randomised experiment by Mahalanobis distance matching.

Alternatively, matching methods can fix the imbalance but at a cost of losing some observations in the hope of keeping a sufficient number of observations. This happens when procedures like Coarsened exact matching (CEM) and caliper-based techniques are applied.

The matching is used to reduce estimation bias when comparing non-equivalent groups and to better allow for heterogeneity. It is also a useful strategy for making the causal inference from observational data.

The main goal is to examine and figure out the effects of the binary causal variable (the treatment variable) on the outcome variable holding constant the control variables.

Propensity score matching is a method to make two groups look the same in terms of a set of characteristics. It can be defined as the probability of a group of participants receiving treatment based on observed characteristics.

The matching is an important device for evaluating the average causal effect of a treatment. It is a useful technique to avoid the selection bias issue, which reflects the fact that there are differences between these two groups (the treated and untreated) in terms of other factors (covariates) for determining an outcome variable.

It is also useful to enrich the discussion with the subject of counterfactuals. After observing the data, each unit has either received treatment or not. This means that one of the potential outcomes will become an actual outcome, which is what can be seen in the data. On the other hand, the other potential outcome will become a counterfactual outcome. It is counterfactual because it is the outcome that would have happened if the treatment was different.

If a unit had been treated, then the potential outcome for being treated is the one which will be observed, which is in fact, the actual outcome. For instance, if a patient had taken a treatment for cholesterol, then the observer will see what happens to the cholesterol, but the observer cannot see what would have happened to the cholesterol, if the patient did not take the medication, which is the counterfactual outcome.

Causality in this case, can be defined as the difference between the actual outcome and the counterfactual outcome.

Putting it another way, the comparison will be between the actual outcome and the counterfactual outcome, and this comparison is what is going to tell the researcher about the causal effects by the means of the causal inference methods' assumptions, which will allow the researcher to observe the unobservable (the counterfactual outcome) to make the appropriate comparison.

The crucial point is that the individual cannot contemporaneously take and does not take the medication. At this point, it can be said that reconstructing the counterfactuals is crucially important to estimate the unbiased casual effect.

The possibility to overcome this issue is via calculating the treatment effects either by using the average treatment effect ATE or by using the average treatment of the treated ATT as will be explained soon after.

The propensity score method allows scholars to reconstruct counterfactuals by making use of observational datasets. This can be done by reducing the sources of bias; (1) bias resulting from the lack of distribution overlap and (2) bias resulting from different density weights.

The matching methods are best applied with an extensive, iterative, and manual search across different matching solutions which seek to maximise the balance of covariates between the treated and control groups and the matched sample size simultaneously, (King et al., 2011).

In the potential outcomes framework, there are two possible treatments (active treatment vs control treatment) and an outcome, (Austin, 2011).

The main interest is to estimate the average effect of a binary treatment (Formal Training/ Research and Development Expenditures) on some outcomes (Output per Worker). For unit i , with $i = 1, \dots, N$, (Rubin, 1973).

In the observational research the most commonly estimated quantities that a researcher might be interested in are the average treatment effect on the population (ATE), and the average treatment on the treated (ATT), where the fundamental distinction between the two is that the former involves: how, on average, the outcome of interest would change if all individuals in the sample of interest have decided to undergo a particular treatment relative to their decision if they participated to receive another single treatment, while the latter has to deal with: how the average outcome would change if all participants in a particular treatment had instead received another treatment, (McCaffrey et al., 2013).

Exploring the treatment effects of the treated (ATTs) is also possible and feasible, bearing in mind that the key difference in the case of multiple treatment setting is that

more precision is required when referring to the treatment condition (the treated) by clearly defining the treatment group of interest, and then drawing inferences about the relative effectiveness of the treatment groups which were enrolled in the treatment program, (Burgette et al., 2017).

The advantage of the ATT is that each treatment program is assessed only through the cases it treated, and this is an important feature, because individuals and treatment may be aligned so that the targeted participants by a specific treatment are, in fact, the subset of the population subject to study who may make out the best with this treatment, because it (the treatment) already shown that it is more effective for this group of people than others.

However, the drawback of the ATT is that it does not assist for inferences about the relative effects of the treatment if it has been extended to include a group of persons which is different from the base group of clientele. Essentially, therefore, the ATT cannot help much in determining whether any change in the targeted subset in the entire population would result in better outcome on the whole, but this can be done using ATE, (McCaffrey et al., 2013).

3.2.1 Treatment Evaluation Definition

Treatment evaluation is the estimation of the average effect of a program or treatment on the outcome of interest, meaning that the observations are assigned into two groups; a group (*treated group*) that received the treatment (*formal training/ R&D spending*) (1), and another group (*control group*) which did not receive the treatment (0), and there will be an estimation of the treatment effect on the treated group, whereas the control group will be used as a comparison one.

- Treatment D is a binary variable that determines if the observation has the treatment or not.
- $D=1$ for treated observations and $D=0$ for control observations.

- The second step is to estimate a probit/logit model for the propensity of observations to be assigned to the treated group.
- The x variables that could affect the likelihood of being assigned to the treated group are used in the model.
- The propensity score model is a probit/logit model with D as the dependent (explained) variable and x as the independent variables (explanatory).

$$P(x) = \text{prob}(D = 1|x) = E(D|x)$$

The propensity score model is the conditional (predicted) probability of receiving treatment given the pre-treatment attributes of x.

- The goal is to find a match for each of treated observations, not the control group.
- The next step is to calculate the treatment effect by comparing the outcome y between the treated and control observations, after matching the following

$$y = \begin{cases} y_1 & \text{if } D = 1 \\ y_0 & \text{if } D = 0 \end{cases}$$

- Matching methods; for each treated observation(s) i, a control observation(s) j with similar characteristics needs to be found. There are several matching approaches to implement such as; Nearest neighbour matching, Kernel matching, Radius matching, and Stratification or interval matching.
- Treatment effects; after finding the matches, and each treated observation has a good match from the control observations, we need to calculate the effect of that treatment following one of these ways;
 - 1- Average Treatment Effect (ATE) ; where ATE is the difference between the outcome (output per worker) of treated and control observations.

$$\Delta = y_1 - y_0$$

$$ATE = E(\Delta) = E(y_1|x, D = 1) - E(y_0|x, D = 0)$$

This method is an equivalent to a simple t-test between the outcomes (output per worker) for the treated and control groups. A drawback of this approach though is that it can be appropriate for random experiments but it can be biased if the treated and control observations characteristics are not similar in the observational studies.

In order to account for a potential selectivity bias, the average treatment effect estimation is selected to compare the firms offering training and those which do not offer training programs for their workers during the last three completed fiscal years, (Heckman et al., 1997), (Muehler et al., 2007).

Therefore, this approach requires the construction of an adequate control group where the only remaining difference between the treated group and non-treated group is whether there is a (training program/R&D spending) or not, (Blundell and Dias, 2002), (Caliendo and Hujer, 2006) and (Muehler et al., 2007).

In this case, the average treatment effect for the population (ATE) describes the difference in the expected output per worker (labour productivity) for trained workers and untrained workers, and this can be defined as:

$$\Delta_{ATE} = E(\Delta) = E(\ln OPW^1) - E(\ln OPW^0) \quad \text{Equation 3.25}$$

Where;

$E(\ln OPW^1)$ is the expected log-output per worker for firms with trained workers, and $E(\ln OPW^0)$ is the corresponding expected log-output per worker for firms with non-trained workers.

Nonetheless, the disadvantage of the ATE is that it does not isolate the effect of the treatment (training) on the workers who were not targeted by the treatment when it first planned.

- 2- The more appropriate evaluation parameter is the average treatment on the treated (ATT) or the average treatment effect on the treated (ATET) which focuses on the productivity effect for those workers who were intended when the training program was designed.

In essence, ATT involves the difference between the expected output per worker with and without the training program being offered for production workers. In other words, is the difference between the outcome (output per worker OPW^1) of the treated and the outcome (output per worker OPW^0) of the treated observations if they had not been treated:

$$ATT = E(\Delta|D = 1) = E(y_1|x, D = 1) - E(y_0|x, D = 1) \text{ Equation 3.26}$$

Alternatively,

$$\Delta_{ATT} = E(\Delta|T = 1) = E(\ln OPW^1 | T = 1) - E(\ln OPW^0 | T = 1) \text{ Equation 3.27}$$

The second term on the right-hand side of equation 3.23 [$E(\ln OPW^0 | T = 1)$] denotes a hypothetical outcome without treatment for individual who received the treatment and is not observable. Under the condition where [$E(\ln OPW^0 | T = 1) = E(\ln OPW^0 | T = 0)$], the group of firms without treatment (training) is considered as an adequate control group.

- a) In order for this condition to be valid, two assumptions need to be fulfilled. The first is the so- called (Conditional Independence Assumption), which implies the selection between the workers based on specific observable characteristics (such as; ability, attitude..etc) to be included in the training program or not to be included.
 - b) The second assumption is the (Common Support Assumption) which involves a positive probability to be in the treatment or in the control group to avoid comparing the non-comparable.
- 3- Average Treatment Effect on the Treated (ATET); Where ATET is the difference between the outcome (output per worker) of the treated and the outcome (output per worker) of the treated observations if they had not been treated.

$$ATET = E(\Delta|D = 1) = E(y_1|x, D = 1) - E(y_0|x, D = 1)$$

Where the second term is a counterfactual so it is not observable and needs to be estimated.

3.2.2 Propensity Score Matching

After matching on propensity scores, a comparison between the outcomes (*output per worker*) of treated (*received training/ R&D spending*) and control (*did not receive training/R&D spending*) observations takes place.

$$ATET = E(\Delta|p(x), D = 1) = E(y_1|p(x), D = 1) - E(y_0|p(x), D = 0)$$

If the outcome is continuous (a depression scale), the effect of treatment can be estimated as the difference between the mean outcome for the treated subjects and the mean outcome for untreated subjects in the matched sample, (Rosenbaum and Rubin, 1983). If the outcome is dichotomous (self-report of the presence or absence of a depression) the effect of treatment can be estimated as the difference between the proportion of subjects experiencing the event in each of the two groups (treated vs. untreated) in the matched sample, (Austin, 2011). With binary outcomes, the effect of treatment can also be described using the relative risk or the number needed treat NNT, (Rosenbaum and Rubin, 1983), (Austin, 2008) and (Austin, 2010).

For each treated observation(s) i , a control observation(s) j with similar characteristics needs to be found. There are several matching approaches to implement such as; nearest neighbour matching, kernel matching, radius matching, and Stratification or interval matching.

The general idea of matching is straightforward and to illustrate the notion let T_i denotes a treatment variable for unit i ($i = 1, \dots, n$) where the treatment variable is coded as (1) for units from the treated group, and (0) for units from the control group.

To illustrate, let $T_i = 1$ if a patient is given a certain medication, and $T_i = 0$ if the same patient is given different medication or a placebo.

Assume that $Y_i(t)$ (for $t = 0,1$) is the value that the outcome variable (potential outcome) would take when $T_i = t$, meaning that for each i , $Y_i(1)$ or $Y_i(0)$ is observed, never both. Accordingly, the $Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0)$ is observed, and a vector of

pre-treatment control variable is denoted by X_i .

In addition, the treatment effect of T on Y for the unit i can be denoted by $TE_i = Y_i(1) - Y_i(0)$, if one observation of the treated group is selected, then $Y_i(1) = Y_i$ will be observed, and thereby $Y_i(0)$ will be unobserved.

In order to perform a simple matching for TE_i to be estimated, the unobserved units $Y_i(0)$ need to be replaced by the observed units j from the control group X_i then the observed i will be matched to its counterpart j as $X_i = X_j$. The procedure continues by pruning the unmatched observations from the data set prior to any further analysis is conducted.

In broad terms, matching methods vary based on how the approximate matching is defined. (King et al., 2011).

The primary target of matching is to find a subset of the data closer to exact matching, and therefore any deviations from the exact matching will be considered as an imbalance. The one way to measure such imbalance is the average distance between each unit X_i to its closest unit in the opposite treatment regime, $X_{j(i)}$.

Hence, the imbalance for the original data can be measured as $I(X) = \text{mean}_{i \in \{i\}} d(X_i, X_{j(i)})$. Whereas the imbalance for a particularly matched data subset χ , would be $I(\chi)$, therefore, when imbalance reduction is achieved by matching methods the $I(\chi)$ will be $< I(X)$. (King and Nielsen, 2016). If any imbalance remains, some statistical modelling assumptions need to be considered to deal with it, and the benefit of matching is that it minimises, to a large extent, the reliance of conclusions on such statistical assumptions, (Ho et al., 2007).

3.2.3 Mahalanobis Metric Matching

It is thought that matching is a viable way to find the optimal experimental data that are unseen within the original observational dataset, but some matching techniques, allegedly PSM could approximate a low-standard experimental design and could ignore much of potentially useful information without efficient use, leaving us with higher imbalance, model dependence, and ultimately bias, (King and Nielsen, 2016).

For that reason, a fully blocked randomised experimental design (FB) is arguably a good alternative to a completely randomised experimental design (CR). In the former – FB – treated and control groups are blocked at the beginning exactly on the observed covariates, causing imbalance to be 0, and with no need of pruning observations as happens in the case of exact matching: $X_{FB} = M(X_{FB}|X_i = X_j)$, meaning that $I(X_{FB}) = 0$.

Whereas in the case of the latter – CR – treatment assignment T is dependent only on the scalar probability of treatment π for all units, and therefore it is random with regards to X , and random does not always eliminate imbalance to 0, and bias: $I(X_{CR}) \geq 0$. In other words, the FB is a more powerful, more efficient, research-cost minimiser, and more credible and reliable analysis machine. Therefore, it reduces imbalance to the least level possible, resulting lower model dependence, and less prejudice, (Box and William), (Greevy et al., 2004), (Imai et al., 2008), (Imai et al., 2009), and (King and Nielsen, 2016).

Mahalanobis Distance Matching (MDM), which is the longest standing matching approach that fall into the Equal Percent Bias Reducing class (EPBR), (Rubin, 1976), (Rubin and Stuart, 2006), and Coarsened Exact Matching (CEM), which is the exemplar in the class of Monotonic Imbalance Bounding methods (MIB), (Iacus et al., 2011), these two matching approaches approximate a fully blocked experiment, as they are equipped with adjustable parameters which can be tuned to generate the same results similar to the ones produced by the exact matching, in order to obtain zero imbalance.

To illustrate the point: $\mathbf{X}_{EM} = M(X|A_{CEM}, \delta = 0) = M(X|A_{MDM}, \delta = 0)$. Where EM = exact matching, which implies higher ability of both MDM and CEM to accomplish lower levels of imbalance, and model dependence accordingly. It is worth pointing out that, PSM approximates only a completely randomised experimental design CR, resulting in higher levels of imbalance and bias, due to: $\mathbf{X}_{EM} \subseteq M(X|A_{PSM}, \delta = 0)$, and hence, $I(\mathbf{X}_{EM}) \leq I(\mathbf{X}_{PSM})$, and it is strictly $I(\mathbf{X}_{EM}) < I(\mathbf{X}_{PSM})$, in the less commonly experienced cases, (Rubin and Thomas, 2000).

Mahalanobis distance matching MDM and propensity score matching PSM are designed on specific ideas of distance between observations of pre-treatment covariates. Where the former measures the distance between the two observations X_i and X_j with the Mahalanobis distance,

$$M(X_i, X_j) = \sqrt{(X_i - X_j)' S^{-1} (X_i - X_j)} \quad \text{Equation 3.28}$$

Where S represents the sample covariance matrix of X .

In the PSM the vectors will be collapsed to a scalar or propensity score, which in fact represents the likelihood of an observation receives treatment given the covariates, and it is usually estimated using a logistic regression,

$$\pi_i \equiv \Pr(T_i = 1|X) = 1/(1 + e^{X_i\beta}) \quad \text{Equation 3.29}$$

Thereby, the distance between observations with vectors X_i and X_j is the sample scalar difference between the two estimates $\hat{\pi}_i - \hat{\pi}_j$ or $(X_i\beta - X_j\beta)$, (King et al., 2011).

A popular application of the two matching methods MDM and PSM is the one-to-one nearest neighbour greedy matching without replacement, (Austin, 2009), where each treated unit t is matched in some arbitrary sequence to the nearest unit in the control group c using the distance metric.

Then some procedures such as calipers are applied to eradicate the unreasonably distant treated units from the control units to which they were matched in the first step, (Stuart and Rubin, 2008, Rosenbaum and Rubin, 1985).

The fundamental objective of any effort aims to evaluate a particular intervention, is to examine whether the programs designed were effective to reach the principal goals of interest and desired results.

The credible and reliable evaluation of the impact of a corrective and curative program (treatment) is thought to be a primal challenge when constructing the counterfactual outcome, meaning that, what would have happened if the participants were not exposed to the treatment, and this counterfactual outcome is not observed, therefore, it entails some statistical methods to be estimated, (Heinrich et al., 2010).

3.3 Data

3.3.1 Cross Sectional Firm Level Data for The Middle East and North Africa and Eastern Europe and Central Asia

The substantive and relatively comprehensive interpretation of the observed differences in per capita income, GDP growth rates, and productivity across countries has been a big challenge for decades. The use of firm-level data is an attractive and valid option to avoid these issues which are related to the macro analysis. This does not mean that the firm-level approach tackles a great deal of the cross-country unobserved heterogeneity problems, but it provides tighter framework to connect the institutional specific measures with the pertinent outcomes, (Bartelsman et al., 2009).

The use of firm-level data can provide some advantages. One of which is to examine in detail whether firms could have benefited from the available skills and the output of the education system supplied in the labour market, and how these skills are being reflected in better and higher efficiency and performance levels across manufacturing firms.

One of the criticisms of using survey data for measuring firm performance is that due to its self-reporting nature, it is prone to bias. However, it is more likely that accounting data is subject to a greater element of bias as there are significant incentives in distorting financial data particularly in the areas of tax, asset reporting and remuneration. The MENA and BEEPS survey measure the business environment and does not, of itself, measure firm performance. The questions relating to performance tend to be at the end of the interview when the respondent has become comfortable with the non-judgmental nature of the process and it could therefore be argued less susceptible to bias, (Beck and Demirguc-Kunt, 2006).

In addition, the variations in the aggregate data provided from different sources, and the disparities between methodologies of accounting national statistics in the Central and Eastern Europe region, and those adopted in the Western institutions, resulted in inconsistent measures of national performance and unreliable

productivity estimates. Moreover, In the CEE region and ECA region, by extension, the prices do not imply the resource allocation connotations as in the market economy in the West, along with the distortion of the exchange rates. Consequently, it is neither possible to measure the performance nor to identify or correct the failures. Furthermore, the policy advancement will be restricted, and it will not be implemented as effectively as expected, (Piesse and Thirtle, 2000).

The selection of countries is mainly due to data availability. This is where 2013 is the year for which the latest firm-level data in the two regions of MENA and ECA was available at the time this research first started in 2014.

The choice of the manufacturing private sector is due to technicality issues. The decision to focus on the manufacturing sector firms is mainly because of data unavailability in a high percentage of the service sector firms in the Business Environment and Enterprise Performance Survey sample.

Those firms neither reported their capital's net book value nor their capital's replacement cost. Meanwhile in the sample at hand, more observations are available from the manufacturing private sector. This is where more than 2284 and 1800 firms in this sector from MENA and ECA respectively, reported their capital figures, either as net book values or as replacement cost of their machinery, equipment, land, and buildings. From a technical point of view, the missing capital observations in the services sector do not help much when setting the stochastic frontier production function in an appropriate manner.

It is worth noting that the MENA sample is heterogenous, and the ECA sample is even more heterogenous due to the differences in the economic, political, and historical contexts. They are also heterogenous in terms of the nature and pace of the transition process which has been taking place in each of these nations since the demise of the Soviet Union in 1990s.

However, the MENA sample can be clustered into sub-groups of countries based on some economic and political features that make them more similar. The Middle East and North Africa nations can be classified into three main groups from an economic point of view: the high income and natural resources rich countries

including the Gulf states; the middle-income labour abundant countries including Egypt, Algeria, Morocco, and Tunisia; and the middle- and low-income war-torn nations, such as: Libya, Iraq, Yemen, and Syria. The low income with small population nations, such as: Mauritania, Djibouti, and Gaza and the West Bank.

On the other hand, Eastern Europe and Central Asia can be divided into six similar regions in terms of their history, political systems, and economic transition.

1. Central Eastern Europe CEE: which includes the Czech Republic, Poland, Slovakia, Slovenia, Bulgaria, Hungary, and Romania.
2. The Balkans: which comprises Serbia, Bosnia-Herzegovina, Croatia, Macedonia, Kosovo, Montenegro, and Albania.
3. The Baltic states: they include Estonia, Lithuania, and Latvia.
4. The Caucasus region: which consists of Azerbaijan, Armenia, and Georgia.
5. The Western Commonwealth of Independent States CIS: including Russia, Ukraine, Belarus, and Moldova.
6. The Central Asia region CA: which comprises Kazakhstan, Tajikistan, Turkmenistan, Kyrgyzstan, and Uzbekistan.

In terms of the transition nature since the beginning of the 1990, the gap between the ECA economies has been widening between the Baltic states and the CE countries on one side, and the rest of the region on the other.

However, cross-country heterogeneity in both regions is captured both by country-level variables such as; GDP per capita, the strength of legal rights index, distance to frontier scores, life expectancy at birth, total (years), and taxation. In addition, the sample is pooled with country dummy variable named as country specific effects, and a sector dummy variable (low, medium, and high technology industries) named as sector specific effects using the stochastic frontier analysis.

Moreover, and to better allow for firm heterogeneity the analysis was extended to two types of matching analysis, propensity score matching (PSM) and Mahalanobis distance matching (MDM).

There are various reasons for choosing these two regions, besides the panel firm-level data unavailability and inaccessibility for researchers in the human capital field in some regions.

The main reason for this choice is the different organisational structures and the dissimilarities between production functions across economies in different developmental phases, which can be a suitable platform for analysing the distinctive effects of human capital composition in each region in comparison with the others.

3.3.1.1 The Middle East and North Africa Data

The dataset which is used for the estimation of the maximum likelihood stochastic frontier production function, was sourced from the joint World Bank Group – European Bank for Reconstruction and Development – European Investment Bank Enterprise Survey, undertaken in 2013, and spanning more than (6000) private enterprises across the Middle East and North Africa region, covering both the manufacturing and services sectors. However, the researcher main focus will merely be on the manufacturing sector private firms, the survey also encompasses different firm-characteristics such as size, age, involvement in innovation and imitation, their inputs and outputs, exports and imports, spending on research and development and formal training.

The 9 middle-income MENA nations were grouped into 64 local regions as follows; (Egypt 22 regions, Israel 5, Jordan 5, Lebanon 6, Mauritania 2, Morocco 12, Tunisia 5, Yemen 8, West Bank and Gaza 2).

With regard to formal training data in MENA, more than (3200) firms from different manufacturing firms (low-tech, medium-tech, high-tech) with different sizes and ages across the MENA area are included in the analysis.

The aim of this analysis is to examine whether there is a statistically significant impact of training on firms' performance mainly labour productivity.

3.3.1.2 Eastern Europe and Central Asia Data

The ECA sample is collected from The Business Environment and Enterprise Performance Survey (BEEPS) by the World Bank.

The survey was conducted in (2013) and it includes more than (4300) manufacturing firms with different sizes and ages covering the Eastern European and Central Asian nations.

The manufacturing firms in the sample are chosen based on their response to the questions about the net book values and the replacement cost of their capital as these details are crucial and facilitate the estimation of the stochastic frontier production function. Subsequently, other firms among the whole population of firms, which did not report those values of capital are replaced by (blank) in the sample due to a lack of response.

The countries which are selected to be included in the sample are; Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, FYR Macedonia, Georgia, Hungary, Kazakhstan, Kosovo, Kyrgyz Republic, Latvia, Lithuania, Moldova, Mongolia, Montenegro, Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Tajikistan, Ukraine, and Uzbekistan.

Using the (BEEPS) firm level data, the stochastic frontier estimation allows for technical efficiency to be impacted by human capital components, which is represented by average years of education, university degree holders, college or technical school attendees, and those who completed a secondary or vocational training school.

This is with other variables of interest, such as firm size, the percentage of foreign ownership in the firm, and loans received. There are some other control variables at the country level, such as GDP per capita across countries, and life expectancy rates at birth, which are included in the estimation to capture country specific effects, where the higher these two variables are, the more developed the country is. Another country variable is used, which is the country's distance to the frontier score, which shows the

distance of each economy to the frontier of the best regulatory performance observed on each of the indicators across all economies. The results are taken from the Doing Business sample observed since (2005). This allows observers to assess the gap between a specific economy's performance and the best practice in the regulatory environment. More details about this measure are available in the *World Bank Doing Business* periodical publications.

Regarding the formal training data in ECA, more than (4300) manufacturing firms from different economic activities with different sizes and ages reported whether they offered training over the last three completed fiscal years.

The core of analysis is to examine whether there is a statistically significant impact of training on firm's performance.

3.3.1.3 Variables for Stochastic Frontier Production Functions in MENA and ECA

The variables for each firm in shorthand along with their definitions are explained as follows:

1. **Ln Q (Annual Gross Sales in US dollars):** Total Sales (as the output variable); This represents the value of all annual sales counting the manufactured goods and goods the establishment has bought for trading divided by the exchange rates of each country's local currency.
2. **Ln Capital Input:** (Capital Input); This total capital stock that a firm holds during the year it has been surveyed. It is calculated by adding up the net book value of machinery and equipment to the net book value of land and building and denoted by KA in other words, it is the actual cost of assets at the time they have been acquired, plus the costs incurred to make the asset ready to use minus the annual accumulated depreciation since the time of purchase.

Alternatively, its capital input is measured by aggregating the rental cost of machinery and equipment with the replacement cost of land and buildings in the year in which the establishment was surveyed. This is denoted by KB.

3. **Ln Labour Input:** (Labour Inputs); This is represented by full time workers equivalent which effectively, considers the number of permanent full-time employees last completed year (prior to the year when the survey was conducted) who are paid and contracted for one or more than a fiscal year or guaranteed a renewal of their employment contract and working up to 8 hours a day plus temporary worker who have been hired for less than a year.
4. **Ln Squared Labour:** This denotes for squared labour inputs.
5. **Ln Squared Capital:** This represents squared capital input.
6. **Ln K*L:** This represents capital input multiplied by labour input.

3.3.1.4 Determinants of Technical Efficiency in MENA and ECA

One of the main objectives for studying the efficiency factors is to provide governments and regulatory systems designers with the analyses and assessments of the effects of their policies implications to increase the ability of production units (firms) to achieve the optimum level of production or the produce with the lowest level possible of cost.

Another important goal is to identify the causes of inefficiency across firms in different industries, which could assist the policymakers to project more concrete macroeconomic plans to improve the business environment.

1. **Ln Average Years of Education:** This variable is represented by the average number of years of education of a typical full-time permanent production worker employed in the plant.
2. **Ln Highly-Skilled Labour (University Degree):** The percentage of the firm's employees at the end of the fiscal year (when the survey was conducted) who had a university degree.

3. **Ln Intermediate-Skilled Production Labour** : According to the Enterprise Survey Module the numbers of different types of permanent, full-time skilled production workers; are workers (up through the line supervisor level) engaged in fabricating, processing, assembling, inspecting, receiving, storing, handling, packing, warehousing, shipping (but not delivering), maintenance, repair, product development, auxiliary production for plant's own use (e.g., power plant), recordkeeping, and other services closely associated with these production operations. Employees above the working-supervisor level are excluded from this item.

Also, these workers are skilled in that they have some special knowledge or (usually acquired) ability in their work. A skilled worker may have attended a college or technical school. Or, a skilled worker may have learned his skills on the job.

4. **Ln Low-Skilled Labour (Secondary School Workers)**: in MENA this variable represents the number of full-time permanent employees in the establishment who had completed secondary school including vocational as their highest level of education.
5. **Size**: The firm size is represented by a scale of (0 – 3) where 0 denotes for micro size enterprises, 1 proxies small size enterprises, 2 for the medium size, and 3 represents the large size establishments.
6. **Ln Low-Skilled Production Labour (Unskilled Workers)**: in ECA this variable represents the workers (up through the line supervisor level) engaged in fabricating, processing, assembling, inspecting, receiving, storing, handling, packing, warehousing, shipping (but not delivering), maintenance, repair, product development, auxiliary production for plant's own use (e.g., power plant), recordkeeping, and other services closely associated with these production operations. Employees above the working-supervisor level are excluded from this item. Also, these workers are **unskilled** in that it is not required that they have special training, education, or skill to perform their job.

7. **Loan:** This is a dummy variable represents whether the firm received a fund in the form of a loan from different financial sources. Institutions that granted loan are in most cases: (private, government, commercial bank etc.).
8. **Loan from a Commercial Bank:** This dummy variable demonstrates whether the enterprise received a loan from a commercial bank or not, denoted by (0 = No, the firm did not receive a loan from a commercial bank, 1 = yes, the firm did receive a loan from a commercial bank).
9. **Firm Age:** This variable represents the age of the firm in the year when the establishment was surveyed.
10. **Labour Total Cost:** Total cost of labour, including wages, salaries and benefits is the total annual wages and all annual benefits, including food, transport, social security (i.e. pensions, medical insurance, and unemployment insurance).
11. **Total Cost:** this is the product of the aggregation of (Electricity, Communication services, Fuel, Transport for goods and workers (excluding fuel), Water, Rental of land/buildings, equipment, furniture).
12. **Foreign Shareholders:** Foreign ownership refers to the nationality of the shareholders. If the primary owner is a foreign national resident in the country, it is still a foreign-owned firm. If the shares are held by another company or institution and the shareholders of that institution are foreign nationals, then it is foreign-owned. This variable is proxied by the percentage of foreign ownership in the establishment in the previous year when the survey was conducted.
13. **Research & Development Expenditures:** This variable investigates whether the establishment did spend on research and development activities during the last three completed fiscal years, either in-house or contracted with other companies (outsourced). Research and development (R&D) is defined as creative work undertaken on a systematic basis to increase the stock of

knowledge. For example, (laboratory research for a new chemical compound of paint would be research and development while market research surveys or internet surfing would not be research and development).

14. **New Management Practices:** This is also a dummy variable which represents whether a firm during the last three years, introduced any new or significantly improved organizational or management practices or structures to its market. Meaning any changes in the management structure, changes in the way workers work together, introducing new incentives for performance, changing hiring and firing practices, or changing the systems of information and monitoring that aim to enhance efficiency.
15. **New Marketing Approaches:** it represents whether a firm introduced new or significantly improved marketing methods we mean design, branding or packaging that changes the look of the product or perception of the service, or a new channel or form of promoting, pricing or selling the products and services including a) changes in product form and appearance that do not alter the product's functional characteristics; b) new marketing methods in product placement such as introduction for the first time of a franchising system, of direct selling or exclusive retailing, and of product licensing; c) new marketing methods in product/service promotion such as the development and introduction of a fundamentally new brand symbol, the introduction of a personalized loyalty cards.
16. **Technology licensed from a foreign owned company:** It measures access to foreign technology. The license may be held by the establishment's parent company. The answer is "no" if the establishment uses foreign technology without a license or a formal agreement.
17. **GDP Per Capita:** Gross domestic product (GDP) is the sum of value added by all resident producers plus any product taxes (fewer subsidies) not included in the valuation of output. GDP per capita is gross domestic product divided by

midyear population. Growth is calculated from constant price GDP data in local currency and then converted into US dollar for comparison purposes.

18. **Strength of Legal Rights Index:** measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit.
19. **Distance to Frontier:** the country's distance to frontier score, which shows the distance of each economy to the frontier of the best performance observed in terms of regulatory performance on each of the indicators across all economies in the Doing Business sample since 2005. This allows observers to assess the gap between a specific economy's performance and the best practice in the regulatory environment.
20. **Life Expectancy at Birth, Total (Years):** Life expectancy equals the average number of years a person born in a given country is expected to live if mortality rates at each age were to remain steady in the future. It is derived from male and female life expectancy at birth from sources such as (1) United Nations Population Division. World Population Prospects. (2) Census reports and other statistical publications from national statistical offices, (3) Eurostat. (4) United Nations Statistical Division. (5) U.S Census Bureau.
21. **Taxation:** This represents total tax rate and measures the amount of taxes and mandatory contributions payable by businesses after accounting for allowable deductions and exemptions as a share of commercial profits. Taxes withheld (such as personal income tax) or collected and remitted to tax authorities (such as value added taxes, sales taxes or goods and service taxes) are excluded.
22. **Rural Population:** It refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population using the urban share reported by the United Nations Population Division.

3.3.1.5 Variables for OLS, Probit and Propensity Score Models in MENA and ECA

Given that formal training is not the sole variables being involved as influential factors on performance, there are other determinants of firm's performance (control variables) such as;

1. Ownership shares (foreign, domestic, government, etc.).
2. Access to finance as an obstacle (scale 0 - 4).
3. Receiving fund from different sources in the form of loans (0, 1).
4. Size of the firm (micro, small, medium, large).
5. The intensity of bureaucratic barriers (scale 0 - 4).
6. Inadequately educated workers as an obstruction to the firms' operations. (0 - 4).
7. Access to infrastructure (scale 0 - 4).
8. The ratio of international exports as a percentage of the firms' trade transactions.
9. Licensed technology in use (0, 1).
10. The intensity of bureaucratic barriers (scale 0 - 4).
11. The firm's ability to introduce and practices of new management performance-enhancing strategies and organisational structures over the last three years to the survey is measured and included in the investigation as a dummy variable (1,0).
12. The introduction of any new production methods over the last three years prior the survey (1,0).
13. Sector dummy variables are included to capture the specific effects of a high-tech, med-tech, or low-tech manufacturing plant.
14. Macro variables and country level specific characteristics were also included, as controls, in the estimation, such as: GDP Per Capita, Industry sector GDP share, and Legal Rights Index. These variables were meant to capture country-specific effects on the firm's performance.
15. Sector dummy variables are included to capture the specific effects of a high-tech, med-tech, or low-tech manufacturing plant.

16. Macro variables and country level specific characteristics were also included, as controls, in the estimation, such as GDP Per Capita, and Legal Rights Index. These environmental variables were meant to capture countries heterogeneity effects on the firms' performance.

Chapter 4: The Role of Education and Formal Training in the Manufacturing Firms' Performance: Evidence from the Middle East and North Africa Economies.

4.1 Introduction

This chapter principally aims to investigate and examine the contribution of human capital represented by several proxies (different levels of education; high school, college, university, average years of schooling) to technical efficiency using firm level data from the MENA countries.

The data is sourced from the joint conducted WBG-EBRD-EIB Enterprise Surveys, produced by The European Bank for Reconstruction and Development, The World Bank Group, and The European Investment Bank during 2013-2014.

As was already mentioned in section 3.3.1, the results of this survey span and comprise more than 6000 firms from different industries, with different sizes and ages in 9 middle-income economies across the MENA area, yet the analysis in this research will only be centred around the (2284) manufacturing firms which reported their capital inputs in 2013, which in turn will be included in the stochastic frontier analysis. As for the PSM and MDM analysis, more than 3200 manufacturing firms will be considered. These are the firms that reported whether they offered training for their full-time permanent employees during the last three completed fiscal years. The objective is to analyse the role of human capital and formal training in determining the firms' performance.

The first technique applied to analyse the contribution of human capital components and formal training was the stochastic frontier analysis. This allowed the study to

identify the determinants of productive efficiency relative to the simultaneously estimated stochastic production frontier.

The results show that, in MENA countries, education at both levels: secondary (low skilled workers) and tertiary (high-skilled workers) is statistically significant and negatively associated with inefficiency – that is education at both levels is positively related to productive efficiency. Especially in the low, medium and high technology manufacturing firms.

In the stochastic frontier analysis, the formal training programs were found to have insignificant effects on productive efficiency.

To better allow for firm heterogeneity the analysis was extended to two types of matching analysis, propensity score matching (PSM) and Mahalanobis distance matching (MDM), this where both analyses test individually whether there is a significant “treatment” effect on the log of output per worker effect for the training programs. The PSM and MDM analysis both found the training to individually have insignificant effect on the log of labour productivity.

Overall the chapter concludes that education, and knowledge acquired by R&D spending are all important determinants of firm level productivity in MENA countries. That is, human capital is important for understanding productive efficiency in the region.

However, the contribution of formal training to firms’ productivity remains unclear and ambiguous at time, despite using two different methodologies to examine this relationship in the private manufacturing sector in MENA.

4.2 The Role of Education in the Manufacturing Firms’ Performance in the Middle East and North Africa (MENA).

4.2.1 Empirical Results, Stochastic Frontier and Economic Analysis

According to the maximum likelihood estimates reported in table 4.1, efficiency levels appear to be higher in firms that are hiring a higher ratio of low skilled labour

(Those are full time permanent workers who have completed secondary school as their highest level of education).

It is also found that firms that are employing a higher percentage of high skill workers (Those with a university degree) seem to be more efficient than other firms with a lower ratio of university degree holders.

The negative sign associated with the low-skilled labour parameter indicates that firms with higher ratio of high school level workers, are expected to perform better in terms of lowering their inefficiency levels.

The share of labour with the university level of education are also positively contributing to productive efficiency at the firm level. The expected results indicate that the higher the percentage of university workers is, the more efficient is the firm.

These empirical results are in line with the theoretical expectations and consistent with the majority of the previous literature in this field.

The t-statistics values of the coefficients of the low skill and high skill labour demonstrate the statistical significance of the results.

On the other hand, the maximum likelihood estimates suggest that the effect of intermediate-skilled workers on efficiency is negative and statistically significant. This result tends to be an unexpected result, given that the contribution of the low-skilled workers is proved to be significant and positive to firm level efficiency. It was expected to see a positive contribution from the intermediate-skilled workers as well, assuming that they hold better skills and higher level of education, but still that is not the case.

The worker and allocative impacts of human capital are believed to raise the levels of productivity, while the human capital effects in terms of diffusion and research have their significant inputs in the growth rates of productivity.

In MENA economies it appears to be the case that primary, secondary and tertiary education do matter for the growth in the manufacturing private sector.

The argument here is that semi-skilled human capital is more important for promoting growth than highly and intermediate skilled human capital in the less affluent economies.

In the middle-income countries though, and in MENA in particular, it is found – based on the SFA results in this study– that both semi-skilled and highly skilled human capital are important ingredients for growth, mainly in the manufacturing firms where the portion of more educated workers, in particular, can play a better role in implementing the advanced technologies in production.

This analysis is done by combining all the 9 countries in the sample together, by applying the Cobb Douglas functional form, which is preferred as the adequate form for this dataset based on the likelihood ratio test results which demonstrated the acceptances of the null hypothesis.

The procedure involves ruling out the zero observations from firms that did not report their capital net book value and the replacement costs for their fixed assets (land, buildings, machinery, and equipment). This was primarily implemented to avoid any potential wrong skewness error that could occur in the OLS residuals for the stochastic frontier model before the maximum likelihood estimation even begins – where this wrong skewness error is one of the main issues facing researchers since the stochastic frontier model was established – where the exclusion of the zero capital observations helps in fitting the stochastic frontier with a normal exit using the NLogit 5 econometric software, which ensures that the OLS residuals are not to be skewed in the wrong direction, but this is at a cost of losing a part of the data.

Then a likelihood ratio test was conducted with a preference displayed to the Cobb-Douglas frontier production function (see table 4.2).

The test results indicate the acceptance of the null hypothesis at a 99% level of confidence.

The Cobb Douglas stochastic production function for the MENA region is set as follows:

$$\ln \text{Gross Sales}_i = \beta_0 + \beta_1 \ln (\text{Capital}_i) + \beta_2 \ln (\text{Labour}_i) + (v_i - u_i) \quad \text{Equation 4.1}$$

Whereas the technical inefficiency function is defined as follows:

$$\begin{aligned} \text{Technical Inefficiency} = & \delta_0 + \delta_1 (\text{Low skilled}_i) + \delta_2 (\text{Highly skilled}_i) + \\ & \delta_3 (\text{Intermediate skilled}_i) + \delta_4 (\text{Yrs of Shooling}_i) + \\ & \delta_5 (\text{GDP per Capita}_i) + \delta_6 (\text{Formal Training}_i) + \delta_7 (\text{Loan}_i) + \\ & \delta_8 (\text{International Exports Share}_i) + \delta_9 (\text{Country Dummies}_i) + \\ & \delta_{10} (\text{Sector Dummies}_i) + \delta_{11} (\text{Firm Size}_i) + \\ & \delta_{12} (\text{Licensed Technology in Use}_i) + \delta_{13} (\text{Foreign Shareholders}_i) + \\ & + \delta_{14} (\text{Distance to Frontier}_i) + \delta_{15} (\text{R\&D Spending}_i) + W_i \quad \text{Equation 4.2} \end{aligned}$$

The estimation of equations 4.1 and 4.2 using the stochastic frontier analysis resulted in the figures reported in table 4.1.

The degree of the asymmetry of the error term distribution can be represented by the λ (lambda) parameter, which can be calculated as $\lambda = \frac{\sigma_u}{\sigma_v}$, where the larger the value of λ is, the more pronounced the asymmetry will be in the error term distribution. If λ value equals zero, then the asymmetric error term will dominate the one-sided error term when determining ε_i , and the composite error term $(v_i - u_i)$ will be explained by the random disturbance term v_i , where it follows a normal distribution, and the result is that ε_i will have a normal distribution as well.

In the case of MENA stochastic frontier model, the value of λ is equal to $\frac{1.32748}{1.00508} =$

1.32077. or $\lambda = \sqrt{\gamma/(1-\gamma)} = \sqrt{\frac{.63562}{(1-0.63562)}} = 1.32075$ which indicates that the

assumption of the asymmetry of the distribution holds. There is an equivalent test for

the null hypothesis $\gamma = 0$ versus the alternative $\gamma > 0$. Where $\gamma = \frac{\sigma_u^2}{\sigma^2} = \frac{1.76219}{2.77239} =$

.63562. If the value of γ is equal to zero, then deviations from the technology frontier

can be entirely due to noise, but if the value of γ equals the unity (1) then all deviations would be attributed to technical inefficiency. When $0 < \gamma < 1$ the deviations from the frontier can be ascribed to both the random noise and the inefficiency effects.

Table 4.1 Maximum Likelihood Estimates in MENA Countries in the Manufacturing Sector and the Effects of Human Capital Composition on Inefficiency in (2013) with the Correction for Heteroscedasticity in the One-Sided Error Term (u) only.

Production Function Dependent Variable Ln Q = (ln Gross Sales in USD)	Model 1 (Cobb-Douglas)		Model 2 (Translog)	
	Param (S.E)	T-Statistics	Param (S.E)	T-Statistics
Stochastic Frontier Production Function				
Constant	7.66633*** (.15169)	50.54	8.17323***(.45072)	18.13
Ln Capital Input	.30848*** (.01200)	25.72	.22856***(.06412)	3.56
Ln Labour Input	.74860*** (.02624)	28.53	.75929***(.12694)	5.98
Ln K ²	-	-	-.00335(.00269)	-1.24
Ln L ²	-	-	-.07580***(.01186)	-6.39
Ln (K×L)	-	-	.04505***(.00951)	4.74
Inefficiency Function (heteroscedasticity in u only)				
Constant	28.5556***(6.25735)	4.56	28.8167***(6.49612)	4.44
Ln Low-Skilled Labour Proportion	-.00029** (.00013)	-2.22	-.00026*(.00014)	-1.88
Ln Intermediate-Skilled Labour	.00040** (.00020)	2.03	.00044**(.00021)	2.05
Ln Highly-Skilled Labour Ratio	-.00063***(.00017)	-3.62	-.00057***(.00018)	-3.23
Ln Average Years of Education	-.81197D-04(.00015)	-.56	.48861D-05(.00015)	.03
Firm's Size	-.16946* (.08697)	-1.95	-.16599*(.08743)	-1.90
Foreign Ownership Shares	.00052 (.00171)	.31	.00016(.000171)	.10
International Exports Percentage	-.00092* (.00055)	-1.67	-.00082(.00055)	-1.50
Licensed Technology in Use	-.00081 (.00084)	-.96	-.00086(.00084)	-1.03
Loan Received	.00100* (.00060)	1.67	.00088(.00059)	1.48
GDP Per Capita	-.00079*** (.00015)	-5.45	-.00086***(.00016)	-5.41
Sector Specific Effects (a Sector Dummy)	-.23491*** (.05860)	-4.01	-.23643***(.06044)	-3.91
Distance to Frontier	-.01967 (.02415)	-.81	-.01793(.02760)	-.65
Formal Training	-.00074 (.00289)	-.26	-.00063(.00298)	-.21
R&D Spending	.00056 (.00144)	.39	.00063(.00145)	.43
N. Observations	2284	-	2284	-
Log-likelihood function	-3677.05293	-	-3661.15327	-
Likelihood Ratio	392.70784	-	-	Reject H ₀ (u homosce.)
σ_u	1.32748	-	1.31282	-
σ_u^2	1.76219	-	1.72350	-
σ_v	1.00508	-	1.00202	-
σ_v^2	1.01019	-	1.00404	-
$\sigma = \text{Sqr} [\sigma_u^2 + \sigma_v^2]$	1.66505	-	1.65153	-
Gamma	.63562	-	.63189	-
Deg. freedom for inefficiency model	16	-	16	-

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Robust Standard Errors reported in parentheses.

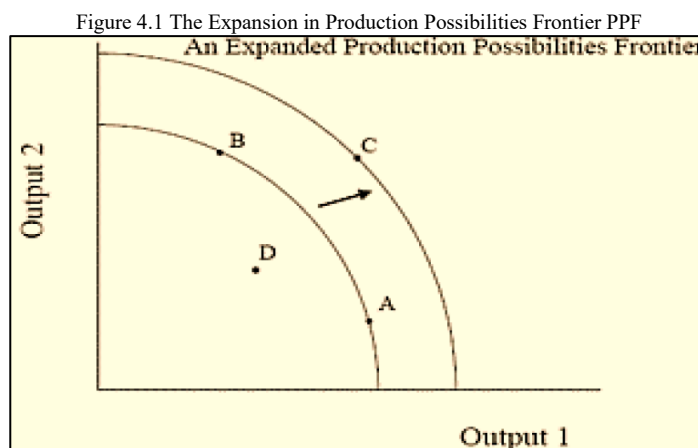
Given that the focus in this analysis is on investigating and estimating the gains in technical efficiency using the one-side error component which follows a half normal distribution for this particular World Bank enterprise survey dataset, then in the lower part (inefficiency function) of the maximum likelihood estimation, the positive sign of the estimated coefficient suggests that the worker's effect of intermediate-skilled human capital on inefficiency in manufacturing private firms in MENA is positive and

statistically significant, meaning that, the higher percentage of this component of human capital in the total number of the firm's workers leads to higher levels of technical inefficiency (negative impact on technical efficiency).

This effect then indicates the ability of firms to produce a specific good with education as a production factor along with the other resources utilised in the process.

In fact, this effect implies the positive marginal productivity of learning with regard to generating that commodity.

Therefore, and based on the assumption that employees with high levels of education are expected to be performing more efficiently in dealing with the resources at hand, the effective outcome of labour hours worked is likely to be high, accordingly, and all of this, to some extent, is affiliated with the degree of the production process complexity. Meaning that, the more sophisticated the production technologies are, the more freedom or space will be given to the worker's impact to upgrade the level of production technical efficiency and the level of productivity in the physical unit, which shifts the production possibilities frontier towards the right-hand side. See figure 4.1.



Source: R. Massey and J. A. Nelson, *Microeconomics in Context*. 2008.

It should be marked, as important, that the impact of human capital investment on growth is closely connected to the level of development that the region is already in, which suggests that higher education outcomes, in the advanced and more developed economies, are more beneficial to growth, while primary and secondary education in less developed and transition economies seems to have played a greater role in growth.

Furthermore, the allocative effect of the intermediate-skilled workers is not statistically significant at any confidence level, which in effect refers to the better qualified workers' know-how to allocate the limited resources (inputs) between a variety of substitutes, in order to achieve the highest level possible of allocative efficiency; and therefore, increase the firm's total revenues.

This unexpected finding, for both the worker's impact and the allocative impact, may suggest a kind of underinvestment in intermediate-skilled human capital in the private manufacturing sector in this part of the world. Knowing that, then the role of the middle-skilled workers in the job market in MENA accounts for more than 60% of all the formal sector jobs, whereas the high-skilled employees stand on average at more than 20% according to a recent estimate from the World Economic Forum in 2017.

From an economic point of view, better vocational training and technical education programs are crucially needed to provide this proportion of the labour force with the necessary skills for higher chances of engagement and employability in the job market and to perform with higher marginal productivity in MENA. This may also have positive spillovers on the supply side in the labour market, and offer some advantages to firms, and more flexibility in terms of recruiting and hiring better skilled workers, in order to improve their levels of efficiency and to be more productive and competitive, both locally and internationally.

Whilst on the other hand, the significantly positive contribution of both highly-skilled and low-skilled workers whether with respect to the worker effect or the allocative effect, can be ascribed to an overinvestment in this level of human capital. In truth, gains in technical efficiency in MENA can be channelled through these two components of human capital. To put it into context, this outlines the fact that middle income countries largely depend on both imitation and innovation activities to improve efficiency and growth rates.

By similar economic reasoning, human capital, represented by more educated workers, provides firms with the opportunity and ability to implement technologically advanced technologies in production lines. This could also imply that if human capital was treated

as an input factor of production, its impact on firm's efficiency and performance might not appear directly, but might be of an indirect contribution via its potential ability to attract more foreign direct investments, to accumulate financial capital, and encourage the transference and application of technology from more developed countries.

In fact, the availability of highly educated workers for MENA manufacturing enterprises will allow for the raising of the marginal productivity of financial capital and ICT capital, in particular due to the better knowledge and the expertise embodied in the labour force; this is in order to deal with more sophisticated technologies in a more efficient manner across the production units.

The economic importance and statistical significance of tertiary education in the economic development process, manifests itself in the percentage of the university degree holders in two of the largest economies in the region; Saudi Arabia and Egypt, where the two countries have developed their working age population (25–54) educational attainment notably especially in the primary education, which motivated the progress in secondary and higher education as well. In other countries the percentage of those who have not completed primary and secondary school levels is still fairly large, especially in the war-torn lower-middle income countries, such as Yemen and Sudan; this is where both nations account for about $\frac{3}{4}$ of the total number of children out of school in the whole region.

Despite that, the participation shares of high-skilled labour in employment in both countries Saudi Arabia and Egypt; are about 25% and 38% according to the World Economic Forum, Human Capital Index 2016.

This is in sharp contrast to countries like Algeria, Mauritania and Tunisia that have already worked on improving their tertiary education systems, and this has created a considerably good percentage of high-skilled workers in the job market.

Just the same as the financial capital, human capital also seeks the fastest and highest returns, where tens of thousands of students from MENA study in many of the advanced countries, such as the U.S., the U.K., and Canada, etc., many of whom are

sponsored by education ministries and governments in their countries to obtain more advanced cognitive skills in different disciplines, and once they have graduated from these universities, some of them would then have to decide whether to stay in their hosting countries, and have better jobs and higher wages, or just return to their home countries and receive lower remunerations for the knowledge they have acquired. However, some decide to stay for the reasons just mentioned above, and this brain drain siphons off many of these highly educated people from the developing economies, while some are eager and choose to return home, and then cope with the new realities in their own countries.

This brain drain adds more to the problems found in the MENA economies, in terms of optimising their human capital and offering more highly paid occupations, instead of the lowly paid jobs for the highly skilled individuals returning from the advanced countries.

In addition, it can be observed that the average number of years of schooling, as an additional indicator for human capital stock, has not been proven to have played any significant part in promoting efficiency in MENA. To put it another way, this proxy does not appear to be always a valid one, in order to examine and represent the human capital effects on efficiency and growth, and this underlines the fact that identifying growth in a country cannot be easily achieved in a self-assured way by relying only, or mainly on, the average number of years of education.

Just the same, as in the microeconomic research on the educational economic returns, a substantial part of the macroeconomic analysis, on the economic benefits of learning, considers the average years of education as a quantitative measure of human capital stock of the labour force in an economy. The issue with the average years of schooling, as a measure of educational achievement, is that it takes for granted that the stock of knowledge delivered, and the level of skills obtained via an additional year at school, do not differ irrespective of the differences between the education systems across nations.

In addition, this measure assumes that the non-school factors do not play any important role in providing the skills, and offering the quality of knowledge required, in the outcomes of the education process when compared to the formal education, which is assumed to be the major source of all the expertise needed in the labour market.

Table 4.2 Generalised Likelihood-Ratio Tests of the null hypothesis.

Null Hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 4, \dots, 16$			99.5% $\rho = (0.005)$	34.3
	Translog	-3661.15327	99% $\rho = (0.01)$	32.0
H ₀ is accepted	Cobb - Douglas	-3677.05293	95% $\rho = (0.05)$	26.3
	LR Test	31.79932	90% $\rho = (0.1)$	23.5

Table 4.2 shows the likelihood ratio test results. According to the table, the null hypothesis – the Cobb Douglas stochastic frontier function – is accepted as a more suitable form to represent this dataset.

When applying the approach of (Hadri, 1999) in table 4.5 to correct for heteroscedasticity in both the one-sided error term u , and the two-sided error term v , the results show no drastic changes in the estimates of the parameters neither in the stochastic frontier production function nor in the inefficiency function except for small changes in some covariates.

Economically speaking, and prior to the Great Recession across large parts of the world, and the Arab uprisings across the MENA region, private firms, particularly the manufacturing ones achieved relatively higher levels of productivity than in their counterparts in the middle-income group of economies in other regions. But during this, and then in the aftermath of the two-forementioned crucial events, productivity then decreased dramatically, and the magnitude of the international trade declined significantly in 2009 in particular.

The larger firms in MENA are proved to be more efficient, where this can be cemented by the statistical significance of the firm size coefficient shown in tables 4.1 and 4.5. Therefore, and as a corollary, it tends to be the case that they have been dominating the labour market for years in MENA, and they seemed to rely more on more capital-intensive production strategies than on labour-intensive ones in recent years. See table 4.3 for more details on the large firms' ascendancy in the labour market in MENA. The high levels of efficiency in these firms have gained them vital advantages to get access

to finance and funds, more than the other less efficient firms, which are mainly small and medium-sized enterprises.

Table 4.3 represents the percentage of the jobs' distribution in MENA, provided by large firms in the labour market, during the completed fiscal year 2012, for a selected sample of 2284 firms from this region with different sizes and ages.

Table 4.3 The percentage of jobs offered by firms with different size to workers with different qualification in MENA in 2013

Firm size	Intermediate Skilled Workers	Highly Skilled Workers	Low Skilled Workers	Grand Total Number of Workers
Micro	0.03%	0.03%	0.01%	0.01%
Small	5.57%	5.33%	5.00%	5.14%
Medium	17.25%	16.25%	16.72%	16.00%
Large	77.16%	78.39%	78.28%	78.84%
Grand Total	100.00%	100.00%	100.00%	100.00%

Source: Author's calculations of the contribution of the private manufacturing firms to the job creation based on WB Survey dataset 2013.

The ascendancy of the large firms in the job market is apparent from the figures shown in the table, where they provided more than 78%, 77%, and 78% of the jobs for the three levels of human capital composition for low, intermediate and highly skilled workers with a grand total for all workers at 78.84%.

In addition, small and medium size plants in MENA appear to encounter major difficulties that are impeding them from improving their performance, gross sales, and efficiency due to a number of obstacles relating to the discouraging business environment in this region, such as: inaccessibility to adequate funds and financial resources to improve their production operations, and the wide-spread political turmoil that sweeps through large parts of the region, especially in countries such as Syria, Egypt, Libya, Yemen, the West Bank and Gaza, Tunisia and Lebanon.

In fact, the political instability and the consequential havoc that occurred in recent years throughout important economies in MENA such as Libya, Syria, and Iraq are perceived as major determinants of low performance by firms across the region.

The banking system's operations, in terms of providing firms with the funds necessary to operate and compete at the international level in MENA, are relatively focused on the large firms more than on the small and medium-sized ones. Some firms in countries, such as the West Bank and Gaza as well as Tunisia, rely hugely on microfinance as a major source of finance to fund their economic activities. Whilst other sources of funds,

such as credit from suppliers and bank credit and equity finance, have a smaller role in financing small and medium firms.

As mentioned earlier, larger firms play, comparatively, a considerable role in the job market, but it is only the more productive firms that seem to pay relatively higher salaries, and despite the weak firm dynamism in the region, the fast-growing enterprises with high levels of labour productivity tend to attract more labour, which indicates some kind of resources reallocation in the direction of the more productive firms who have the potential to grow faster and offer more lucrative and well-paid jobs.

On the other hand, and due to the larger firms' reliance on the capital-intensive production operations, the wages are less likely to grow, and are more likely to stagnate in some instances. These firms, in fact prefer to give priority in their production strategies to capital allowances instead of labour earnings.

Another major impediment, which firms in MENA are facing, is the lack of the adequately educated labour, where formal training is one of the common tactics that some firms – especially the fast-growing firms – have adopted to tackle this issue in order to optimise their human capital potential, and improve the skills profile of their workers and deploy them across their life course for a more promising performance in the future. This is true, especially, with the potential change in the core skills needed for jobs throughout the upcoming years, especially in countries that are enjoying relatively higher levels of per capita income, and larger financial excesses, such as the Gulf Cooperation Council nations, Libya, and Iraq, as a result of the oil prices boom some years ago after 2007, and the future prospects seem to be more promising with the recent increase in oil prices in 2017.

The GDP per capita was found to have a positive and statistically significant impact on firm's efficiency in MENA, according to the results shown in tables 4.1 and 4.5, respectively.

From an economic point of view, the growth of per capita income in some countries in the MENA region was found to be comparatively low over the past two decades, mainly due to the high growth rates in population in countries such as Egypt, Yemen, Morocco, Tunisia, and Algeria.

There can be another reason for this low level of per capita income, particularly in those countries that rely heavily on oil exports as a source of revenue, and government expenditures where oil prices have continued to be relatively low during the last two and a half decades before they started to increase in 2007 and 2008.

In fact, the continuous decline in oil prices during the 1980s and 1990s, and the beginning of the 2000s, did not allow the oil exporting countries to continue their investments, in both human capital and physical capital, with the same scale and pace as they did during the 1970s; this was when the higher oil prices have been a crucial and vital factor in that boom, and when most of the oil countries in MENA invested heavily in formal education and training in parallel with considerable investments in the infrastructures sector and educational vital facilities across the region.

The stagnation in wages during the 1980s and the 1990s in MENA and especially in the petroleum economies, is another element of the problem, where it posed a stumbling block and has contributed negatively to the growth in human capital investment, due to individuals' incapability to afford and spend on education and training for better labour quality and skills.

At the macroeconomic level, the contractionary fiscal policies that were vastly adopted and implemented in the 80s and the 90s, in several countries in the region, were a major source that caused the wages to be stagnant. These are where government expenditures have been reduced and income tax rates increased significantly in order to fight the inflationary pressures. Such measures left households with less disposal income to spend, and therefore, there were lower levels of aggregate demand AD and consumption. By means of the AD-AS model, the contractionary policies resulted in a left ward shift in the aggregate demand curve.

The increase in the levels of corporate taxation that meant less profit would be available for enterprises, which led them to decrease their spending on new projects and to halt some future businesses in the region.

Given that private investments, household consumption, and government spending constitute and compose a fairly large ratio of real GDP, therefore, GDP growth fell markedly during that period, especially, when the consequential impacts of the multiplier with the marginal propensity to consume, and the marginal propensity to save

effects, are all taken into consideration when estimating the net effects of these fiscal tactics on output.

Furthermore, the scale of international trade was profoundly affected by the increased tariffs imposed on imports following a set of strict protectionism strategies, and taking severe measures to shield the laggards and nascent private domestic industries from the strong foreign competition by imposing more taxes on imported commodities.

In fact, these protective policies might have acted as a double-edged sword that choked businesses by not allowing them to grow and thrive. The ramifications of these policies, in effect, were antithetical to the fiscal policymakers' beliefs in these countries who expected to gain a budget surplus and pay off part of their international indebtedness.

Keynesian economists in MENA opposed these controversial policies, considering them as invalid and an ineffective means to secure any signs of stabilisation in the economy. In fact, these measures were regarded as throttling expedients acting against the tide of the business cycle by holding the economy back from growing and booming.

Trade embargos and international economic sanctions, which have been imposed on particular nondemocratic political regimes in the MENA area, also inflicted serious difficulties on some of the vital industries, such as civil aviation, both private and commercial, oil extraction, and also farming in some of the affected countries, which restrained growth in these economies.

The Middle East and North Africa nations can be classified into three main groups from an economic point of view: the high income and natural resources rich countries including the Gulf states; the middle-income labour abundant countries including Egypt, Algeria, Morocco, and Tunisia; and the middle and low income war-torn nations, such as: Libya, Iraq, Yemen, and Syria. This is where Iraq and Libya fall in the middle-income group and they are ranked 4th and 7th, respectively, in terms of their crude oil reserves according to OPEC 2016 estimates. Both countries are also ranked 5th and 3rd in the Middle East and North Africa, respectively, in terms of their proven natural gas reserves according to OPEC in 2015.

The degree of competitiveness, represented by the share of international exports as a percentage of the firm's total exports, was also found to have a positive impact on efficiency. This suggests the vital importance of international trade to improve the performance of firms in the Middle East and North Africa. The meaning of this is that firms, which are oriented towards the international market, seem to be more efficient than those which are concentrating more on the local markets. This proxy reflects the fact that more productive and exporting firms have more advantages to receive foreign investments than other less productive and domestically-focused firms, which in turn will enhance their ability to improve, compete, and retain their international exporting efforts in the longer run.

Typically, the international trade measure is the percentage of exports and imports relative to the GDP. Therefore, the higher this percentage is, the more open the economy is, and the more able the economy becomes in order to benefit from more effective strategies of production leading to a faster growth in productivity, the higher the GDP per capita levels would become.

In comparison with the world's leading region in competitiveness which is the U.S, the Middle East and North Africa region has lagged behind, and shows a relatively low average level of regional competitiveness. This is where the most competitive state in the region seems to be Israel. This is where Israel came in the 23rd place and jumped to the 18th place on the table of the World Economic Forum's human capital index in 2016 and 2017, respectively.

In relation to this, the trade relationships which Israel has been developing with the European and the North American regions during the recent decades, played an important role and had positive effects on their firm's ability to compete in their selected markets; relying on their stocks of human capital, their capacity to innovate, and the quality of the existing domestic infrastructure along with the future possibilities for it to be better developed, and all of these are regarded as fundamental assets for a better business environment and higher competitiveness.

Moreover, trading with the frontier can be a way in which firms can understand what the innovation is and what drives it, and then they can embody it in their own structures and gain experience from the innovation frontier.

The estimated parameter of the shares of foreign ownership, shown in table 4.1, signifies the fact that foreign ownership in MENA does not appear to play an important role in improving firms' efficiency. This can be attributed to the disproportionately small shares of foreign direct investments FDI flows into the region compared to other regions in the developing world and transition economies.

Table 4.4 The Concentration of Firms' Ownership Shares within MENA in 2013

Firms Size	Private Ownership Shares	Foreign Ownership Shares	Government Ownership Shares
Micro	0.38%	0.00%	0.00%
Small	40.05%	16.89%	9.31%
Medium	38.62%	36.93%	15.33%
Large	20.94%	46.17%	75.36%
Grand Total	100.00%	100.00%	100.00%

Source: Author's calculations of the concentration of ownership shares in the manufacturing firms based on WB Survey dataset 2013.

Table 4.4 shows the distribution of different ownerships concentration in the region. This is where government and foreign ownership are more oriented towards the larger firms in MENA with a marked advantage for government ownership, which is 75.36% over foreign ownership and 46.17% in this respect. The private ownership is more focused in the small and medium-sized enterprises with 40% and 38.62%, respectively. The foreign ownership also demonstrated a notable share in the medium size firms with nearly 37% of the market.

This gives the impression that government-owned large firms have more advantages than other firms in receiving the funds needed for their economic activities and to compete to improve their position in the international markets.

On the other hand, this poor performance in MENA in terms of attracting more FDI, when compared to other regions is due to numerous hindrances, such as the lack of political stability and security, the high cost of doing business in MENA, the complex bureaucratic procedures and business progress impediments to set up and operate as a foreign-owned firm, the lack of vital infrastructure, the relatively high labour cost, the lack of a highly skilled labour force in some business fields, and the market size.

Loans and credit, received from different financial institutions, appear to contribute negatively to the firms' efficiency in MENA. This can be ascribed to the deficiency in

the financial system in this region in terms of the availability of an adequate fund for firms.

In MENA the banks are mostly public, owned to a large extent by the state, and they favour funding the firms that are government-owned, large, and from overseas. Therefore, it is very difficult for small and medium enterprises to have access to adequate financial resources to fund their operations and to enhance their operating capital.

Table 4.5 Maximum Likelihood Estimates in MENA Countries in The Manufacturing Sector. The Effects of Human Capital Composition on Inefficiency in (2013) with the Correction for Heteroscedasticity in the One-Sided Error Term (u) and in the Two-Sided Error Term (v).

Stochastic Frontier Production Function Dependent Variable Ln Q = (ln Gross Sales in USD)	Heteroscedastic Model (Cobb-Douglas)	
	Param (S.E)	T-Statistics
Stochastic Frontier Production Function		
Constant	7.75874*** (.15600)	49.74
Ln Capital Input	.30281*** (.01203)	25.16
Ln Labour Input	.72899*** (.02831)	25.75
Technical Inefficiency function (Heteroscedasticity in u and v)		
Constant	29.5245*** (6.56854)	4.49
Ln Low-Skilled Labour Proportion	-.00030** (.00014)	-2.15
Ln Intermediate-Skilled Labour	.00039** (.00021)	1.86
Ln Highly-Skilled Labour Ratio	-.00066*** (.00017)	-3.84
Ln Average Years of Education	-.28129D-04 (.00015)	-.19
Firm's Size	-.30684*** (.10364)	-2.96
International Exports Percentage	-.00099* (.00056)	-1.76
Licensed Technology in Use	-.00088 (.00081)	-1.09
Loan Received	.00129* (.00077)	1.67
GDP Per Capita	-.00079*** (.00014)	-5.50
Sector Specific Effects (a Sector Dummy)	-.24264*** (.04141)	-3.95
Distance to Frontier	-.02672 (.02578)	-1.04
Formal Training	-.00078 (.00339)	-.23
R&D Spending	.00073 (.00164)	.44
N. Observations	2284	-
Log-likelihood function	-3676.24970	-
Likelihood Ratio	394.3143	Reject H ₀ (u and v homosced.)
σ_u	1.28633	-
σ_u^2	1.65463	-
σ_v	1.01895	-
σ_v^2	1.03826	-
$\sigma = \text{Sqr} [\sigma_u^2 + \sigma_v^2]$	1.64100	-
Gamma	.61444	-
Deg. freedom for inefficiency model	16	-

Notes; * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance.
Robust Standard Errors reported in parentheses.

This comes as no surprise when looking at the details provided in table 4.6, where large firms in this sample dominate the loans and subsidies received from different sources by 35.33% and 57.25%, respectively; this is despite the fact that they only represent 23.12% of the total number of firms in the aggregate sample.

Whereas, small and medium firms received 23.55% and 40.94% of the loans granted, respectively, while they aggregate to more than 76 percent of the total sample of firms.

This kind of prejudice causes a huge imbalance in the market in the MENA region. This is where disadvantaged small and medium enterprises are deprived from benefiting from the financial resources offered from the financial systems in an adequate manner, and therefore, they are not able to improve their efficiency, and the fund sources available for these firms are not enough to develop their performance, let alone to increase their market shares locally and internationally over time.

Table 4.6 The loans distribution across firms with different size in MENA in 2013

Firm Size	Percentage of The Total Size of The Sample	Percentage of Firms with No Loan	Percentage of Firms with Loan	Percentage of Firms with Subsidies
Micro	0.35%	0.42%	0.18%	0%
Small	38.18%	44.00%	23.55%	10.14%
Medium	38.35%	37.17%	40.94%	32.61%
Large	23.12%	18.41%	35.33%	57.25%
Grand total	100%	100%	100%	100%

Source: Author's calculations of the loans distribution in MENA based on the WB survey in 2013.

The rise in the global production networks, which created a pattern of commodity chains where goods are manufactured and distributed in different stages and locations, has its impact on the international trade and the firms' competitiveness in MENA, especially with the rise of China and India as significant international manufacturing and trading hubs on the global stage – given that both economies are relatively close to the MENA region – along with the growth in services trade, as a result of the revolution in information and telecommunication technologies, which all have had their impact on firms' performance in this region.

Based on the International Standard Industrial Classification of All Economic Activities (ISIC), Rev.4 (Uns, 1990), the sample of the 2284 manufacturing firms was dissected and classified into 1127 Low-Technology manufacturing firms, 287 Intermediate-Technology manufacturing firms, and 802 High-Technology manufacturing firms. The objective, here, is to explore more of the contribution of the (endogenous) human capital composition as an explanatory variable of technical inefficiency across the three levels of ISIC categories.

The MLE results, shown in table 4.7, suggest that highly-skilled workers have a positive and highly statistical significant role in promoting the efficiency level in low, and intermediate-tech firms, and mainly high-tech manufacturing private plants in MENA.

The results also provide an indication that low-skilled workers are of a vital and statistical importance in reducing the levels of inefficiency in high-tech plants, which in turn suggests that the high level ISIC category function with a combination of (low, high) skilled labour, is providing the evidence on the heterogenous impact of human capital not merely across the nations but also within the same economy, and in this case, in particular, this suggests the reliance on both imitation and innovation activities for further improvement in technical efficiency in the middle income economies in MENA specifically.

Table 4.7 Maximum Likelihood Estimates in Low, Med, and High-Technology Manufacturing Firms across MENA Countries in (2013).

Production Function Dependent Variable Ln Q = (Ln USD Gross Annual Sales)			
Firms classified based on ISIC Rev.4	Model (1) Low-Tech Firms	Model (2) Med-Tech Firms	Model (3) High-Tech Firms
Stochastic Frontier Production Function	CD Param (S.E)	CD Param (S.E)	CD Param (S.E)
Constant	7.76799***(.21445)	7.15953*** (.47350)	4.61995*** (.39241)
Ln Capital	.30433***(.01700)	.32696*** (.03622)	.55636*** (.01798)
Ln Labour	.73347***(.03119)	.73937*** (.07274)	.18851*** (.02392)
Technical Inefficiency Function (heteroscedasticity in u only)			
Constant	30.4791**(20.8067)	13.8314 (16.6163)	.57436*** (.05492)
Ln Intermediate-Skilled Labour	.00057*(.00031)	.00016 (.00063)	.00116* (.00060)
Ln Highly-Skilled Labour	-.00051**(.00024)	-.00120* (.00066)	-.00130*** (.00035)
Ln Low-Skilled Labour	-.36403D-04 (.00022)	-.00113 (.00077)	-.00078** (.00034)
Firm's size	-.13596 (.11453)	-.85412 (.58816)	-
Legal rights index	-	-	2.02806*** (.57807)
Country Specific Effects (a Country Dummy)	-.05657 (.19354)	.000607 (.10496)	-.98346 (.73013)
Life Expectancy Rate at Birth, total (years)	-.40660***(.14264)	-.13386 (.15199)	-.74665* (.41194)
GDP per Capita	-.00041 (.00060)	-.59474D-04 (.8391D-04)	-
Distance to Frontier	-.11172** (.04644)	-.07453 (.25956)	-.41294** (.17056)
Log Likelihood Function	-1775.03062	-430.82930	-1427.30672
Sigma (U)	1.54283	1.01186	1.54951
Sigma (V)	.91069	.96266	1.33267
Gamma = [Sig(U)^2/Sigma^2]	.74161	.52490	.57481
Degrees of Freedom for inefficiency model	10	9	8
N. Observations [K]	1127 [14]	287 [13]	802 [12]

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Standard Errors reported in parentheses.

CD = Cobb Douglas Production Technology.

Another major issue of concern in this region seems to be that which is relating to the mismatch between the low quality of jobs offered across labour markets in MENA, and the skills and knowledge acquired and embodied in university graduates over the years, which is whilst they were investing their resources and time for better education. This is where these graduates are not able to capitalise their knowledge to employ and transmit the cognitive skills into beneficial economic activities, and materialise them into goods and services of economic values, in order to generate a flow of income, either at the individual level or at the economy level.

Table 4.8 Generalised Likelihood-Ratio Tests of the null hypothesis in Low-Tech manufacturing firms

Null Hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 4, \dots, 10$			99.5% $\rho = (0.005)$	25.2
	Translog	-1772.42920	99% $\rho = (0.01)$	23.2
H ₀ is accepted	Cobb - Douglas	-1775.03062	95% $\rho = (0.05)$	18.3
	LR Test	5.20284	90% $\rho = (0.1)$	16.0

Put simply, the scarcity of adequate jobs for university graduates in MENA gives rise to more leakages of highly-skilled workers towards the informal sector, who are seeking better opportunities and more experience. This phenomenon poses serious questions on the level of human capital stock utilisation, and the challenges that lie ahead with respect to optimising human resources in MENA, and the possible loss for the economy resulting from the withdrawal of an important segment of human capital from the formal labour force via the leakages into the informal sector.

Table 4.9 Generalised Likelihood-Ratio Tests of the null hypothesis in Med-Tech manufacturing firms

Null Hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 4, \dots, 9$			99.5% $\rho = (0.005)$	23.6
	Translog	-423.74015	99% $\rho = (0.01)$	21.7
H ₀ is accepted	Cobb - Douglas	-430.82930	95% $\rho = (0.05)$	16.9
	LR Test	14.1783	90% $\rho = (0.1)$	14.7

Table 4.10 Generalised Likelihood-Ratio Tests of the null hypothesis in High-Tech manufacturing firms

Null Hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 4, \dots, 8$			99.5% $\rho = (0.005)$	22.0
	Translog	-1424.53401	99% $\rho = (0.01)$	20.1
H ₀ is accepted	Cobb - Douglas	-1427.30672	95% $\rho = (0.05)$	15.5
	LR Test	5.54542	90% $\rho = (0.1)$	13.4

Moreover, and additional to the loss in the labour force, graduates in MENA choose to work in the informal sector, for more experience, to be better equipped, and to find better jobs in the formal sector in the future. But, in reality, things seem to be far from being ideal, where it tends to be the case that the relationship between the informal sector and the formal sector, in terms of the influx of workers, appears to be weak, and the mobility of workers towards the formal sector is constrained, which is due to some plausible reasons from an economic point of view. This is due to the fact that the hourly wage in the informal sector is quite low, which causes a lack of motivation to perform better, from the worker's point of view, and thereby, leading to comparatively lower output per worker/hour and lower levels of efficiency and less experience, which undermines the worker's chances to be transferred into the formal sector, and have better jobs with better wages and working conditions.

This introduces another issue of concern, which lies in the barriers which could confront university graduates who ended up in the informal sector hoping for better opportunities to deploy their skills into economic value and perfect their experience. Apparently, the circumstances and the environment in this sector are not as encouraging as graduates would have expected. This is because of the fact that, apart from the level of knowledge and skills graduates acquired from university, the sector that offers better paid jobs would attract workers anyway, regardless of their education level, and would stimulate them to perform better through polishing up their skills and expertise.

Furthermore, given the fact that the formal sector employers in MENA – the large firms mainly – tend to rely on capital intensive activities, the chances for those who are moving from the informal sector in pursuit of the jobs that match their education will seem to be low, and are as a result of a number of factors, which are including, their lack of certain levels of experience, as well as country wide problems such as corruption, bribery, the arbitrary decisions made by policymakers at the macroeconomic level in the economy especially during the times of financial turmoil, political disenfranchisement, and the circumstances of economic uncertainty.

The licensed technology that is in use, which measures access to foreign technology, seem to have a positive impact on efficiency but is not statistically significant. This is not saying much, given the fact that the variables of foreign ownership shares in MENA's firms do not have a significant impact on efficiency.

Foreign direct investment is one of the main means for a licensed technology transfer and assistance, as well as the importation of capital goods from the developed world. As was discussed above, the MENA economies are comparatively underperforming in the field of FDI attraction for the economic and political reasons that were mentioned earlier in the analysis.

Additionally, the proprietary technology is so expensive for small and medium firms in the Middle East and North Africa, and it is usually sold based on contractual terms between the intellectual property rights owner or the patentee and the user, and it is not easy to have access to it.

Moreover, private enterprises can expand by either innovating or transferring their technological knowledge to other firms. Other firms can replicate and imitate the technology and knowledge that was created by others, but in order to succeed in doing so they will first need to create the proper environment, and establish the pertinent mechanisms for workers to be educated and trained, not only by means of provision, but also by broadening their advanced education for the better dissemination and implementation of cutting-edge technologies, which allows for the better accommodation of these technologies to suit the local circumstances of production and services in MENA.

Furthermore, some of the sophisticated technology might be in use in the public domain in some countries, and it could be owned by governments, but it needs to be taken into account that the governance in the MENA region is not comparatively rational and favours larger firms over the small and medium ones. In fact, there will be some bias in favour of large enterprises, which are mostly owned by the government, and considerably funded by state-owned banks, where they will have the advantage to make use of the patented and licensed technology, or they might be the favourites when it comes to importing technologies that are built in some capital commodities.

The country's distance to the frontier score was found to have a positive impact on technical efficiency in low, medium, and high technology firms in the sample of the subject of study. However, it is only significant in the low and high technology firms.

Distance to the frontier, shows the distance of each economy to the frontier, which represents the best-practice performance observed in terms of regulatory performance on each of the indicators across all economies which have been integrated in the Doing Business measures of business regulations for local firms.

This is where – according to the World Bank (2017) – a high ease of doing business ranking means that the regulatory atmosphere is more conducive and favourable to the starting and operation of local enterprises.

Tables 4.11 and 4.13 illustrate the maximum likelihood estimates of the human capital compositions effects on firms' technical efficiency in the presences of

heteroscedasticity in u , as shown in table 4.11, and in u and v , as shown in table 4.13. The countries are pooled with a country dummy variable this time. However, the estimates do not seem to substantially differ from the estimate presented in tables 4.1 and 4.5, and they do not change dramatically even with the inclusion of a country dummy variable. The effects of different levels of education on technical efficiency remain relatively the same.

Table 4.11 Maximum Likelihood Estimates in MENA Countries in The Manufacturing Sector. The Effects of Human Capital Composition on Inefficiency in (2013) with the Correction for Heteroscedasticity in the One-Sided Error Term (u) with a Country Dummy Variable

Stochastic Frontier Production Model Dependent Variable Ln Q = (ln Gross Sales in USD)	Heteroscedastic Model (Cobb-Douglas) (Heteroscedasticity in u only)	
	Param (S.E)	T-Statistics
Stochastic Frontier Production Function		
Constant	7.66699*** (.15107)	50.75
Ln Capital Input	.31443*** (.01211)	25.97
Ln Labour Input	.73403*** (.02643)	27.77
Technical Inefficiency Function		
Constant	-3.18934 (7.87530)	-.40
Ln Low-Skilled Labour Proportion	-.00025** (.00013)	-1.97
Ln Intermediate-Skilled Labour	.00040** (.00020)	2.01
Ln Highly-Skilled Labour Ratio	-.00059*** (.00017)	-3.46
Ln Average Years of Education	-.00016 (.00014)	-1.12
Firm's Size	-.16116* (.08474)	-1.90
Foreign Ownership Shares	.00106 (.00150)	.71
International Exports Percentage	-.00090* (.00049)	-1.84
Licensed Technology in Use	-.00083 (.00080)	-1.03
Loan Received	.00100* (.00057)	1.75
GDP Per Capita	-.00067*** (.00012)	-5.40
Country Specific Effects (a Country Dummy Variable)	.06613 (.06808)	.97
Distance to Frontier	-.01200 (.02400)	-.50
Formal Training	-.00060 (.00287)	-.21
R&D Spending	.00043 (.00137)	.31
N. Observations	2284	-
Log-likelihood function	-3685.20694	-
σ_u	1.35694	-
σ_u^2	1.84128	-
σ_v	.99907	-
σ_v^2	.99813	-
Sigma	1.68506	-
Gamma	.64847	-
Deg. freedom for inefficiency model	17	-

Notes; * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance.
Robust Standard Errors reported in parentheses.

Tables 4.12 and 4.15 show the results of the likelihood ratio tests for the Cobb-Douglas and Translog comparison in tables 4.11 and 4.13 respectively. Both tables indicate that the H_0 is accepted, and that the Cobb-Douglas functional form is the adequate form for this set of data.

Table 4.12 Generalised Likelihood-Ratio Tests of the null hypothesis.

Null Hypothesis, H_0	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
$H_0: \beta_{ij} = 0, i = 4, \dots, 17$			99.5% $\rho = (0.005)$	35.7
	Translog	-3668.94353	99% $\rho = (0.01)$	33.4
H_0 is accepted	Cobb - Douglas	-3685.20694	95% $\rho = (0.05)$	27.6
	LR Test	32.52682	90% $\rho = (0.1)$	24.8

Table 4.13 Maximum Likelihood Estimates in MENA Countries in The Manufacturing Sector. The Effects of Human Capital Composition on Inefficiency in (2013) with the Correction for Heteroscedasticity in the One-Sided Error Term (u) and in the Two-Sided Error Term (v) with a Country Dummy Variable

Stochastic Frontier Production Model Dependent Variable Ln Q = (ln Gross Sales in USD)	Heteroscedastic Model (Cobb-Douglas) (Heteroscedasticity in u and v)	
	Param (S.E)	T-Statistics
Stochastic Frontier Production Function		
Constant	7.70836*** (.16236)	47.48
Ln Capital Input	.30889*** (.01269)	24.34
Ln Labour Input	.73616*** (.02721)	27.05
Technical Inefficiency Function		
Constant	23.5176***(.965132)	2.44
Ln Low-Skilled Labour Proportion	-.00027** (.00014)	-1.98
Ln Intermediate-Skilled Labour	.00043** (.00020)	2.15
Ln Highly-Skilled Labour Ratio	-.00064*** (.00017)	-3.86
Ln Average Years of Education	-.79625D-0 (.00014)	-.56
Foreign Ownership Shares	.00121 (.00141)	.85
Firm's Size	-.21774** (.09343)	-2.33
International Exports Percentage	-.00098* (.00056)	-1.75
Loan Received	.00095* (.00056)	1.68
Licensed Technology in Use	-.00079 (.00071)	-1.11
GDP Per Capita	-.00070*** (.00012)	-5.90
Country Specific Effects (a Country Dummy Variable)	.07727 (.06421)	1.20
Distance to Frontier	-.01223 (.02437)	-.50
Formal Training	-.00065 (.00342)	-.19
R&D Spending	.00067 (.00134)	.50
N. Observations	2284	-
Log-likelihood function	-3661.48768	-
σ_u	1.35357	-
σ_u^2	1.83216	-
σ_v	.98355	-
σ_v^2	.96736	-
Sigma	1.67318	-
Gamma	.65445	-
Deg. freedom for inefficiency model	16	-

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance.
Robust Standard Errors reported in parentheses.

Table 4.14 Generalised Likelihood-Ratio Tests of the null hypothesis.

Null Hypothesis, H0	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
$H_0: \beta_{ij} = 0, i = 4, \dots, 16$			99.5% $\rho = (0.005)$	34.3
	Translog	-3647.14361	99% $\rho = (0.01)$	32.0
H_0 is accepted	Cobb - Douglas	-3661.48768	95% $\rho = (0.05)$	26.3
	LR Test	28.68814	90% $\rho = (0.1)$	23.5

4.3 The Impact of Formal Training on the Firm Level Productivity in the Manufacturing Sector across the Middle East and North Africa Countries.

In this section the formal training impact on firms' performance in MENA is investigated and is found to have no significance. This might be partly attributed to either the low quality of training programs content, or to the quality of assessment of training programs' outcome.

4.3.1 Empirical Results and Economic Analysis

The growth in labour productivity in MENA was found to be higher than those in other peer economies with a similar level of income, and the gains in labour productivity that can be ascribed to innovation are found to be in line, sometimes, with those in the developed economies, but on the down side, private sector firms in this region are lagging behind those in other developing economies, with regard to growth in total factor productivity.

Table 4.11 presents the estimates of both OLS and Probit specifications, which report the effects of both micro and macro level variables as essential determinants of productivity change.

Several barriers seem to be affecting the performance in MENA, and they are relating to the business environment in which these firms function. These obstacles mainly comprise the obstructive institutional and regulatory frameworks, the legal environment, corruption, and taxation, the availability of finance and the cost of doing business, and the availability of innovation and technical support in production operations.

In table 4.15 labour productivity, which is measured as output per worker, is positively associated with a mixture of micro and macro level factors that have significant effects on the firms' performance in MENA.

The firm size was found to have a positive and significant impact on output per worker in private manufacturing firms, which suggests the existence of a certain level of economies of scale in production operations in MENA. Therefore, firms will be allowed to increase their ability to proportionally produce more goods than the attendant rise in the production costs. In other words, the average cost per unit of production tends to fall as the production scale of goods expands in the long run.

4.3.1.1 Ordinary Least Squares and Probit Models' Estimates

The positive relationship between a firm's size and labour productivity is shown in table 4.11 with a high statistical confidence at 99%, and this relationship appears to be more obvious and well documented in the manufacturing sector than in the service sector.

The international trade and openness to international markets was also found to have its positive contribution in promoting labour productivity in the manufacturing sector in MENA. The exporting firms appear to be more productive than non-exporting firms.

The export-oriented emerging markets in the adjacent region of South East Asia such as: Malaysia, Thailand, Vietnam and Indonesia can be good examples for the Middle East and North Africa region to simulate, in terms of the importance of exports growth in increasing GDP. Where in Malaysia for instance, the share of trade represented more than 100% of GDP.

Thanks to FDI, R&D investments, and higher education, where growth is being driven forward, noticeably, in both Malaysia and Thailand. Malaysia though demonstrated the strongest performance in terms of having the highest proportion of the highly technological-intensive manufactured exports.

Tables 4.16, 4.17, and 4.18 illustrate the percentage of direct, indirect and national exports by firm size, and by type of ownership, in the sample of manufacturing firms selected in this analysis.

Table 4.15 The Effects of Formal Training on Firm's Performance in MENA Countries

	Model [1] OLS	Model [2] Probit
	Ln Output Per Worker	Training
Training [0, 1]	0.242*** (0.0770)	-
Firm Size	0.118*** (0.0250)	0.180*** (0.0289)
Direct International Exports Ratio	0.356*** (0.0420)	0.182*** (0.0474)
Loan [0, 1]	0.554*** (0.0662)	0.256*** (0.0665)
New Management Practices [0, 1]	0.286*** (0.0760)	0.275*** (0.0828)
GDP Per Capita	0.0000809*** (0.00000667)	-
Life Expectancy Rates at Birth [Total]	0.0542*** (0.0131)	-
Strength of Legal Rights Index	-0.275*** (0.0371)	-
Sector dummy Medium Technology.	0.409*** (0.0749)	-
Sector dummy High Technology	0.344*** (0.0532)	-
Government Ownership Shares	-	0.0165*** (0.00450)
New Marketing Approach [0, 1]	-	0.237** (0.0759)
Subsidies [0, 1]	-	0.392*** (0.103)
Licensed Technology in Use [0, 1]	-	0.426*** (0.0919)
New Production Approach [0, 1]	-	0.540*** (0.0807)
Cons	4.757*** (0.909)	-2.355*** (0.108)
N	2855	3275
R ²	0.286	Pseudo R ² = .2262
LR chi2 [10]	-	610.22
F [10, 2844]	141.63	-
Prob > F	0.0000	-
Prob > chi2	-	0.0000

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Large government-owned and foreign-owned firms have the capacity, more than small and medium enterprises, to export directly, and have more ability to access the international markets.

Table 4.16 The Percentage of Direct Exports of Total Sales by Firm Size in MENA

Firm size	Foreign-owned firms	Gov -owned firms
Small	7.90%	5.73%
Medium	33.09%	4.87%
Large	59.01%	89.40%
Grand Total	100.00%	100.00%

Source: Author's calculations based on the World Bank enterprise survey dataset in MENA in 2013

In the indirect exports, see table 4.13, the medium government enterprises and foreign owned enterprises perform better, where products are domestically sold to a third party,

in order to export them outside of the country. The small foreign-owned firms showed some improvement, and they seem to be better at being indirect exporters rather than being direct exporters in MENA. But the large firms remain dominant and have the lion's share in this field as well.

Table 4.17 The Percentage of Indirect Exports of Total Sales by Firm Size in MENA

Firms size	Foreign-owned firms	Gov-owned firms
Small	24.85%	6.09%
Medium	41.93%	34.02%
Large	33.22%	59.89%
Grand Total	100.00%	100.00%

Source: Author's calculations based on the World Bank enterprise survey dataset in MENA in 2013

The small foreign-owned enterprises are the best player in the national market among the percentage of firms with a high share of foreign shareholders. The large firms, owned largely by the state, dedicated a considerable proportion of their sales to the domestic market, and in general, they appear to be well engaged in the exporting business in MENA in comparison with the firms that have access to foreign investments.

Table 4.18 The Percentage of National Sales of Total Sales by Firm Size in MENA

Firm size	Foreign-owned firms	Gov-owned firms
Small	55.90%	15.21%
Medium	24.11%	16.23%
Large	20.00%	68.56%
Grand total	100%	100%

Source: Author's calculations based on the World Bank enterprise survey dataset in MENA in 2013

However, another crucial role, on the part of the MENA governments, can be collectively played besides their role as full, majority, or significant minority owners; they can also boost the business environment through designing modern investment policies and regulations that accommodate private enterprises characteristics, so that they can benefit from these reforms in order to flourish and participate effectively in the job creation process in the region, given that the public sector is not able to create the jobs needed with the hoped-for scale and quality.

Despite the resultant considerable mayhem, in the wake of what has been named as the Arab Spring and given the contiguous effects of it, one might think of the reverse

region-wide effect of the positive initiatives that can be taken by MENA governments, who can adopt a new set of policies, to unify the educational standards and develop more flexible labour market rules, to allow young educated people to move all over the region and mitigate labour mobility restrictions to search and apply for jobs more easily. The Gulf Cooperation Council has a good reputation, in this respect, with its more harmonised model of residency legislations across the six nations of GCC.

The strength of the legal rights index was found to have a negative impact on labour productivity, in the selected sample in MENA. This variable measures the degree to which collateral and bankruptcy laws can protect the rights of loanees and lenders, and thus ease lending. It includes 8 aspects related to legal rights in collateral law, and 2 aspects in bankruptcy law. A score of 1 is assigned for each of the features of the laws. The index ranges from 0 to 10, with higher scores indicating that collateral and bankruptcy laws are better designed to expand access to credit.

From the Probit model, in the above table 4.15, it can be understood that firms offering training programs to their full time permanent workers are more likely to be:

- 4- larger.
- 5- export-oriented.
- 6- a loanee.
- 7- one of those which introduced new or developed some existing management practices.
- 8- state-owned.
- 9- subsidised.
- 10- one of the firms that introduced new or improved some marketing strategies.
- 11- one of those which used foreign licensed technology in its production.
- 12- one of the firms which introduced or invented some production approaches.

All of the above conclusions confirm the importance of economies of scale in lowering the cost of production, in the long run, to allow firms to use the surplus left after meeting the average cost, and to enhance their performance through several methods; one of which might be improving the skills of their employees by exposing them to more proper training.

The above findings are also in line with the fact that most of the large firms in the Middle East and North Africa are government-owned, and they have dominated the finance as well as the labour market. This implies more financial resources to be deployed to training programs, yet the question remains about the level of the quality of these programs, and the way they are designed to meet the employees' needs, and how well they are evaluated in terms of the level of skills targeted and required.

The empirical results indicate that exporting firms – international exporters mainly – are more likely to provide training for their workers. They need more educated and highly skilled individuals to strengthen their position in the international market, and sustain their gains from the international trade via a more experienced labour force who are able to enhance the firm's ability to compete and maintain their status as international trade businesses.

The changes of the economic structure towards an increased economic openness, and more liberalised trade and markets have caused the labour demand for low-skilled workers to decline significantly, leading to a marked reduction in the number of labour-intensive firms across many regions, MENA included. Hence, the scale of unemployment has enlarged considerably, and the wage and educational gaps have become wider in many parts of the developing world.

Loans and subsidies are also pivotal factors in the story of encouraging firms to use some of their resources in developing and implanting specific training schemes for their labour force.

Those firms that are better linked with foreign agents, which assist them to have access to advanced licensed and patented technology, are more likely to be in need of a certain level of technological knowledge, and cognitive skills, to be embodied in their workers. This is in order to deploy and make use of the modern technology in production with some kind of appropriateness and adequacy in the procedures followed to benefit from the technical progress.

4.3.1.2 Propensity Score Matching: Nearest Neighbour Matching

The estimated impact of formal training on worker's productivity is obtained as the average of all of the treated observations.

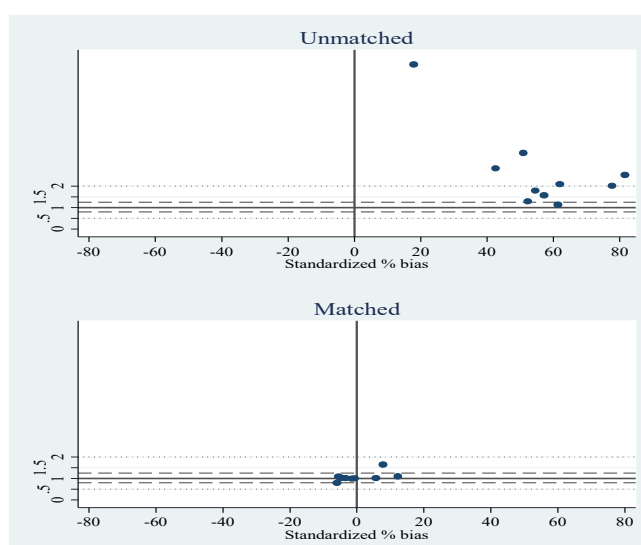
The matching is often performed using a sample of the comparison group without a replacement. This implies that each member of the comparison group can be used only once as a matched case. But in the case of overlap of the propensity scores, or when the control group is small, and given that treated cases will be matched to observations that are not definitely similar, the matching without replacement can perform relatively poorer. To overcome this issue, it would be better to use sampling with replacement to allow for one case of the comparison group to be used as a match, more than once for the treated units.

Table 4.19 Nearest Neighbour Matching (NNM) with Replacement, and without Caliper using Output Per Worker as Outcome.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.4401373	10.2691647	.170972674	.162567977	1.05

The t-test in table 4.19 appears to provide evidence on the insignificance of the training programs. This means that the performance of worker's who lack the necessary skills does not seem to have improved after receiving the treatment (training), and does not increase the output per worker over the period of the subject of the study.

Figure 4.2 NNM with Replacement, and No Caliper using (lnopw) as Outcome



The lower box of figure 4.2 shows that the covariates in the matched group are clustered around the centre (zero) which indicates that the balancing is good, and the bias is reduced in most covariates.

Table 4.20 Treatment assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,377	2,377
Treated	401	401
Total	2,778	2,778

There is a good level of common support as shown in table 4.20 where all of the treated observations are included in the average treatment on the treated estimation.

Table 4.21 Summary of Output Per Worker If Training = 1 (Formal Training Provided)

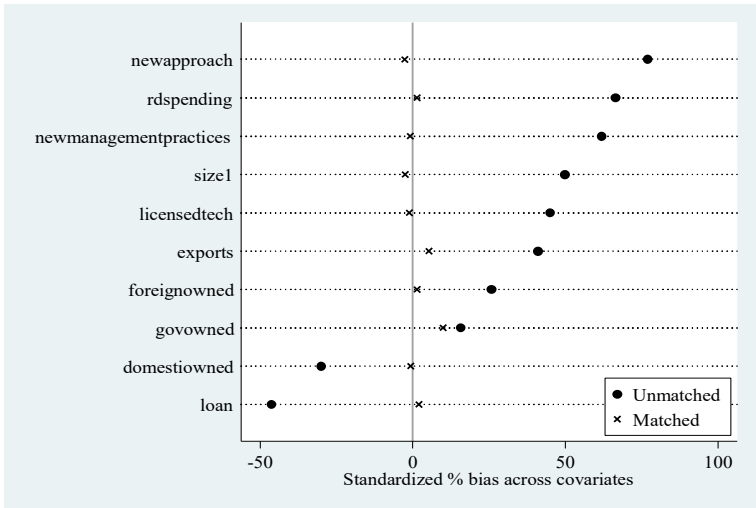
Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Output Per Worker	401	10.44014	1.541182	3.37115	14.65484

Table 4.22 Summary of Output Per Worker If Training = 0 (No Formal Training Provided)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Output Per Worker	401	10.26916	1.461183	6.486872	17.97648

The mean of output per worker in table 4.21 is greater than the mean in table 4.22 which means that there is an improvement in labour productivity in firms that offered formal training for their workers, but the effect does not seem to be significant from a statistical point of view.

Figure 4.3 Nearest Neighbour Matching



The above figure 4.3 shows the better balance obtained from the nearest neighbour matching, imposing the replacement option in the procedure. It illustrates the balance of the matched sample when allowing for one unit in the comparison to be used multiple times as a match for the treated units.

Table 4.23 Nearest Neighbour Matching (NNM) without Replacement, and without Caliper using Output Per Worker as Outcome.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.4401373	10.2456454	.194491979	.109990732	1.77

It might be an option to impose some forms of common support. Hence, we could use the caliper matching (0.02) and (0.04) and see whether the matching is going to be feasible after a possible exclusion of some of the observations from the sample.

The caliper is a way to impose a common support from the view point of the propensity score, by eliminating a treated unit that is unmatched, and whose nearest match is further away – further than the caliper – where a number of treated units, who have a match, might be left out of the analysis because they are divergent in terms of the propensity scores, and they are excluded in order to find a close enough and more reliable match.

Table 4.24 Nearest Neighbour Matching without Replacement, and with (0.02) Caliper using Output Per Worker as Outcome.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.3829819	10.2150818	.167900118	.115538969	1.45

The t test in table 4.24 shows no sign of significant impact of the binary treatment – formal training – on output per worker – the outcome variable – which suggests that there is evidence that training programs in manufacturing firms in MENA did not improve productivity.

Table 4.25 Treatment assignment (caliper 0.02)

Psmatch2: Treatment Assignment	Psmatch2: Common Support		Total
	Off Support	On Support	
Untreated	0	2,377	2,377
Treated	44	357	401
Total	44	2,734	2,778

Table 4.25 shows high level of common support where just 44 treated observations are excluded from the matching when choosing to do the matching without replacement.

Table 4.26 Nearest Neighbour Matching without Replacement, and with (0.04) Caliper using Output Per Worker as Outcome.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.3734607	10.2150818	.158378952	.11532254	1.37

The summary of units off and on support in table 4.27 shows that 44 treated units were discarded when applying the without replacement option. Therefore, the number of the on support treated units became slightly smaller, with 357 observations that remained to do the matching.

Table 4.27 Treatment assignment (caliper 0.04)

Psmatch2: Treatment Assignment	Psmatch2: Common Support		Total
	Off Support	On Support	
Untreated	0	2,377	2,377
Treated	44	357	401
Total	44	2,734	2,778

It can be noticed that more than 10% of the data will be lost (*Display 1-r mean = .10972569*), but the result was a much better balancing of the X’s at a cost of losing a chunk of the data.

It should be also noted that the differences in the ATT estimation in both cases (0.02 and 0.04 calipers) do not differ significantly. The differences in both cases are positive suggesting a positive but not significant causal impact of training on firm-level productivity.

Figure 4.4 (Output per Worker Kernel density) NNM With Replacement, Without Caliper

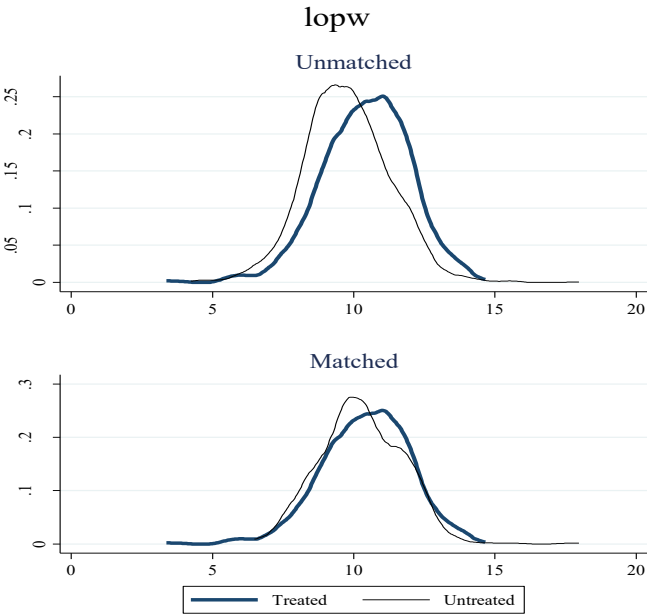


Figure 4.4 illustrates the high level of common support where the densities of both the treated and untreated matched groups are intersected with each other. The middle area between the two lines represents the region of common support.

Figure 4.5 NN Matching, No Caliper, With Replacement

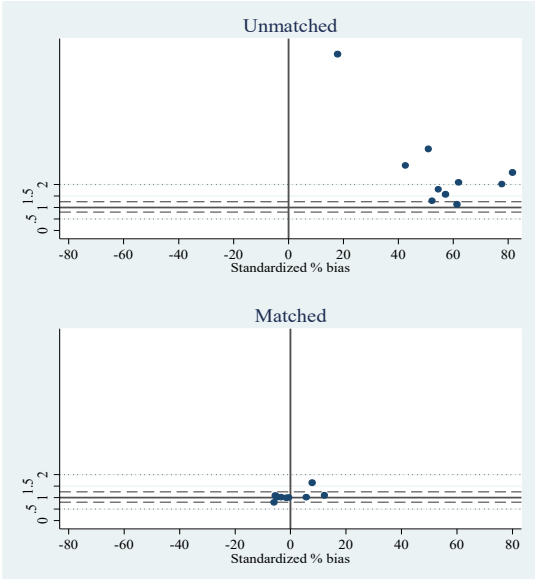
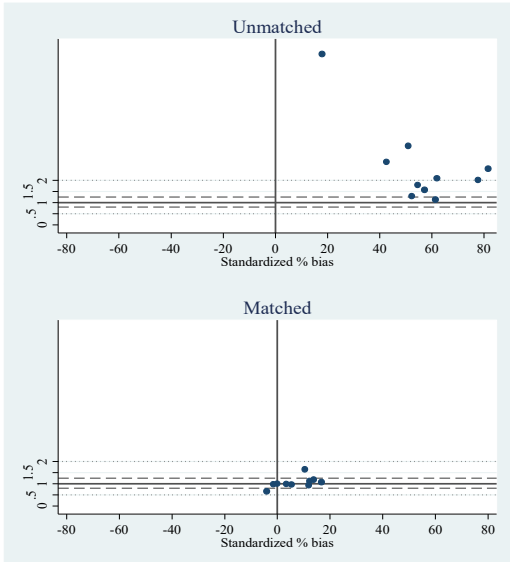
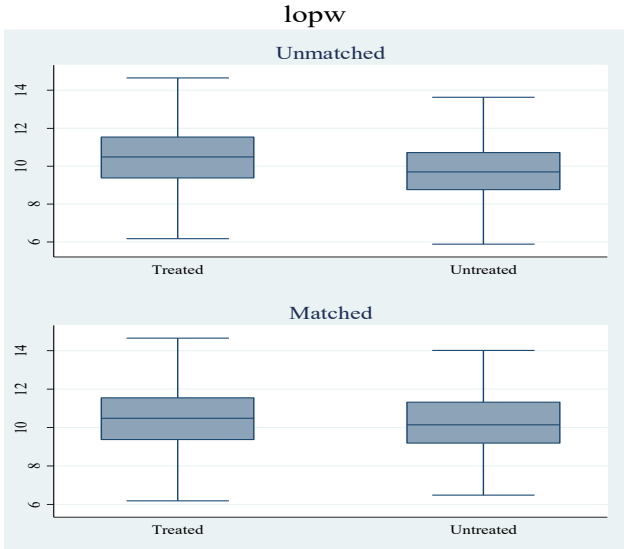


Figure 4.6 NN Matching, No Caliper, No Replacement



The propensity scores are much better aligned with the imposed calipers 0.02 and 0.04 and with replacement. These results mechanically depend largely on the strictness of the caliper. But, and despite the more balanced covariates after imposing the caliper and replacement options, the training causal effect on the outcome variable (output per worker) was found to be insignificant from a statistical point of view again.

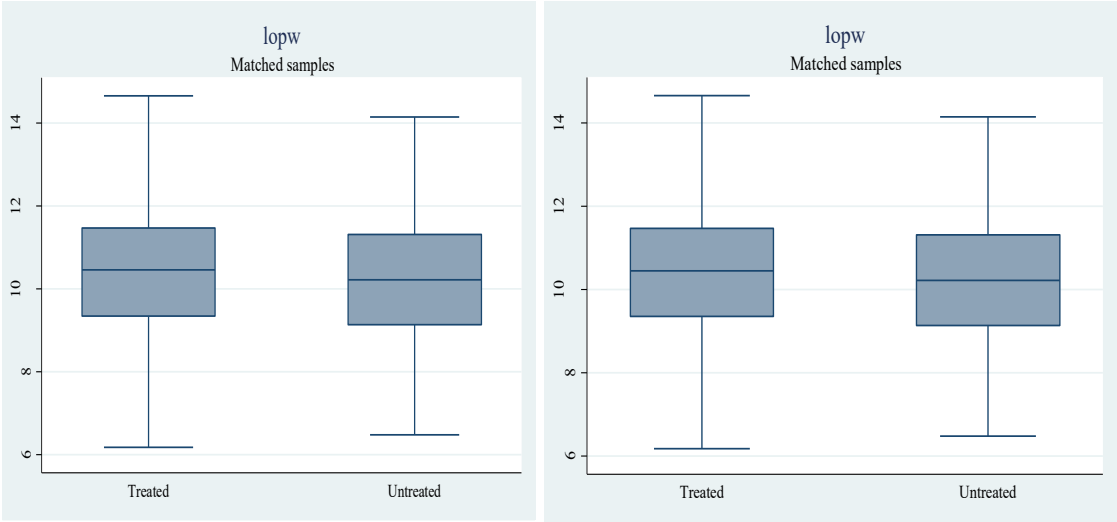
Figure 4.7 NN Matching, With Replacement, With Caliper (0.02)



The alignment of the scores in the matched samples (treated and untreated) are similar when using the two calipers (0.02 and 0.04) and without replacement to reduce the sample size and bias.

Figure 4.8 NN Matching, No Replacement, With Caliper (0.02)

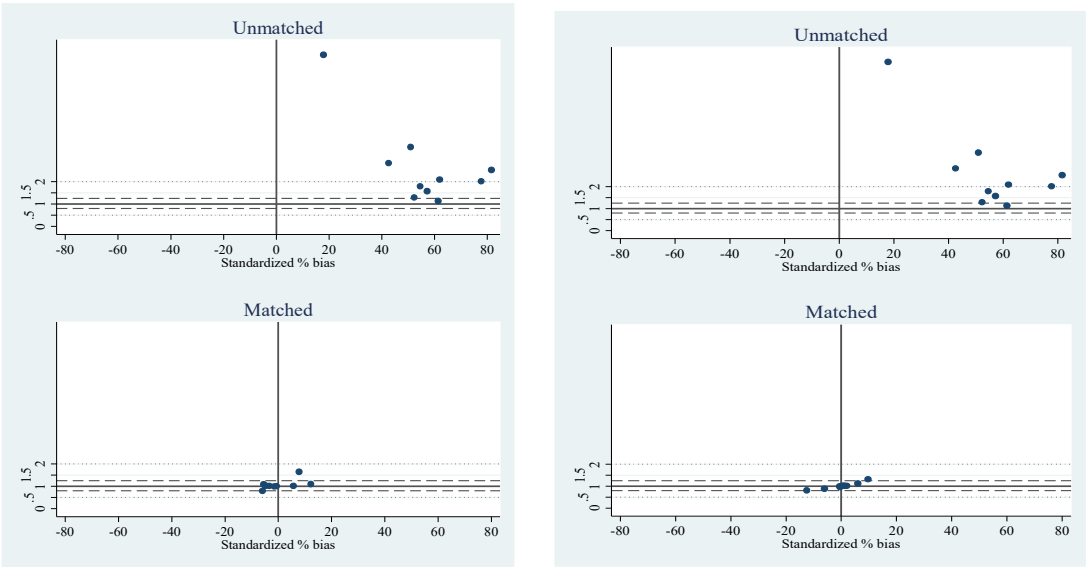
Figure 4.9 NN Matching, No Replacement, With Caliper (0.04)



More important than just checking if the probabilities used for matching were balanced, is whether matching on these probabilities balances the regressors. See figures 4.10, 4.11, 4.12 and 4.13.

Figure 4.10 NN Matching, with caliper (0.02), with Replacement

Figure 4.11 NN Matching, No Replacement, With Caliper (0.02)



The covariates are better balanced and centred around the zero in figure 4.11 than in figure 4.10 which reflects the effect of the matching procedure without replacement along with strict caliper 0.02 to reduce the model dependence and bias.

Figure 4.12 NN Matching, No Replacement, Caliper (0.04)

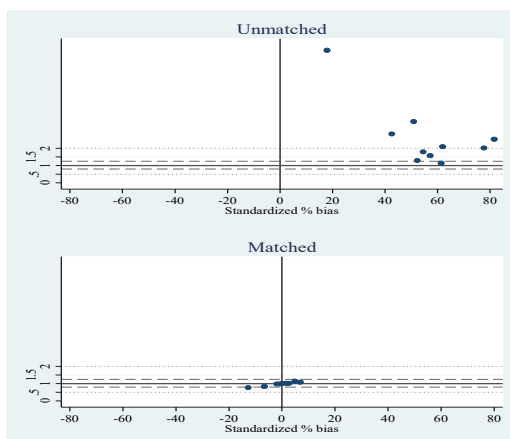
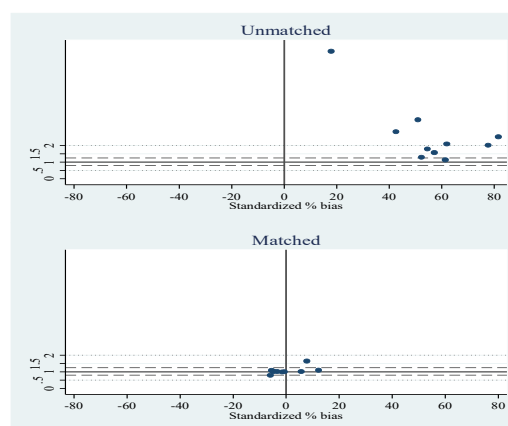


Figure 4.13 NN Matching, With Replacement, Caliper (0.04)



It is important to say that matching with a caliper and without replacement has decreased the bias extremely well, and overall, the two groups are jointly balanced.

The impact of formal training on firm-level productivity is not found to have any significance. Now the investigation turns to a fully blocked matching experiment – Mahalanobis metric matching – to examine whether there is any significant causal effect of training on firms' performance in MENA.

4.3.1.3 Mahalanobis-Metric Matching

One of Mahalanobis matching advantages is that it prunes – discards – the bad observations from the sample in a more systematic and efficient way than in propensity score matching to achieve higher percentage of bias reduction.

The empirical results suggest that there is no statistical evidence on the causal effects of training on labour productivity in MENA, which is neither based on the results obtained from the applied propensity score matching, nor from the results obtained from the Mahalanobis matching.

Despite the estimates show that the impact of formal training programs on firms' labour productivity in MENA is found to be insignificant, the propensity score and Mahalanobis metric matching results do not give a clear answer for why is it insignificant? Which appears to be a limitation in the analysis.

The reasons for the insignificance of the formal training programs' effects are difficult to pinpoint, but it could be put down to the fact that training programs were either inappropriately-designed, or insufficiently-organised, to suit the workers' needs and are inefficiently evaluated as well. Another reason that can be worthy of pointing out is that the labour force skills, and levels of knowledge, are not professionally assessed, given that the high levels of unemployment, among the youth university graduates across MENA, provide firms with an opportunity and invaluable advantage to recruit good quality workers with relatively low costs (recruitment cost and on-the-job-training), and there is a lower degree of competition with local competitors at the same time.

There can be other obstacles for training activities to be effective in MENA, which might include the outdated technology that is in use in the firm's production processes, when considering the depreciation of equipment and machinery deployed in the manufacturing activities, where it can hinder productivity enhancing-efforts from being successful.

Table 4.28 Mahalanobis-metric Matching, Output per Worker as Outcome.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.4401373	10.3041555	.135981895	.182396324	0.75

The reported ATT estimation, in tables 4.28 and 4.30, using the Mahalanobis and Augmented Mahalanobis matching indicate the insignificant impact of training programs on productivity in MENA. To judge the efficacy of the matching strategy and to trust this result, this research needs to check the balancing in the below figures (4.14, .. 4.17), which show the good balancing achieved by this procedure.

Table 4.29 Treatment assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,377	2,377
Treated	401	401
Total	2,778	2,778

The level of common support is still high with the Mahalanobis matching but still no sign of significant impact of training on productivity.

Table 4.30 Augmented Mahalanobis-metric Matching, Output per Worker as Outcome, (Score included)

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	Unmatched	10.4401373	9.76632746	.673809888	.082305998	8.19
	ATT	10.4401373	10.1537117	.286425663	.17693503	1.62

The augmented Mahalanobis matching includes the propensity scores in the estimation which resulted in an improvement in the statistical significance, but it is still below the level of confidence which cannot be used as evidence of any contribution from training to productivity improvement.

Table 4.31 Treatment assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,377	2,377
Treated	401	401
Total	2,778	2,778

Although some of the countries in MENA made pronounced efforts, with regard to more investments in technical and vocational training and education, namely in Egypt, this kind of education continues to be under used in most formal job markets in the region.

Figure 4.14 Mahalanobis-Metric Matching

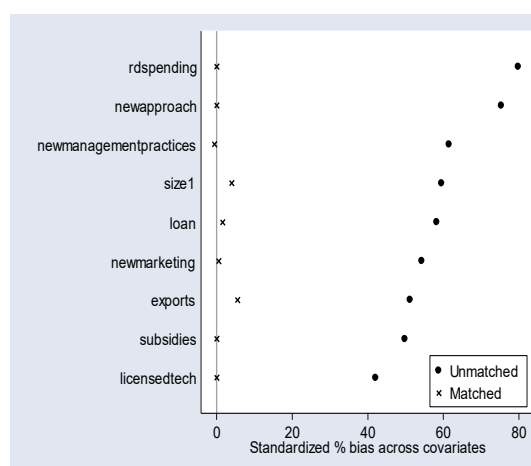
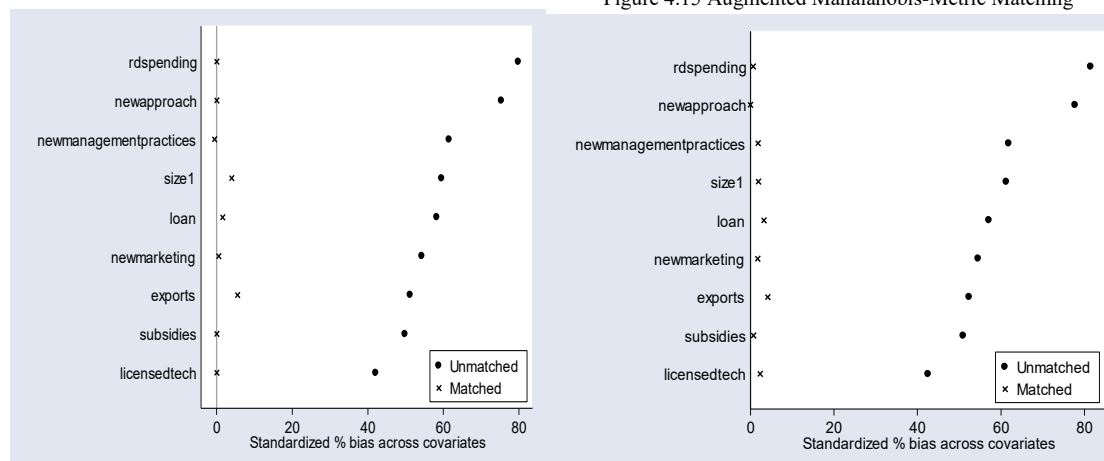


Figure 4.15 Augmented Mahalanobis-Metric Matching



The results obtained might underestimate the importance of the effects of training on productivity, but this might be due to the wage pressure and imperfect competition in the labour markets in MENA, which might lead to a mismeasurement of the benefits that productivity can capture from training. This is especially when a worker's wage is used as a measure of their productivity.

Figure 4.16 Mahalanobis-Metric Matching

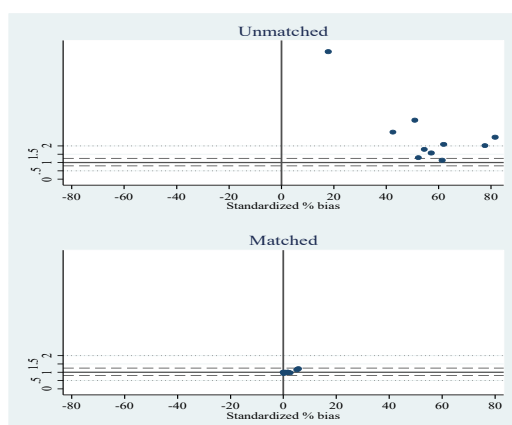
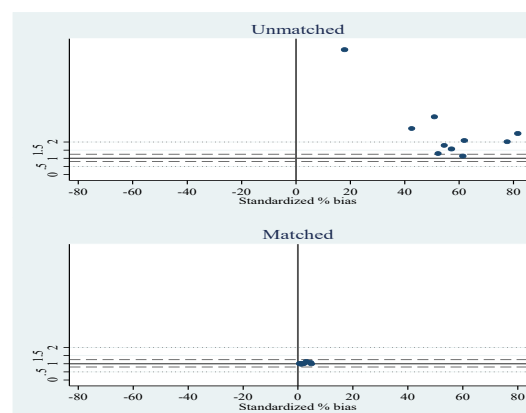


Figure 4.17 Augmented Mahalanobis-Metric Matching



A good balancing was achieved for the confounding covariates via Mahalanobis metric matching, which is even better when it is including the propensity scores in the augmented Mahalanobis matching. However, the resulting estimates are not particularly close to the benchmark, which suggests that these are sufficient enough to control for selection.

4.3.1.4 Comparison between propensity score matching and Mahalanobis metric matching

The bias reduction in the covariates using the augmented version of the Mahalanobis matching, has shown better improvement than in other matching techniques. The figures in the table below, represent the percentage of the bias reduction in the vector of the observed regressors in the ATT estimation.

Table 4.32 Bias Reduction Percentage (%) Using Propensity Score Matching and Mahalanobis Metric Matching

Variable	Propensity score matching with replacement and without a caliper	Propensity score matching with a 0.02 caliper	Propensity score matching without replacement and with a 0.02 caliper	Mahalanobis metric matching	Augmented Mahalanobis metric matching
Firms size	90.2	90.2	79.7	91.8	94.9
Government ownership	56.6	56.6	45.6	99.3	93.3
Innovative marketing strategies	93.7	93.7	98.8	96.8	96.8
Subsidies	97.0	97.0	98.3	100.0	98.5
Licensed technology	71.3	71.3	85.9	98.2	94.6
R&D spending	93.1	93.1	98.3	97.7	98.5
International exports	90.5	90.5	99.2	89.1	91.3
Loan	91.5	91.5	89.4	95.3	91.5
New management practices	91.0	91.0	96.6	98.0	97.0
New production approaches	99.2	99.2	100.0	97.7	99.2

For more details, see Appendix A, chapter 4 appendices, matching methods sub-section 2.

In summary, the obtained results in this section suggest that the contribution of formal training to firms' productivity remains unclear and ambiguous, despite using two different matching methodologies, in order to examine this relationship in the private manufacturing sector in MENA.

Several factors such as; firms size, percentage of international exports – as a measure of firms' openness to the international markets – government ownership shares, new management practices, and the licensed technology, which was deployed in the firms' production processes, all have played important and positive roles in the firms' decisions whether to offer formal training programs to their workers. Despite all that, and from an economic point of view, the causal effects of formal training on the firms' productivity did not seem to be significant.

4.4 Chapter Conclusions

In summary, this chapter was intended to address the two main questions of this research in MENA about 1) What are the effects of education on technical efficiency in the manufacturing sector? considering the three levels of education residing in the full-time permanent workers at the firm level. 2) What impact do formal training programs have on labour productivity in MENA's private manufacturing firms?

The main purpose of this chapter is to establish economic evidence on the importance of human capital investment in the MENA countries, for enhancing the international competitiveness within the region and within the less developed economies, as well as in the global markets. Human capital is measured by the shares of low, intermediate, and high-skilled workers with different degrees of education, which are primary and secondary, technical and vocational training schools, and a university degree. With an additional factor that is represented by the average years of schooling. The worker and

allocative effects of low and highly-skilled workers were found to be significantly positive on technical efficiency.

The empirical results give the impression that highly-educated labour (workers with tertiary education and those with university degrees) and pre-intermediate labour (secondary school attendees) seem to have a positive impact on firms' efficiency. In other words, firms with a higher percentage of second (secondary school) and third (university) level of education workers tend to be more efficient compared to those firms with intermediate workers, which are those of whom their educational attainment lies at the level of technical schools and college. In fact, the impact of the latter (intermediate workers) gives the impression of being negative in some cases.

These findings are in line with (Krueger and Lindahl, 2001a) with respect to the positive significant effects of education, as a growth driver in the underdeveloped economies, whereas, these findings conflict with (Ang et al., 2011) where they argue that education only contributes positively to growth in more developed countries.

The intermediate skilled workers were found to be contributing negatively to technical efficiency across the spanned sample in this region, and this seems to be, to some extent, in line with the empirical evidence of (Corvers, 1997), where he suggested that it is only the highly skilled labour that is of a significant impact on productivity of the manufacturing sector in the EU; this is pointing to the possible underinvestment of human capital in some manufacturing sectors in this component of human capital.

Moreover, the maximum likelihood estimates indicate that the average years of schooling as an additional proxy for human capital stock of the manufacturing firms in MENA was found to be insignificant. This conclusion mirrors and compares well with those suggested by (Aghion et al., 2009) referring to the possible insufficient validity of this proxy to be used when predicting and interpreting the causes of growth with

confidence and at the same time raise the question about the scepticism and indefiniteness about the cogency of years of education as an adequate proxy for human capital stock.

In the main, the firms' performance and growth in MENA was held back as a result of numerous economic, social and political factors over the past ten years. These factors are mainly related to the elements of the business environment and economic structural problems, starting from the level of an economically active population's participation in the labour force, which was found to be low in comparison with the peer regions, due to the weak growth of the private sector, which requires serious reforms in the investment climate to allow for investments in the region to recover and productivity to grow.

The diversification of the sources for national income revenues is another goal to be considered and is encouraged to lessen the heavy reliance on the oil exports, and to avoid the ensuing economic repercussions of the volatility of the oil prices in the energy markets.

The MENA region has proved, over the past decades, that there is a pattern of a fast-spreading contagion. This is where what takes place in one country goes beyond the borders and affects others, and the looming clouds could have been seen from a distance before moving in, maybe the Arab Spring uprisings in 2011 represent a classic example of this contagion effect. Therefore, rational governance and better management for the financial surpluses, and carefully-tailored fiscal policies with a more robust banking system, are other issues of great concern in MENA, which need to be redressed in the coming years to encourage growth even further.

Chapter 5: The Role of Education and Formal Training in the Manufacturing Firms' Performance: Evidence from the Countries of Eastern Europe and Central Asia.

5.1 Introduction

This chapter principally aims to investigate and examine the contribution of human capital components represented by several proxies (levels of education) to technical efficiency using firm-level data sourced from The Business Environment and Enterprise Performance Survey (known as BEEPS). It was conducted in 2013 by The European Bank for Reconstruction and Development jointly with the World Bank Enterprise Survey. The survey spans more than 4300 manufacturing firms with different sizes and ages in 28 countries across the Eastern European and Central Asia (ECA) region.

The empirical results suggest that highly-educated labour (workers with tertiary education and holding university degrees) appear to have a positive impact on firms' efficiency. In other words, firms with higher levels of human capital represented by the proportion of highly-skilled workers tend to be more efficient than those firms employing intermediate workers whom their educational attainment lies at the level of high school and college.

In fact, the impact of this element of human capital seems to be negative and it appears to throttle improvements in firms' efficiency. The results also indicate that average years of education have no significant effect on efficiency and therefore productivity in these countries.

In addition, firms' size factor (micro, small, medium, or large) tends to play a role in thwarting firms to be more efficient, meaning that the larger the firm is, the less efficient it is anticipated to be.

In the light of other results, it is also found that, funds received from (Private commercial banks) in the form of loans, firm's age, and the percentage of foreign ownership in the firm (whether it is a complete or partial ownership) have their significant positive impacts on efficiency.

The effects of formal training are also investigated in this chapter using two matching methodologies – propensity score matching and Mahalanobis metric matching – to better allow for heterogeneity and reduce bias selection issues.

The results suggest that the treatment variable – formal training– has a positive and significant causal effect on output per worker – as a measure of firms' performance – in manufacturing firms in this region.

5.2 The Impact of Education Composition on the Manufacturing Firms' Technical Efficiency: Evidence from the Eastern Europe and Central Asia Economies (ECA).

This chapter fits translog frontier production functions with inefficiency functions in order to examine the effects of skilled and unskilled labour on productive efficiency in ECA countries using heteroscedastic translog stochastic frontier production models.

The results show the positive and significant impact of university degree holders on firm-level efficiency in this region. However, on the other hand, the other two components of human capital – intermediate and low skilled workers – do not seem to have any significant effect on productive efficiency in manufacturing firms in this region.

5.2.1 Empirical Results and Stochastic Frontier Analysis

From a structural perspective, productivity is an impactful determinant and is of prime importance to competitiveness in the long run, and efficiency is a decisive component of productivity. Thus, there is a vital relationship between efficiency and competitiveness in the longer term. However, as far as the obtained maximum likelihood estimates are

concerned, efficiency tends to be lower in firms with a higher ratio of intermediate skilled labour. (These are those who have attended college or a technical school or received on-the-job training at certain stages.).

The positive sign of the estimated parameter implies that the higher the ratio of medium-skilled labour, as a percentage of the total number of workers in the firm, the higher the inefficiency would be. The variable university degree stands for the percentage of the full time equivalent workers, whose education is at the level of university or above, and the expected results were that the higher this percentage is, the more efficient the firm is. The negative value of the coefficient demonstrates that it goes in line with the theoretical expectations, and it is statistically significant and is positively affecting efficiency, as predicted.

The maximum likelihood estimates of the stochastic frontier model, are obtained using the NLogit 5 econometric software, and presented in table 5.1. While tables 5.3, 5.6, 5.10, 5.11 and 5.12 present the tests of the null hypotheses based on the generalised likelihood ratio (LR) test regarding the most convenient choice of the functional form and the relevance of the inefficiency effects.

According to the likelihood ratio (LR) test, the functional specification of the stochastic frontier production has been specified by testing the sufficiency of the translog configuration to the data relative to the restrictive Cobb-Douglas form. The test shows that the translog specification fits the data better than the Cobb-Douglas restrictive configuration.

The results reported in table 5.1 are from the normal-half normal distribution maximum likelihood estimates. The likelihood ratio test for the Null hypothesis H_0 (Cobb-Douglas model) vis-à-vis the Alternative hypothesis H_1 (Translog model) was performed for the purpose of selecting the most convenient model based on the goodness of fit between them at different levels of statistical significance with 17 degrees of freedom in the heteroskedastic model.

The test results indicate the rejection of the null hypothesis, which represents the Cobb-Douglas frontier production function, which is effectively a special case of the more general translog version. Thereby, the translog functional form was opted as the econometric most-appropriate technology for interpreting this relationship at 90%, 95% and 99%. Given that the sample sourced from this region is more heterogenous, the more flexible version (translog) of the production function turns out to be more convenient and fit to purpose. See table 5.3.

There is evidence on the importance of the third level of education, mainly university degrees, in ameliorating technical efficiency across firms throughout the ECA nations included in this sample.

The second level of schooling including technical school and college level proxied by skilled production workers, does not seem to have any positive impact on technical efficiency in this group of countries.

The results outline that the medium level of skills – intermediate skilled labour in particular – across Eastern Europe, are associated with lower levels of output per worker/hour worked, and that can be comprehensible from the empirical evidence provided. This is also understandably clear in the manufacturing sector – which is the core interest of this research – where there is an indication that industries in the ECA region lack skilled workers, because of the misalliance between supply and demand aggravated by the incompetence in education systems across these nations.

Therefore, the outcome suggests that the higher the share of highly-educated workers – university degree level – as opposed to medium-skilled workers, the more efficiently the enterprise tends to perform.

Other variables are included in the estimation to proxy for human capital stock, such as, the fact that the average years of education of a typical permanent full-time production worker in the firm does not appear to have a positive impact on efficiency levels across establishments, and it is found to be of a statistically insignificant role in reducing the inefficiency level at firm level.

Even though this proxy might ignore the real market value of human capital, it could be shown that it has a significant positive impact on efficiency in the normal-truncated stochastic frontier production model, but when the three components of human capital are disaggregated, and their effects are estimated independently, the average years of schooling proxy is found to have a positive impact on efficiency. However, it is only significant when integrated in the highly-skilled human capital model. See table 5.9 and 5.13.

The real value of human capital is largely determined by the appropriate employment and allocation of the qualified individuals in an efficient manner in the economy, which in turn, depends on how efficient the economy's institutions are in benefiting from the human capital stock. Hence, the average number of the years of education – as a raw figure – can be misleading when examining how important the stock of human capital is to growth.

Therefore, it might be an option to replace it with a more valid alternative, such as the International Maths and Science Test Scores, as a measure of education quality, but with some reservations with regard to the way the test scores are associated with growth. This is where in the average years of education data are combined with the past to produce the average estimate of the labour force, as a whole. The insufficient and the lack of the data on test score, to construct a similar average, is a serious impediment that prevents researchers from doing so.

In Russia, and in some of the satellites of the former U.S.S.R, unemployment rates across transition economies rose significantly in many newly privatised firms during the nineties, as they were attempting to improve their efficiency. This is where in countries like Russia, Hungary, and Poland unemployment levels escalated dramatically to more than 13.26% in 1998, above 12.1% in 1993, and about 19.89% in 2002, respectively.

In the early 1990s economic recession accounts for part of the soaring rates of unemployment, but during the restructuring process, which these countries have

undergone during that period, it played an important role in reducing unemployment to an equivalent level to their peer economies in other regions.

The translog stochastic production function for the ECA region is set as follows:

$$\ln \text{Gross Sales}_i = \beta_0 + \beta_1 \ln (\text{Capital}_i) + \beta_2 \ln (\text{Labour}_i) + \beta_3 \ln (\text{Squared Capital}_i) + \beta_4 \ln (\text{Squared Labour}_i) + \beta_5 \ln (\text{Capital} \times \text{Labour})_i + (v_i - u_i) \quad \text{Equation 5.1}$$

Whereas the technical inefficiency function is defined as follows:

$$\begin{aligned} \text{Technical Inefficiency} = & \delta_0 + \delta_1 (\text{Low skilled}_i) + \delta_2 (\text{Highly skilled}_i) + \\ & \delta_3 (\text{Intermediate skilled}_i) + \delta_4 (\text{Yrs of Shooling}_i) + \\ & \delta_5 (\text{GDP per Capita}_i) + \delta_6 (\text{Formal Training}_i) + \delta_7 (\text{Internet Users}_i) + \\ & \delta_8 (\text{Distance to Frontier}_i) + \delta_9 (\text{Country Dummies}_i) + \\ & \delta_{10} (\text{Active Population}_i) + \delta_{11} (\text{Legal Rights Index}_i) + \delta_{12} (\text{Bribery}_i) + \\ & \delta_{13} (\text{Tax Rate}_i) + \delta_{14} (\text{Rural Population}_i) + \delta_{13} (\text{Foreign Shareholders}_i) + \\ & + \delta_{15} (\text{Life Expectancy Rate}_i) + \delta_{16} (\text{Firm Age}_i) + W_i \quad \text{Equation 5.2} \end{aligned}$$

The estimation of equations 5.1 and 5.2 using the stochastic frontier approach with the correction for heteroscedasticity in u only yielded the estimates shown in tables 5.1 and 5.9 and controlling for heteroscedasticity in both u and v resulted in the estimates shown in table 5.4.

Firms, in most of these countries, were operating under communism before the demise of the Soviet Union in the beginning of the 1990s, and the industries were mostly state-owned, where disguised unemployment was prevalent. When new entrepreneurs entered the market, along with the new privatisation strategies, they had to reduce the labour cost to increase efficiency levels, and to be able to face the competition, which they did by laying off many workers causing massive job losses across the region.

The design of the institutions might have some importance, thus country-specific dummies were included in the analysis to capture the institutional design differences between countries in the ECA region.

Table 5.1 Half-Normal Model: Maximum Likelihood Estimates of the Impact of Human Capital Composition on Inefficiency in Eastern Europe and Central Asia Countries in The Private Manufacturing Firms in 2013 with the Correction for Heteroscedasticity in the One-Sided Error Term (u) only.

Production Function Dependent Variable LnQ= (ln Gross Sales)	Model 1 (Translog)		Model 2 (Cobb-Douglas)	
	Deterministic Component of Stochastic Frontier Models			
Stochastic Frontier Production Function	Param.	T- Statistics	Param.	T-Statistics
Constant	9.05722*** (.20930)	43.27	10.3656*** (.10680)	97.06
Ln Capital (K)	.00659*** (.00286)	2.31	.42196D-04 (.6482D-04)	.65
Ln Labour (L)	1.02518*** (.10059)	10.19	1.05656*** (.02087)	50.62
Ln K ²	.01213*** (.00083)	14.69		
Ln L ²	.00580 (.01202)	.48		
Ln (K×L)	-.01991*** (.00335)	-5.95		
Technical Inefficiency Function (Heteroscedasticity in u only).				
Constant	-17.4492** (7.0247)	-2.48	-17.1424*** (6.56879)	-2.61
Ln Low-Skilled Labour	-.00018 (.00024)	-.78	-.00015 (.00024)	-.61
Ln Highly-Skilled Labour	-.20537* (.10576)	-1.94	-.21061* (.11011)	-1.91
Ln Intermediate-Skilled Labour	.00013 (.00067)	.20	.00022 (.00071)	.31
Ln Average Years of Education	-.00048 (.00034)	-1.40	-.00034 (.00033)	-1.04
GDP Per Capita	-.00054** (.00021)	-2.57	-.00037*** (.00011)	-3.42
Training	-.47537* (.25569)	-1.86	-.49660** (.23937)	-2.07
Internet Users	-.04784* (.02657)	-1.80	.04402** (.02139)	-2.06
Distance to Frontier	.25319*** (.07456)	3.40	.21913*** (.05902)	3.71
Country Specific Effects (a Country Dummy)	.01587 (.03608)	.44	.01609 (.03196)	.50
Economically Active Population (%)	.06077* (.03199)	1.90	.07406* (.04110)	1.80
Strength of Legal Rights Index (0-12)	-.29118* (.18019)	-1.65	-.23193* (.12471)	-1.86
Bribery	.02982** (.01339)	2.23	.02556** (.01153)	2.22
Tax	.06460*** (.02222)	2.91	.05636*** (.01802)	3.13
Rural Population	-.04514** (.02104)	-2.15	-.02972* (.01693)	-1.76
Log-Likelihood Function	-2762.62038		-2874.06771	
Sigma-squared(u)	.68026		.90567	
Sigma u	.82478		.95167	
Sigma-squared(v)	1.03498		1.14385	
Sigma v	1.01734		1.06951	
Gamma (γ) = sigma(u) ² /sigma ²	.39660		.44189	
Sigma = Sqr [(s ² (u)+s ² (v))]	1.30967		1.43161	
N. obs.	N = 1834, K = 23		N = 1834, K = 20	
Deg. freedom for inefficiency model	16		16	
Deg. freedom for heteroscedasticity	15		15	

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Robust Standard Errors reported in parentheses.

For expository purposes, it is worth noting that in this sample larger firms tend to employ a higher percentage of low and intermediate-skilled workers compared to high-skilled workers, while on the other hand, the shares of highly-skilled workers (university degree labour) seem to be higher than the shares of intermediate-skilled labour (intermediate-skilled workers) in small and medium enterprises in Eastern Europe And Central Asia.

This signifies a problem of a skill-mismatch and a low level of skilled labour allocation, because the poorly performing firms – large and medium-sized firms in this region – are not exiting the marketplace, and skilled workers find themselves trapped and captured

by these inefficient enterprises due to the labour market, and product market rigidities, that capture skills and capture firms with low productivity performance.

There seems to be a gap between the quality of jobs offered by the newly privatised firms in ECA economies, and the level of skills needed to perform these jobs in an efficient and more productive manner.

This is a serious issue because workers that are poorly matched to their jobs are not going to receive their marginal product, and hence, they are not going to be paid the wage they deserve for the skills and level of education they hold. This is a natural corollary of workers entrapment in less efficient firms, and they are not able to be transitioned to more productive firms because of the labour markets inflexibility and workers' constrained mobility across jobs and sectors.

High skill-mismatch can have negative consequences on productivity and workers alike. Workers who are poorly assigned to their jobs are not going to perform properly, which impairs productivity growth, and firms are not going to pay skilled workers high wages when they are doing basic or intermediate jobs that do not require a high level of skills, which places a limit on wage growth. This partly explains why workers, who are in these circumstances, tend not to receive their fair share of remuneration.

It can be argued that the reallocation of human resources (skilled-labour), for the occupations that they are best suited for, is achievable at a quicker pace, and with more elasticity in firms in countries that are close to the technological frontier, and those firms that are able to grasp the innovation and R&D fruits from the frontier firms (innovation firms).

The key point, in this respect, is that for firms in countries that are behind the frontier – ECA included – more trading with the productivity and technology frontier countries, and with the firms operating in them, and being exposed to cutting-edge innovation and new technology, are key factors for the firms to develop, and for the transition economies to succeed in the resource-reallocation process, and in the end they will reap a better matching of skills, a higher efficiency of re-allocated skills, and considerable

improvement in alleviating that skill mismatch issue, which will eventually yield a better firm level performance, overall.

Table 5.2 The percentage of jobs offered by firms with different size to workers with different qualification in ECA in 2013

Firm size	Grand Total Number of Workers	Highly Skilled Workers	Intermediate Skilled Workers	Low Skilled Workers
Micro	0.10%	2.50%	0.08%	0.06%
Small	4.48%	44.40%	4.68%	2.90%
Medium	18.27%	34.19%	18.41%	16.92%
Large	77.15%	18.91%	76.83%	80.12%
Grand Total	100.00%	100.00%	100.00%	100.00%

Source: author's calculations of the workers distribution between firms in ECA based on the World Bank survey 2013 dataset.

Equally important are the country characteristics, or what may be named as “policy choices” which are including, the policies that support and promote seed and early stage ventures, exit-entry dynamisms, trade regulations, FDI flows and foreign ownership legislations, labour market rules that support workers transition along with active labour market policies for the unemployed labour force and unemployment benefits, judicial system efficiency, and stock market capitalisation. These are the tools that are in the hands of policy makers, which they can use to modify and reform, in order to improve the capacity of firms to clench and grab innovation from the technology frontier firms, and understand what is new in it, and then embody it in their own structures and organisational frameworks, and gain more and better output from it through higher productivity and efficiency.

The question that arises at this point is, what is it that prevents policy makers from developing, and from transition economies adopting, the policies that help the average existing firms to adapt and deploy the new technology that is already available in the market, and which they are not using yet? When bearing this in mind, the question does not include the state-of-the-art innovations that are still not at the firms' disposal, and which are to be purchased in the technology marketplace. More precisely, what is it that hinders the existing innovation from being diffused to the average firms in the developing and transition countries, which are trailing behind the frontier?

With the economic policy, and diffusion wise, removing the entrepreneurship obstacles, and setting, and maintaining efficient judicial structures, and creating appropriate

policies to encourage and assist the early-stage ventures, then these are the keys for technology dispersal towards the average firms.

The value of λ in the case of ECA is equal to $\lambda = \frac{\sigma_u}{\sigma_v} = \frac{.82478}{1.01734} = 0.81072$, and refers to the validity of the asymmetric distribution assumption of the error term, given the value of is $\lambda > 0$.

Table 5.3 Generalised Likelihood-Ratio Tests of the null hypothesis.

Null hypothesis, H0	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 4 \dots 15$			99.5% $\rho = (0.005)$	32.8
H ₁ is accepted	Translog	-2762.62038	99% $\rho = (0.01)$	30.6
	Cobb - Douglas	-2867.82918	95% $\rho = (0.05)$	25.0
	LR Test	210.4176	90% $\rho = (0.1)$	22.3

In respect of the variance parameter, γ , in which its value lies between zero and the unity ($0 < \gamma < 1$), then the value of *gamma* γ is responsible for the part of the distance to the frontier that is explained by the inefficiency. Where $\gamma = \frac{\sigma_u^2}{\sigma^2}$ is equal to $\gamma = \frac{.68026}{1.7152355} = 0.396598$, and it signifies that technical inefficiency is stochastic and of a relation to obtaining an adequate representation of the data, and the variance of technical inefficiency effects is a significant component of the composite error term variance ($v_i - u_i$).

From an economic point of view, this suggests that the firms' deviation from the optimal level of the obtainable level of output is not only assigned to the random exogenous shocks, but is also due to the presence of endogenous inefficiency.

When heteroscedasticity is assumed in both u and v , the estimated coefficients of the inefficiency function do not change dramatically. In fact, the model parameters reported in table 5.4, seem to a large extent to resemble their equals in the model reported in table 5.1, especially when it comes to the vector of parameters associated with the three main human capital components.

In fact, there appears to be a very high correlation between the two models' efficiencies, noting that the ranking was affected by the change in specifications between the two models. Still the correct accounting for heteroscedasticity was found to be significant on both estimation and efficiency ranking, concurrently, (Hadri, 1999).

Economically, the low skilled young workers in the ECA region seem to have received inadequate education or training, and have not obtained the necessary skills for the job markets, and as a result they are struggling in the labour market, for being unsuitable and inexperienced, for the rewarding jobs provided by firms. This suggests that this group of low skilled workers face low levels of current wages, and restricted, as well as having finite job chances in the job market.

Table 5.4 Half-Normal Doubly Heteroscedasticity Model: Maximum Likelihood Estimates of the Impact of Human Capital Composition on Inefficiency in Eastern Europe and Central Asia Countries in The Private Manufacturing Firms in 2013.

Production Function Dependent Variable LnQ= (ln Gross Sales)	Model (Translog) Deterministic Component of Stochastic Frontier Models	
	Param.	T-Statistics
Stochastic Frontier Production Function		
Constant	8.96292*** (.19617)	45.69
Ln Capital (K)	.00785*** (.00274)	2.87
Ln Labour (L)	1.07726*** (.09245)	11.65
Ln K ²	.01207*** (.00081)	14.97
Ln L ²	.00184 (.01080)	.17
Ln (K×L)	-.02104*** (.00318)	-6.62
Technical Inefficiency Function (Heteroscedasticity in u and v)		
Constant	-24.0424* (12.78596)	-1.88
Ln Low-Skilled Labour	-.00016 (.00020)	-.82
Ln Highly-Skilled Labour	-.21472** (.09008)	-2.38
Ln Intermediate-Skilled Labour	.95859D-04 (.00055)	.17
Training	-.34364* (.20482)	-1.68
Foreign Shareholders	-.00086* (.00049)	-1.77
GDP Per Capita	-.00057** (.00024)	-2.40
Internet Users	-.05108** (.02267)	-2.25
Distance to Frontier	.23720*** (.07462)	3.18
Economically Active Population (%)	.07222* (.03786)	1.91
Country Specific Effects (a Country Dummy)	.02044 (.03517)	.58
Ln Life Expectancy Rate at Birth, total (years)	.09953 (.14181)	.70
Strength of Legal Rights Index (0-12)	-.33880** (.16925)	-2.00
Bribery	.03178** (.01318)	2.41
Tax on Profits	.05988*** (.01575)	3.80
Rural Population	-.04772** (.02132)	-2.24
Log-Likelihood Function		
Sigma-squared(u)	.71635	
Sigma u	.84637	
Sigma-squared(v)	.99283	
Sigma v	.99641	
Gamma (γ) = sigma(u) ² /sigma ²	.41912	
Sigma = Sqr [(s ² (u)+s ² (v))]	1.30735	
N. obs.	N = 1834, K = 35	
Deg. freedom for inefficiency model	16	
Deg. freedom for heteroscedasticity	15	

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance.
Robust Standard Errors reported in parentheses.

The low and intermediate skills are the ones who are more easily exposed to mechanisation than any other level of skills in the firm, because they are thought to be routine jobs and they are less required than other skills, depending on the role that technology and machinery are playing in the economy as whole. It seems to be the case that in countries, where there is already a greater reliance on technology, that this

segment of skills faces lower levels of risk of losing their jobs than in countries where mechanised jobs still represent a low percentage in the economy.

The gap between education outputs resulting from the divergence and dissimilarity in the social surroundings, and the economic circumstances of educated workers in most European countries, suggests a certain degree of underutilisation of human capital potential in these countries, which is due to the inequality to have access to appropriate amounts of learning to acquire the adequate levels of skills. Even if education – especially tertiary – is accessible to most individuals, and in some countries such as, the Southern Eastern Europe nations, the education system is not compatible with the needs of labour markets. This became more obvious since the beginning of the transitional reforms, from the centrally planned economy towards the free market economy in this region, where unemployment has become a common phenomenon in Eastern Europe and Central Asia ever since.

By way of comparison, the Eastern European nations, in particular, and the region of ECA, in general, trails behind their neighbouring Western European region in terms of the acquisition and endowment of human capital, as well as the extent to which they deploy and utilise the existing stock of human capital with the exception of Slovenia, Hungary, Lithuania, Czech Republic, and Estonia. They have managed to accumulate a certain amount of human capital among their labour force, but they are still unable to approach what is in place in Western Europe. The biggest challenge they are facing is the evolution from an economic growth that is mainly driven by an efficiency-enhancing strategy to a growth that is also prompted by innovative activities.

The reforms in the labour market in ECA varied widely throughout these nations. Some countries witnessed profound cyclical swings between unemployment and employment across the transition process. In the late 90s things started to change and employment rates improved noticeably.

The self-management system of enterprises that is inherited from the centrally planned economy is still oppressing the outcomes of the labour markets in a number of these countries. Meaning that governments have had to strike a balance between job security and protecting the transition process by making firing cost high for firms and by expanding the unemployment programs, which is through better subsidies, job

placement services, benefit administration, providing training schemes, and job creation and information.

The results obtained from the truncated-normal model indicate that the effects of the firm's size – classified into micro, small, medium, and large – is significant and of a positive nature on inefficiency, meaning that the larger the firm is, the less efficient it tends to be, which turns out not to be consistent with theory, because if the large size of the firm leads to the realisation of costs advantages, then the relationship between the size and efficiency is expected to be positive.

Table 5.5 Truncated-Normal Model: Maximum Likelihood Estimates of the Impact of Human Capital Composition on Inefficiency in Eastern Europe and Central Asia Countries in The Private Manufacturing Firms in 2013.

Production Function Dependent Variable LnQ= (ln Gross Sales).	Model (Translog) Deterministic Component of Stochastic Frontier Models	
	Param.	T-Statistics
Stochastic Frontier Production Function		
Constant	9.19561***(.15018)	61.23
Ln Capital (K)	.00440**(.00193)	2.28
Ln Labour (L)	1.03771***(.06629)	15.65
Ln K ²	.01244***(.00078)	15.98
Ln L ²	.00048 (.00841)	.06
Ln (K×L)	-.01801***(.00235)	-7.68
Technical Inefficiency Function (Heteroscedasticity in u only)		
Constant	-.24398***(.06569)	-3.71
Ln Highly-Skilled Labour	-.00023***(.00010)	-2.28
Ln Intermediate-Skilled Labour	.00012 (.00011)	1.16
Ln Years of Education	-.00014* (.8346)	-1.65
Firm's Size	.20051***(.04598)	4.36
Bank Loan	-.15227**(.07213)	-2.11
Foreign Shareholders	-.00076***(.00014)	-5.25
Training	-.36791***(.08053)	-4.75
Firm's Age	-.00054***(.00020)	-2.72
R&D Spending	-.31697***(.13092)	-2.42
EU Membership	-3.04689**(.13659)	-2.23
New Management Practices	-.26391***(.09816)	-2.69
Country Specific Effects (a Country Dummy)	-.04394***(.00657)	-6.68
Life Expectancy Rate at Birth, total (years)	-.14724***(.02804)	-5.25
Strength of Legal Rights Index (0-12)	-.07415***(.01907)	-3.89
Bribery	.01547***(.00159)	9.73
Industry Value Added (% of GDP)	-.03697***(.00624)	-5.92
Population Aged 14-65 (% of total)	.01069*(00458)	2.33
Log-Likelihood Function	-7096.05103	-
$\sigma(u)$.33966	-
Ln-sigma u	15.9684***(.280174)	5.70
$\sigma(v)$	1.14488	-
Ln -sigma v	.13530***(.00860)	15.74
γ	.228798	-
$\sigma = \text{Sqr} [(s^2(u)+s^2(v))]$	1.19420	-
N. obs. [K]	4387 [26]	-
Deg. freedom for inefficiency model	19	-

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Robust standard Errors reported in parentheses.

Plants are said to enjoy a level of economies of scale if they could increase their ability to generate output to a proportionate degree more than the increase in the production

costs. In other words, the average cost per unit of production is expected to decrease as the output grows in the long run.

On the other hand, diseconomies of scale exist when the average cost per unit of production rises with the increase in production. Even so, and having said that, there can be some economic rationalisation for the presence of diseconomies of scale. Where larger enterprises can encounter bureaucratic conflicts, lack of motivation and empowerment among workers, and even some difficulties in monitoring the levels of performance than in smaller enterprises.

The likelihood ratio test shown below in table 5.6 refers to the acceptance of the alternative hypothesis which implies that the translog stochastic frontier production function is the most adequate functional form for this data.

Table 5.6 Generalised Likelihood-Ratio Tests of the null hypothesis.

Null hypothesis, H0	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H0: $\beta_{ij} = 0, i = 1, \dots, 17$			99.5% $\rho = (0.005)$	35.7
H1 is accepted	Translog	-7096.05103	99% $\rho = (0.01)$	33.41
	Cobb - Douglas	-7246.77902	95% $\rho = (0.05)$	27.59
DF Heteroskedasticity (17)	LR Test	301.46	90% $\rho = (0.1)$	24.77

There is another reasoning that can be relevant to market imperfections, and which can result in the ability of larger plants to remain and survive the harsh conditions during the economic slowdowns, which is despite the economic problems they have already been suffering from in their organisational structures and due to the high levels of inefficiency. This is due to the impact of the market selection mechanism, where only small firms, which could show on average higher levels of efficiency than larger ones, sometimes, can survive the ramifications of economic turbulent times.

The foreign-owned firms in the ECA region are more productive and more efficient than those that are purely domestically-owned, and they are more active in the labour market in terms of creating more jobs.

There are many positive effects of global markets, and a more liberalised trade on a firm's performance, which could stimulate more of a reallocation of capital inputs and labour inputs, with different levels of skills throughout the economic activities in the

economy, based on the firms' decision relating to them developing their external orientation, and their foreign investments.

Table 5.7 The distribution of firms' ownership and exports destination in ECA in 2013

Firm Size	Foreign Ownership	Domestic Ownership	World Exports	National Exports	Local Exports	Share of Loans
Micro	1.46%	0.82%	0.00%	0.24%	1.84%	0.64%
Small	10.96%	33.26%	14.86%	30.00%	36.41%	28.99%
Medium	34.06%	41.26%	36.49%	42.20%	41.01%	40.72%
Large	53.53%	24.65%	48.65%	27.56%	20.74%	29.64%
Grand Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Source: author's calculations of the ownership and exports distribution between firms in ECA based on the World Bank survey 2013 dataset.

The larger firms created more jobs than the small and medium firms, and the foreign ownership appears to be more concentrated in the larger firms than in the small and medium ones. Large firms also are in the ascendant in the exportation activities to the global markets, as can be seen in table 5.7.

The trade and investment relationships between ECA and Western Europe were increasingly important determinants of development over the period since 1990, and the integration between the two regions is becoming more important for the scale of international trade and the global economy's growth. This is where the flows of financial capital, and that of goods and services in a free-border environment, provides firms in ECA with the opportunities to access the markets in Western Europe, and reap handsome rewards in the form of more investments, a higher quality in goods and services, and better economic growth.

Many countries in ECA were acceded to the European Union and the World Trade Organisation throughout the last 24 years, which softened the quantitative barriers of tariffs, and lessened the intensity of other protective measures for firms in the ECA countries, to trade with the rest of the world, and it assisted them to develop and improve and harmonise the regulatory and political, as well as market institutional frameworks, in which firms are assumed to operate and progress.

Table 5.8 The percentage of foreign-owned&domestically-owned firms that received loans

Firm Size	Foreign-owned	Domestically-owned
Micro	1.50%	1.17%
Small	11.27%	35.35%
Medium	37.95%	40.52%
Large	49.28%	22.96%
Grand Total	100.00%	100.00%

Source: author's calculations of the ownership distribution between firms in ECA based on the World Bank survey 2013 dataset.

The maximum likelihood estimates also show the importance of funds in the form of loans in promoting firms' efficiency in this region. These are especially the loans received from commercial banks where many countries relied on foreign funding to fuel credit growth.

The privatised financial sector in ECA played an essential role in offering the financial tools needed for firms to develop. The important point here is that many banks in Eastern Europe were parented by banks from the Western economies.

Prior to the Great Recession period, the domestic demand in most ECA economies was relatively strong, and the growth in TFP accounted significantly to the growth in GDP, but during the same period the private consumption and the gross fixed capital formation became a more important leading, and at the same time there was less of an importance of net exports, in terms of its contribution as a ratio of the aggregate demand growth.

The banks offered comparatively higher levels of funding to ECA economies, than in the other economies in Latin America and Asia before the crisis in 2008, but during, and in the wake of the crisis, GDP in Eastern Europe dropped, and its real growth decelerated more than in other regions, such as in Latin America and Asia.

However, countries have varied widely regarding the cross-border bank capital flows, and in the importance of foreign direct investments, and that might be due to various reasons, including the intensity of the reforms that were supposed to take place in the restructuring of governance and the business environment. This is where some

economies in Central Europe, which conducted more compelling reforms, were more attractive to FDIs than other economies in the region, and therefore, they become less contingent – conditional – on banks' capital flows.

The conditions of the manufacturing sector, and its importance in the economy, were another element of the different effects of the cross-border bank flows. Meaning that, in countries where the manufacturing sector was performing better, the economic and trading links with the adjacent Western economies were stronger and FDIs flows were more intense.

It can be also noted that formal training and the R&D spending effects were found to be boosting efficiency in the manufacturing sector in ECA firms. The impact of these two factors, in particular, was investigated in more depth and independently later in this chapter.

The effects of the environmental variables, such as the life expectancy rate at birth measured in years, the strength of the legal rights index, industry value added as a percentage of total GDP, and the economically active population aged between 14 and 65 as a percentage of the total population, were all found to have positive influences on firms' efficiency in ECA economies. These variables, as noted before, are included to reflect the cross-country heterogeneities, as an additional vector of explanatory variables to the mean of the inefficiency term.

The differences in growth in per capita income, the resources endowments of the country, and differences in institutions in ECA countries contributed, at some point, to the ease of transition from the planned economy to the market economy, where for instance, the level of per capita income in Poland grew by almost 51% over the period from 1992 to 2002, meanwhile, it dropped substantially to 63% in Ukraine during the same period.

In respect of human capital utilisation in Eastern Central Europe and the Central Asia region, the surveyed sample of countries shows a low level of utilisation, and it is much lower than the rest of the other European Union nations. Denmark and Netherlands tower above the others in Western Europe, as being the best in terms of utilising their

human capital, meanwhile, Croatia, Slovakia, and Poland are lagging far behind as the worst utilisers of human capital in Eastern and Central Europe. By contrast, Slovenia, the Czech Republic and the Baltic nations are the best human capital utilisers in this region. Yet they still trail behind the Western Europe region in this respect.

Table 5.9 Half-Normal Model: Maximum Likelihood Estimates of the Impact of Human Capital Composition on Inefficiency in Eastern Europe and Central Asia Countries in The Private Manufacturing Firms in 2013 with the Correction for Heteroscedasticity in the One-Sided Error Term (u) only

Production Function Dependent Variable LnQ= (ln Gross Sales)	Translog Frontier Production Function Deterministic Component of Stochastic Frontier Models	
	Param.	T-Statistics
Stochastic Frontier Production Function		
Constant	9.07906*** (.20921)	43.40
Ln Capital (K)	.00682** (.00286)	2.39
Ln Labour (L)	1.04068*** (.10001)	10.41
Ln K ²	.01204*** (.00082)	14.64
Ln L ²	.00443 (.01199)	.37
Ln (K×L)	-.02004*** (.00334)	-5.99
Technical Inefficiency Function (Heteroscedasticity in u only).		
Constant	-11.2946** (5.26300)	-2.15
Ln Low-Skilled Labour*Ave. Years of Education	-.39114D-04 (.00024)	-.16
Ln Highly-Skilled Labour*Ave. Years of Education	-.29935** (.11633)	-2.57
Ln Intermediate-Skilled Labour* Ave. Years of Education	.00026 (.00083)	.31
Ln Average Years of Education (Squared)	-.18922 (.46538)	-.41
Ln Average Years of Education	.48939 (.45995)	1.06
GDP Per Capita	-.00040** (.00013)	-3.05
Training	-.52498** (.25900)	-2.03
R&D Spending	-.05713 (.31733)	-.18
Internet Users	-.05197** (.02380)	-2.18
Distance to Frontier	.18925*** (.05279)	3.59
Country Specific Effects (a Country Dummy)	-.00660 (.02942)	-.22
Economically Active Population (%)	.06562** (.03025)	2.17
Strength of Legal Rights Index (0-12)	-.13945 (.12405)	-1.12
Bribery	.02036* (.01085)	1.88
Tax	.06014*** (.02005)	3.00
Rural Population	-.03589** (.01721)	-2.09
Log-Likelihood Function	-2759.45599	
Sigma-squared(u)	.74044	
Sigma u	.86049	
Sigma-squared(v)	1.02035	
Sigma v	1.01012	
Gamma (γ) = sigma(u) ² /sigma ²	.42052	
Sigma = Sqr [(s ² (u)+s ² (v))]	1.32694	
N. obs.	N = 1834, K = 24	
Deg. freedom for inefficiency model	17	
Deg. freedom for heteroscedasticity	16	

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Robust Standard Errors reported in parentheses.

High-income economies and smaller European nations, such as the Nordics and Switzerland, along with the U.S. and Germany leading the Global Human Capital Index, 2017. As for Eastern Europe, Slovenia (9), Estonia (12), and Russia (16) are ranked among the index's top 20 nations with the Czech Republic in the 22nd place. One nation from Central Asia, Kazakhstan, was ranked 29th, but it came in the 2nd place in the capacity sub index, which measures the level of formal education among young and older generations, as a result of investments in education in the past. It considers literacy

and numeracy, and education attainment rates in primary, secondary, and tertiary education.

High unemployment plays crucial role in this problem of human capital under-deployment in the ECA region. This is where countries that have experienced low rates of employment, across different age groups, were prevented from improving their human capital skill profiles at a quicker pace, as in those countries with lower rates of unemployment. This is partly due to the inability of labour markets to employ and absorb talented people, given the skills and capability they currently hold.

Foreign direct investments contributed substantially to the Eastern Europe and Central Asia labour markets by improving employment levels, through the high demand for labour in the host nations, where they are mainly attracted by the low levels of wages, but the foreign direct investments usually tend to deploy more advanced, and sometimes sophisticated technologies in production, and the less skilled workers in these nations do not hold the level of skills that could qualify them for the jobs offered, which resulted in a decrease in the demand for low-skilled labour, and shifted the interest of the foreign firms towards the highly-educated workers by offering them better paid jobs. The resultant increase in output implied an improvement in the level of wages in the ECA region, but the wage gap between these nations, especially those that joined the EU over the last decade and some of the Western European nations, is still significant despite the slow-moving GDP growth that was achieved in the ECA region, but it does not seem to be sufficient to bring unemployment rates down and create more job opportunities for the low skilled labour.

As for the average years of education variables, they are found to have a positive impact on a firm's efficiency only through their interaction with the percentage of workers with a tertiary education, while this does not seem to be the case when looking at the interaction terms of the average years of education, with the shares of both low and semi-skilled workers with lower levels of education, where the average years of education are not key for technical efficiency in this case. See table 5.9.

This suggests that the efficiency externalities of human capital stock mainly rely on the share of highly-educated labour in ECA countries.

However, this quantitative measure of human capital accumulation implicitly assumes the similarity in the quality of the knowledge of skills received by students in different education systems. This assumption is one of the major drawbacks of this proxy, as discussed earlier.

A measure of education quality – based on international student achievement tests – might be an option to assess the average educational performance of the total labour force of an economy, and could be more definite when associating human capital accumulation with growth. However, the problem is the shortage of data, and the lack of sources that document the developing countries performance in terms of students' scores in the international science and mathematics tests.

Economically, the importance of the proportion of workers with tertiary education in the transition economies over those workers with primary/secondary education, emphasises the different contributions of different components of human capital to growth, which largely depends on the level of development in a country/region. Highly skilled individuals are the key, and are better suited to activities relating to generating new ideas and technologies and inventing new equipment and machines to enhance growth. While low skilled and semi-skilled individuals seem to be better associated with adoption activities, and the absorption of technologies produced in the advanced economies (technology frontier), in order to be implemented in low and middle-income economies (backward economies) as a means to converge with the technological frontier.

In table 5.13, human capital composition is disaggregated into three levels (high, intermediate, and low) and skilled labour and the maximum likelihood estimation is performed for each component separately using three stochastic frontier production functions.

Overall, the outcome of the estimation does not differ considerably from the results obtained from the estimation, reported in table 5.1, where the three components effects on inefficiency are estimated in the same model. The average years of education of a permanent full-time worker gives the impression of positively contributing to the firms' efficiency. However, it seems to be only significant when associated with the percentage of workers with tertiary education as shown in model (1) in table 5.13.

Table 5.10 Generalised Likelihood-Ratio Tests of the null hypothesis. Highly-Skilled labour

Null hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 1, \dots, 12$			99.5% $\rho = (0.005)$	28.3
H ₁ is accepted	Translog	-2764.67119	99% $\rho = (0.01)$	26.2
	Cobb - Douglas	-2871.69729	95% $\rho = (0.05)$	21.0
DF Heteroskedasticity (12)	LR Test	214.0522	90% $\rho = (0.1)$	18.5

As far as the LR test results are concerned, H₁ hypothesis is preferred over H₀. This means that the translog form of the stochastic frontier production function is the more adequate functional form to represent this data. The results are reported in tables 5.10, 5.11, and 5.12.

Table 5.11 Generalised Likelihood-Ratio Tests of the null hypothesis. Intermediate-Skilled labour

Null hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 1, \dots, 12$			99.5% $\rho = (0.005)$	28.3
H ₁ is accepted	Translog	-2767.72859	99% $\rho = (0.01)$	26.2
	Cobb - Douglas	-2875.12609	95% $\rho = (0.05)$	21.0
DF Heteroskedasticity (12)	LR Test	214.795	90% $\rho = (0.1)$	18.5

Table 5.12 Generalised Likelihood-Ratio Tests of the null hypothesis. Low-Skilled labour

Null hypothesis, H ₀	Production Function Form	Log Likelihood Function	ρ	Critical Values of the χ^2 Distribution
H ₀ : $\beta_{ij} = 0, i = 1, \dots, 12$			99.5% $\rho = (0.005)$	28.3
H ₁ is accepted	Translog	-2767.53177	99% $\rho = (0.01)$	26.2
	Cobb - Douglas	-2875.00566	95% $\rho = (0.05)$	21.0
DF Heteroskedasticity (12)	LR Test	214.94778	90% $\rho = (0.1)$	18.5

Table 5.13 Maximum Likelihood Estimates in Eastern Europe and Central Asia Countries in The Private Manufacturing Sector in (2013).
(The Effects of Highly, Intermediate, and Low-Skilled Disaggregated Human Capital on Inefficiency) with the Correction for Heteroscedasticity in (u) only

Production Function Dependent Variable Ln Q = (ln USD Gross Annual Sales)						
Stochastic Frontier Production Function						
Human Capital Variables	(Model 1) Highly-Skilled Human Capital		(Model 2) Intermediate-Skilled Human Capital		(Model 3) Low-Skilled Human Capital	
Variables	(Translog function)	t-statistics	(Translog function)	t-statistics	(Translog function)	t-statistics
Constant	9.00159*** (.20527)	43.85	9.01789*** (.20625)	43.72	9.03406*** (.20774)	43.49
Ln Capital	.00705** (.0287)	2.46	.00685** (.00288)	2.38	.00673** (.00288)	2.34
Ln Labour	1.02927*** (.10020)	10.27	1.0194*** (.10006)	10.19	1.01013*** (.10034)	10.07
Ln Capital Squared	.01232*** (.00083)	14.89	.01236*** (.00083)	14.90	.01235*** (.00083)	14.90
Ln Labour Squared	.00704 (.01198)	.59	.00783 (.01193)	.66	.00851 (.01191)	.71
Ln K*L	-.02056*** (.00336)	-6.12	-.02042*** (.00337)	-6.06	-.02029*** (.0337)	-6.03
Technical Inefficiency Function (Heteroscedasticity in u only)						
Constant	-31.9057** (15.02651)	-2.12	-31.4819** (15.01583)	-2.10	-31.1302** (15.13292)	-2.06
Ln Low-Skilled Labour	-	-	-	-	-.00016 (.00022)	-.71
Ln Highly-Skilled Labour	-.20664** (.10143)	-2.04	-	-	-	-
Ln Intermediate-Skilled Labour	-	-	.0028 (.00066)	.42	-	-
Ln Average Years of Education	-.0059* (.00030)	-1.94	-.00046 (.00029)	-1.59	-.00043 (.00031)	-1.40
GDP Per Capita	-.00064*** (.00024)	-2.69	-.00059*** (.00022)	-2.68	-.00062** (.00025)	-2.54
Internet Users	-.05883* (.03051)	-1.93	-.06495** (.03226)	-2.01	-.05905* (.03182)	-1.86
Distance to Frontier	.27050*** (.08031)	3.37	.23938*** (.07441)	3.22	.25957*** (.08320)	3.12
Country Specific Effects (a Country Dummy)	.03427 (.04491)	.76	.03086 (.0459)	.68	.03850 (.04597)	.84
Ln Life Expectancy Rate at Birth, total (years)	.16276 (.17169)	.95	.17608 (.17057)	1.03	.14660 (.17236)	.85
Strength of Legal Rights Index (0-12)	-.34118* (.20152)	-1.69	-.27238 (.19427)	-1.40	-.32599 (.21028)	-1.55
Bribery	.03061** (.01539)	1.99	.02380 (.01459)	1.63	.02753* (.01577)	1.75
Tax	.07222*** (.02312)	3.12	.07161*** (.02511)	2.85	.07014*** (.02462)	2.85
Rural Population	-.05483 (.02366)	-2.32	-.05476** (.02360)	-2.32	-.05531** (.02421)	-2.28
Active population (15-64) (% total).	.06889* (.03533)	1.95	.07328** (.03634)	2.02	.06828* (.03596)	1.90
Log-Likelihood Function	-2764.67119		-2767.72859		-2767.53177	
Sigma-squared(u)	.65951	-	.66116	-	.65510	-
Sigma u	.81210	-	.81312	-	.80938	-
Sigma-squared(v)	1.04175	-	1.04304	-	1.04423	-
Sigma v	1.02066	-	1.02129	-	1.02187	-
Gamma (γ) = $\sigma(u)^2/\sigma(v)^2$.38766	-	.38796	-	.38550	-
Sigma = $\sqrt{[s^2(u)+s^2(v)]}$	1.30433	-	1.30545	-	1.30358	-
N. obs.	N = 1834, K = 20	-	N = 1834, K = 20	-	N = 1834, K = 20	-
Deg. freedom for inefficiency model	13	-	13	-	13	-
Deg. freedom for heteroscedasticity	12	-	12	-	12	-

Notes: * significant level at 90%. ** significant level at 95%. *** significant level at 99% level of significance. Robust Standard Errors reported in parentheses.

5.3 The Effects of Formal Training on the Manufacturing SME's Performance in Eastern Europe and Central Asia Countries.

5.3.1 Empirical Results and Economic Analysis

5.3.1.1 Ordinary Least Squares, Probit Models and Propensity Score Matching Results

Before evaluating the causal effects of training on productivity using propensity score matching, a probit model – which is regarded as the preliminary step in PSM technique – was estimated.

Table 5.14 The Effects of Formal Training on Output Per Worker in ECA countries' Manufacturing Firms

Explanatory Variables	OLS Model	Probit Model
	Dep Var: Ln. Output Per Worker	Dep Var: Training
Training	0.278*** (0.0411)	-
Firm Size	-	0.223*** (0.0268)
Infrastructure	-	0.0692*** (0.0203)
Loan	0.331*** (0.0401)	0.251*** (0.0426)
New Production Processes	0.124** (0.0434)	0.566*** (0.0448)
GDP Per Capita Income	0.0000988*** (0.00000355)	0.0000198*** (0.00000405)
Legal Rights Index	0.0488*** (0.00852)	-0.0459*** (0.0115)
Sector dummy (Med Tech)	0.286*** (0.0511)	0.0638 (0.0550)
Sector dummy (High Tech)	0.227*** (0.0420)	0.114* (0.0466)
Licensed Technology in Use	-	0.346*** (0.0550)
Industry Share of Gross GDP	-	-0.0128** (0.00444)
Constant	8.349*** (0.0770)	-0.721*** (0.192)
N	4385	4336
R ²	0.210	Pseudo R ² = 0.0895
LR Chi2 (10)	-	504.23
Prob > Chi2	-	0.0000
F (7, 4377)	163.57	-
Prob > F	0.0000	-

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The independent variables included in this model are; the size of the firm, the accessibility to adequate infrastructure, accessibility to funds in the form of loans, the use of foreign

technology imported from a parent company, and other country level variables such as; GDP per capita, the strength of the legal rights index, and the share of industry GDP of total GDP.

The results reported in the OLS model indicate that formal training seems to have a significant causal impact on productivity. This is where it suggests that an increase in the share of permanent full-time production workers by one percentage point is associated with approximately 0.3% increase in productivity.

Table 5.15 The Effects of Formal Training on Output Per Worker in ECA countries' Manufacturing Firms

Explanatory Variables	OLS Model	Probit Model
	Dep Var: Ln. Output Per Worker	Dep Var: Training
Training	0.248*** (0.0405)	
World Exports	0.297*** (0.0620)	0.214** (0.0671)
National Exports	0.408*** (0.0403)	0.161*** (0.0448)
Firm Size		0.208*** (0.0273)
Infrastructure Accessibility		0.0704*** (0.0203)
Loan	0.285*** (0.0402)	0.239*** (0.0428)
New Production Processes	0.0928* (0.0433)	0.555*** (0.0449)
GDP Per Capita Income	0.0000978*** (0.00000356)	0.0000154*** (0.00000389)
Legal Rights Index	0.0395*** (0.00862)	-0.0308*** (0.00918)
Sector Dummy Med-Technology	0.264*** (0.0507)	0.0536 (0.0551)
Sector Dummy High-Technology	0.176*** (0.0420)	0.0933* (0.0470)
Licensed Technology		0.328*** (0.0551)
Constant	8.253*** (0.0774)	-1.222*** (0.0933)
N	4385	4336
R ²	0.229	Pseudo R2=0.0909
LR Chi2 (11)	-	512.34
Prob > Chi2		0.0000
F (9, 4375)	141.70	-
Prob > F	0.0000	-

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results obtained from the probit model in table 5.14 and table 5.15 suggest that the firm that has offered formal training to its employees is likely to be a large-sized firm, exporting firm, has received a fund in the form of a loan from a commercial bank, and is able to have access to vital infrastructure, such as power and electricity sources, water supplies for production, and telecommunications.

The firm is also expected to have introduced and developed new production approaches over the last three complete fiscal years, and used licensed technology in production imported from a patentee or a license holder, which might be the establishment's parent company in some cases.

At the macroeconomic level, the firm is likely to operate in an economy where the level of GDP per capita income is relatively high, and the percentage of the industry sector's GDP share in the total GDP is high as well.

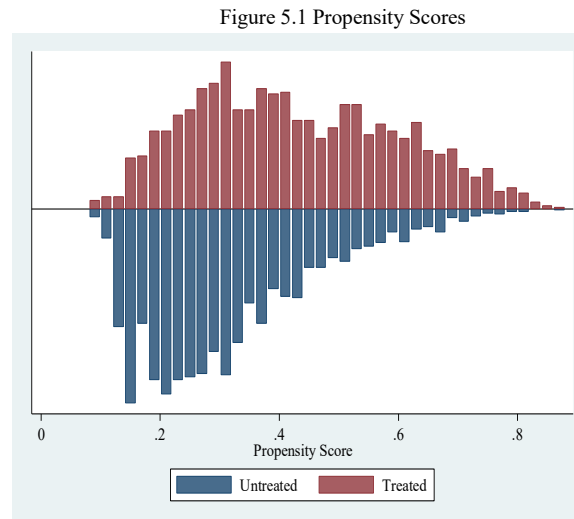
The reason for incorporating a vector of environmental variables into the cross-sectional stochastic frontier production function is to reflect the cross-country economic, regulatory, and legal differences, which is important to explain part of the productivity estimation, and which is also appraised as a necessary step to overcome the shortcomings of cross-sectional data.

Table 5.15 shows that the average treatment of the treated ATT is significant from a statistical point of view, meaning that the impact of formal training on productivity is positive, and firms with training programs, offered for their permanent full-time workers, are more productive than those without training.

By economic reasoning, it can be said that workers need to be well acquainted with the software packages, machines and equipment with which they are going to operate in the production process. Given that some of the skills, which need to be acquired by workers to become more efficient in production, are highly firm-specific, then there is a risk, from the worker's viewpoint, in taking part in some training programs that might be given only a little importance to in other production units.

Firms may incentivise workers to participate in specific training schemes and might entice them with higher wages or promotions, but the firm could back out of its promises claiming that the worker is not able to materialise the skills acquired into goods and services of economic value.

On the other hand, the firm expects the newly-trained worker to take advantage of the specific set of skills and bargain for an increase in remunerations, knowing that an immediate replacement option might not be possible sometimes for the firm, and if so, it will be at a significant cost.



The above graph illustrates the pattern of the treated and untreated units in this sample of firms. This is where the red bars refer to the firms that have offered formal training to their workers, while the blue bars represents to those firms which did not training for their employees.

5.3.1.2 Nearest Neighbour Matching

Table 5.16 Nearest Neighbour Matching, with replacement, and no caliper

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln Output Per Worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3046874	10.1114584	.193229038	.070375754	2.75

The ATT estimation, highlighted in table 5.16, shows the significant causal effect of training on output per worker, and by comparing the means of the outcome variable in tables 5.18 and 5.19 it can be shown that the logged value of the output per worker mean in firms with training is bigger than the mean in firms without training.

However, labour markets in Europe suffer from a high percentage of long-run unemployment, meaning that the workers' outflows from unemployment towards the labour market are weak, which causes a longer period of unemployment on average.

Longer unemployment duration implies an underutilisation of human capital, and a considerable loss in skilful workers who can become demotivated and demoralised, especially during the prevalence of the inappropriate measures of active labour market policies.

The non-utilised ratio of human capital stock in an economy usually includes those who are unemployed, which are the housewives who chose not to work, children, pensioners, and university students. The low level of human capital participation in the active work force can have other consequences in addition to the lack of the economic optimisation of skills, where workers – low and highly skilled – are not just deprived from being part of the labour force, but also, they tend to miss an important part in the skill-acquisition process via the on-the-job-training, or learning-by-doing, and keeping pace with the new innovations in the field that they work in.

In many countries of the surveyed sample, that is in Eastern, Central Europe and Central Asia such as Bulgaria, Slovakia, and Romania, the lack of adequate and efficient internet broadband services, and new technologies in telecommunications, are factors that have caused workers to miss out on some opportunities to re-join and participate quickly in the labour markets, and grasp the new developments in technologies and innovations during their unemployment and job-search period.

Table 5.17 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,801	2,801
Treated	1,535	1,535
Total	4,336	4,336

It is found that the effectiveness of unemployment and human capital improvement programs is low. Training strategies could have positive effects in terms of boosting

individual skills, and the knowledge of the workers, who have been unemployed for a while, but the prospects of the job market for them have not been improved. This means that their ability in finding a job, and encouraging them to return quickly to the labour market through improving their tactics in the search for suitable occupations, is the important issue that needs to be given more attention.

The other fundamental point is the quality of assessing the corrective measures relating to improving the workers' skills. The worker's selection of a training program will be driven mainly by the benefits expected from the program itself. Moreover, there is a time gap between the point at which a worker is laid off and the period before such corrective measures can be implemented. This could affect the worker's decision regarding their participation in a training program, because an individual might be unemployed for some time, and was not able to find a job, and this will drive them to join the program to enhance their job search prospects.

Table 5.18 Summary of Output Per Worker If Training = 1 [fw= weight] (Formal Training Provided)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln output per worker	1535	10.30469	1.335709	4.400592	17.03949

Table 5.19 Summary of Output Per Worker If Training = 0 [fw= weight] (No Formal Training Provided)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln output per worker	1535	10.11146	1.351261	4.063308	15.71845

The means of the logged value of the output per worker in the above tables 5.18 and 5.19, indicate that labour productivity in firms with formal training programs is higher than those firms without training programs.

According to table 5.15, export-oriented firms, either towards national or international markets, appear to be more productive than other firms that are oriented towards their local markets.

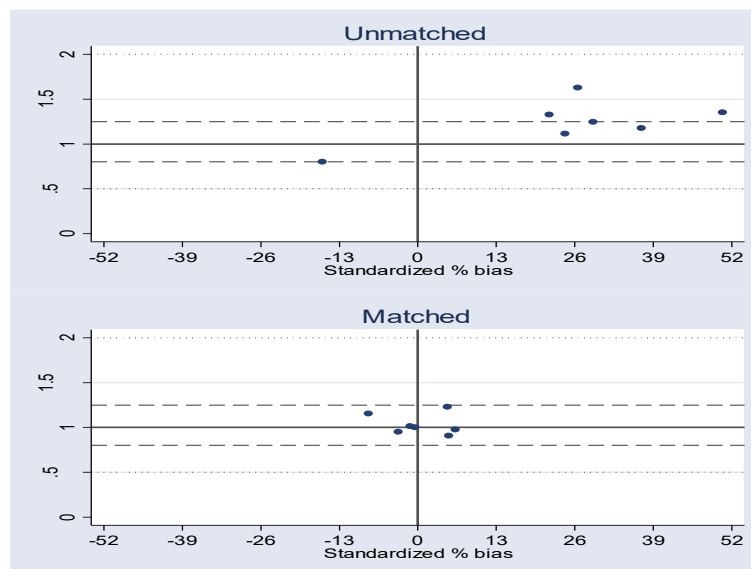
The exporting firms also seem to be providing formal training for their employees more than non-exporting firms.

However, in this sample, large and medium firms' exports are more concentrated towards the intranational market, whereas, small firms' exports are more directed towards the national and local markets, based on the figures shown in table 5.7 in the previous subsection.

Large firms enjoy cost advantages over small firms. From a theoretical viewpoint, the expansion of production can be used as a machine to achieve cost savings. One of the larger size advantages is that the organisation and allocation of resources can be achieved more efficiently.

Figure 5.2 shows the scatter of the observed covariates in the matched and unmatched samples. It can be seen that the balance of the matched sample units needs to improve by imposing an option of common support, such as a 0.02 caliper, in order to obtain better balancing.

Figure 5.2 Nearest Neighbour Matching, with replacement, and no caliper, scatter



In addition, production factors (labour and capital) can be allocated for different tasks in the same enterprise, which usually results in higher capital and labour productivity, as the scale of the operations becomes larger, where in small firms this strategy cannot be implemented because of resources limitations.

Moreover, some small firms might not need a sophisticated technological innovation to operate; whereas, in larger firms the adoption of such technologies is both feasible and affordable where it leads to higher levels of performance and better competitiveness.

Table 5.20 Nearest Neighbour Matching, with replacement, and with caliper 0.02

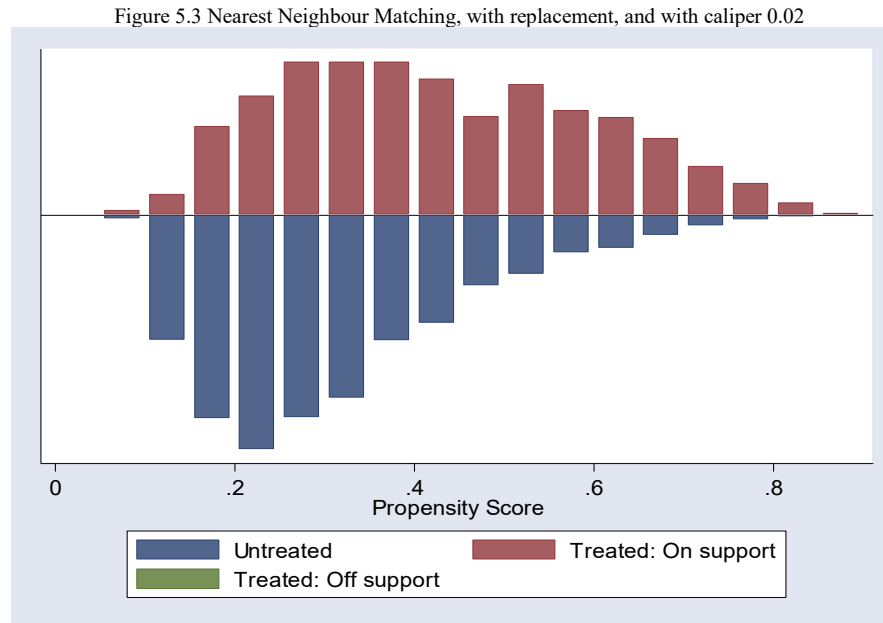
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3039854	10.1094818	.194503667	.070328085	2.77

The ATT estimation, in tabel 5.20, resulting from the nearest neighbour matching with a 0.02 caliper indicates the significant impact of training on productivity. It should be noted that the result does not differ from the results obtained from the nearest neighbour matching without a caliper, which was reported previously, and it is only 1 treated unit that was discarded when applying the with replacement option. Therefore, the number of the on-support treated units became 1,534 observations that remained to do the matching.

Table 5.21 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support		Total
	Off support	On support	
Untreated	0	2,801	2,801
Treated	1	1,534	1,535
Total	1	4,335	4,336

The figure below suggests that the blue bars indicate the untreated units in the sample, while the red bars refer to the on-support treated units, which are included in the matching, after the 0.02 caliper, and the green bars are supposed to represent the treated units that are discarded from the matching. In this case, the green colour cannot be highlighted properly in the figure, because of the very small number of the off-support treated units, this is where only one unit was excluded.



5.3.1.3 Matching Quality

To judge the efficacy of the matching strategy and trust the results obtained regarding the significant causal effect of training on labour productivity, the balancing, in the below figure 5.5, needs to be checked, which shows the good balancing achieved via this procedure.

Table 5.22 Nearest Neighbour Matching, with replacement, and with caliper 0.02

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3039854	10.1094818	.194503667	.070328085	2.77

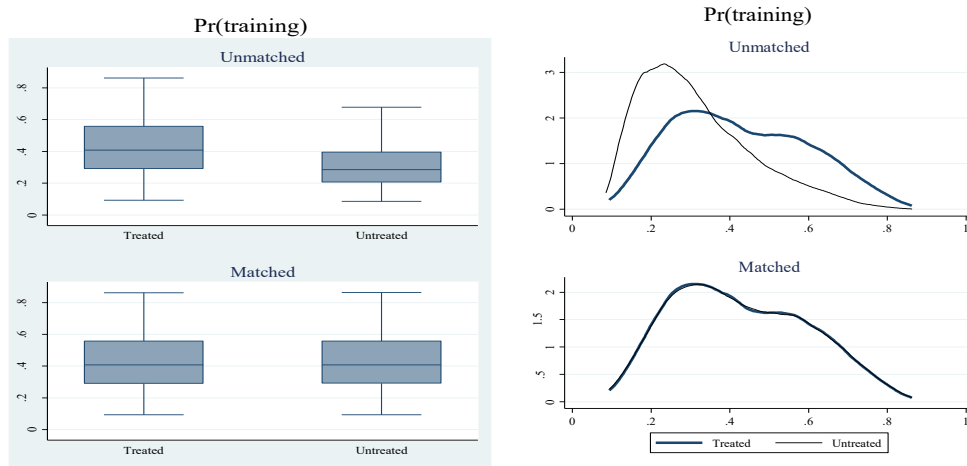
The difference in the ATT estimation is positive. This means that the effects of training of the output per worker are positive, and the T-stat indicates that the causal effects of training are statistically significant at 95%.

Table 5.23 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support		Total
	Off support	On support	
Untreated	0	2,801	2,801
Treated	1	1,534	1,535
Total	1	4,335	4,336

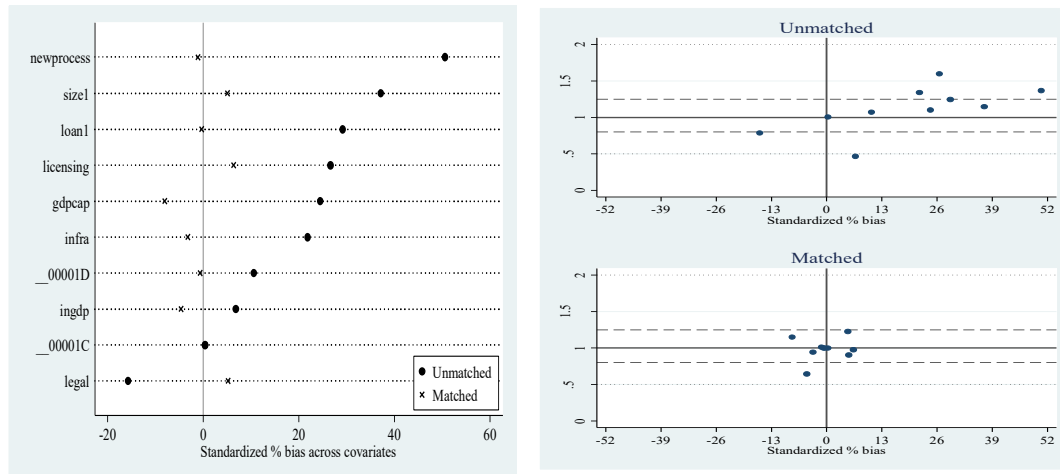
In the treated sample, there is only unit which was not included in the matching.

Figure 5.4 Nearest Neighbour Matching, with replacement, and with caliper 0.02



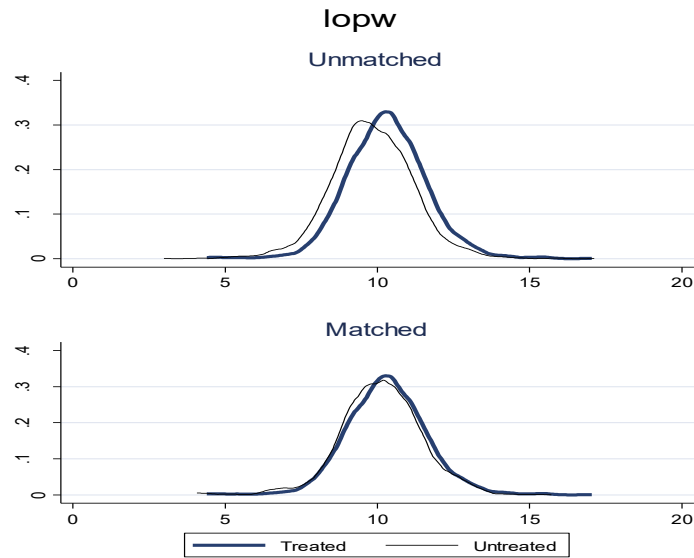
The matched samples – the treated units and untreated units – in the above figures seem to be extremely well aligned, which suggests a good quality of the matching process using a 0.02 caliper.

Figure 5.5 Nearest Neighbour Matching, with replacement, and with caliper 0.02



The covariates balancing is much better this time. This is where the matched units are better clustered around the zero.

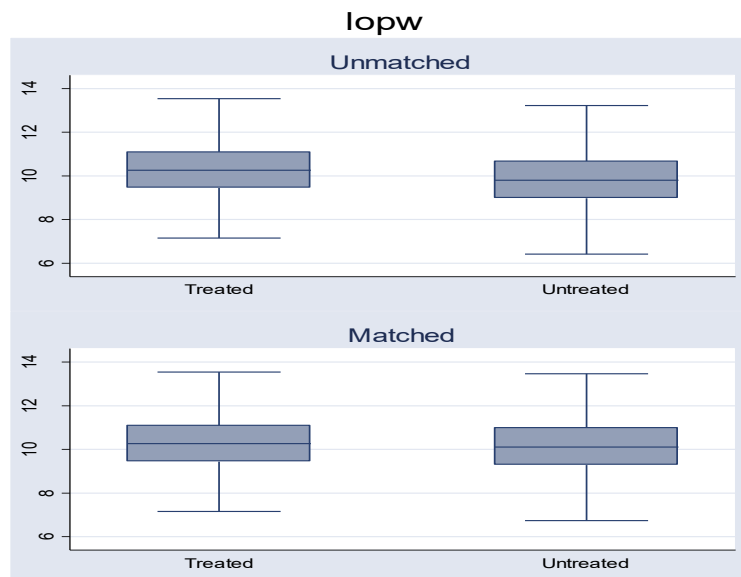
Figure 5.6 Ln output per worker > 21.94 unmatched and matched densities



The intersection between the two curves of the output per worker densities of the matched sample – treated and untreated – suggests a good level common support.

The good alignment in the figure below, between the treated and untreated units in the matched sample confirms the good level of the common support, which has just been mentioned in the above remark.

Figure 5.7 Ln Output Per Worker, Both Box



It is important to note that, when imposing a caliper of 0.04 in the matching, the significance of the treatment effects, and the balancing of the covariates, are exactly the same as the ones obtained when the matching was achieved with a 0.02 caliper.

5.3.1.4 Nearest Neighbour Matching, without replacement, and without a caliper

As was discussed in the methodology chapter, the ‘without replacement’ option has been chosen, in order to prevent each treated unit from being used as a match more than once in the matching with the control units.

Table 5.24 Nearest Neighbour Matching, without replacement, and without caliper

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3046874	10.0170795	.287607958	.048906916	5.88

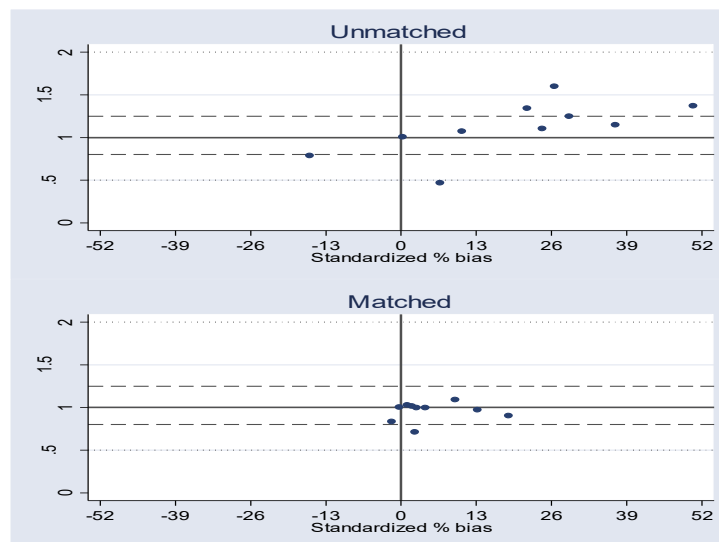
The results show a positive impact of training on firms’ performance with a higher level of statistical confidence. The common support level is good, with 1,535 treated units being included in the matching.

Table 5.25 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,801	2,801
Treated	1,535	1,535
Total	4,336	4,336

The balancing of the regressors, in the figure below, shows that they might need some improvement in the bias reduction, by using a 0.02 caliper.

Figure 5.8 Nearest Neighbour Matching, without replacement, and without caliper



5.3.1.5 Nearest Neighbour Matching, without replacement, and with caliper 0.02

The below figure 5.9 shows the better balance obtained from the nearest neighbour matching when imposing the without replacement option in the matching procedure. It illustrates the balance of the matched sample when allowing for one unit of the comparison case to be used only once, as a match for the treated units.

It might be an option to impose some forms of common support. Hence, the caliper matching (0.02 and 0.04) could be used, and to see whether the matching is going to be feasible after the possible exclusion of some observations from the sample.

The caliper is a way to impose a common support from the propensity score point of view, by eliminating a treated unit that is unmatched whose nearest match is further away – further than the caliper – where a number of treated units who have a match might be left out from the analysis, because they are not similar in terms of their propensity scores, and therefore, they are excluded, in order to find a close enough and more reliable match.

Table 5.26 Nearest neighbour matching, without replacement, and with caliper 0.02

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.2434315	10.0256991	.21773247	.052180437	4.17

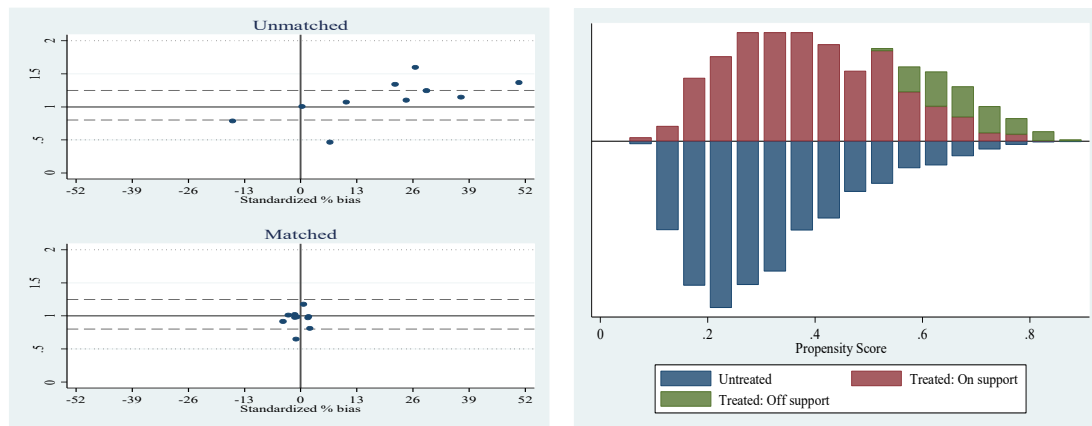
The difference in the ATT estimation, shows a positive and statistically significant impact of training on performance.

Table 5.27 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support		Total
	Off support	On support	
Untreated	0	2,801	2,801
Treated	219	1,316	1,535
Total	219	4,117	4,336

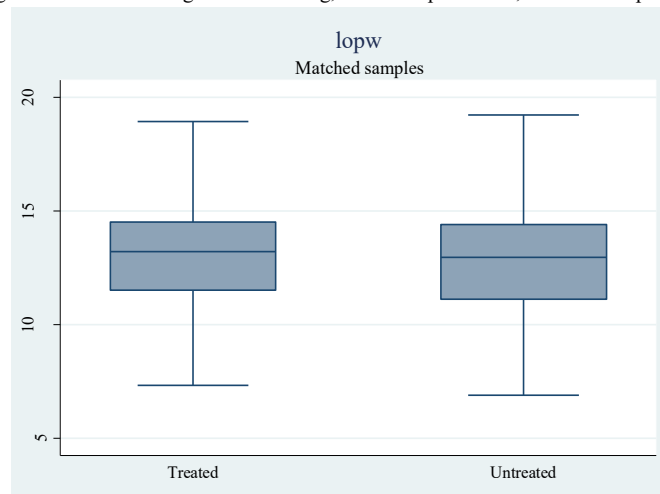
The summary of units off and on support in table 5.27 shows that the ‘*without replacement and caliper*’ matching, discarded 219 treated units. Therefore, the number of the on-support treated units became smaller with 1,316 observations that remained to do the matching.

Figure 5.9 Nearest Neighbour Matching, without replacement, and with caliper 0.02



The green bars in the above figure represent the number of the off-support treated units that are excluded from the matching. Specifically speaking, the green bars represent the 219 units shown in the assignment summary table above. Whereas, the red bars refer to the 1,316 observations treated units that are included in the matching.

Figure 5.10 Nearest Neighbour Matching, without replacement, and with caliper 0.02



The treated and untreated matched units appear to be extremely well aligned when imposing a caliper in the matching without replacement.

5.3.1.6 Nearest Neighbour Matching, without replacement, and with caliper 0.04

The matching results reported in the table below, and obtained from imposing a 0.04 caliper are identical to the results obtained from the same matching when a caliper of 0.02 was imposed in the previous sub-section, and the balancing of the covariates is with the same quality as well.

Table 5.28 Nearest Neighbour Matching, without replacement, and with caliper 0.04

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.244328	10.0256991	.218628976	.052403379	4.17

It is also noted that 219 treated observations were discarded from the matching when the option of “*no replacement*” was implemented, because these observations are not allowed to be used more than once in the comparison with the control group units, this means that 1,316 treated observations remained to do the matching.

Table 5.29 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support		Total
	Off support	On support	
Untreated	0	2,801	2,801
Treated	219	1,316	1,535
Total	219	4,117	4,336

In summary, the output of the 0.04 caliper matching is identical to the output of the 0.02 caliper matching, in terms of the bias reduction in the covariates, the statistical significance of the impact of formal training on firms’ performance, and in terms of the number of the treated units that are discarded from the matching without replacement.

5.3.1.7 Mahalanobis-metric Matching

The t-distribution at 95% and with 7 degrees of freedom is equal to 1.90, which is less than the t-stat of 2.74 reported in the Mahalanobis metric matching table below. The advantage of the Mahalanobis matching is that it provides a better balance for the X’s in the regression, especially with the inclusion of the score, as it appears in table 5.30, where it demonstrates a higher level of statistical significance ($3.18 > 1.90$) for the effects of formal

training on labour productivity in the ECA manufacturing firms at 95% with 7 degrees of freedom.

The reported ATT estimation, in tables 5.30, and 5.32 using the Mahalanobis and Augmented Mahalanobis matching, indicates the significant impact of training programs on productivity in ECA. To judge the efficacy of the matching strategy and to trust this result, the balancing needs to be checked. Where in the below figures, it can be shown that matching using Mahalanobis and Augmented Mahalanobis resulted in a very good balancing.

Economically speaking, although some countries in ECA have made pronounced efforts with regard to more investments in the technical and vocational training and education, to improve their human capital productivity, namely in countries like Slovakia, Bulgaria, Romania, Turkey, Latvia, and others, this kind of education is still in need of more improvement in most of the formal job markets in the region.

A good balancing is achieved for the confounding covariates via Mahalanobis metric matching, and was even better when including the propensity scores in the augmented Mahalanobis matching. However, the resulting estimates are not particularly close to the benchmark, but it suggests that these are sufficient enough to control for selection bias.

Table 5.30 Mahalanobis Metric Matching

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3046874	10.1152925	.189394947	.069035169	2.74

Table 5.31 Treatment Assignment

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	2,801	2,801
Treated	1,535	1,535
Total	4,336	4,336

The balancing of the covariates is good using the Mahalanobis matching technique, and without any loss in the matched observations as can be seen in figures 5.11 and 5.12.

Figure 5.11 Mahalanobis Metric Matching, Scatter

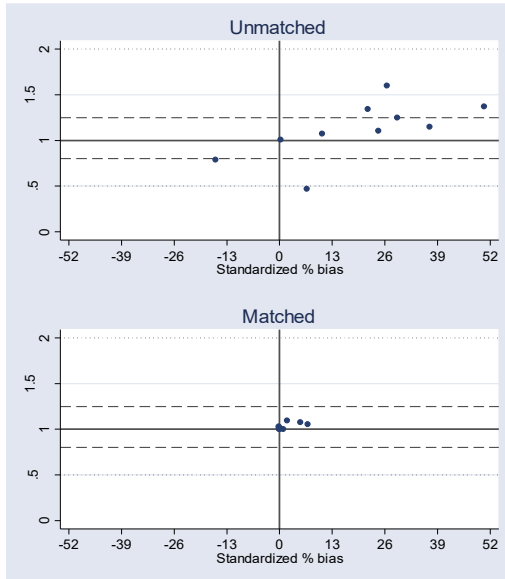
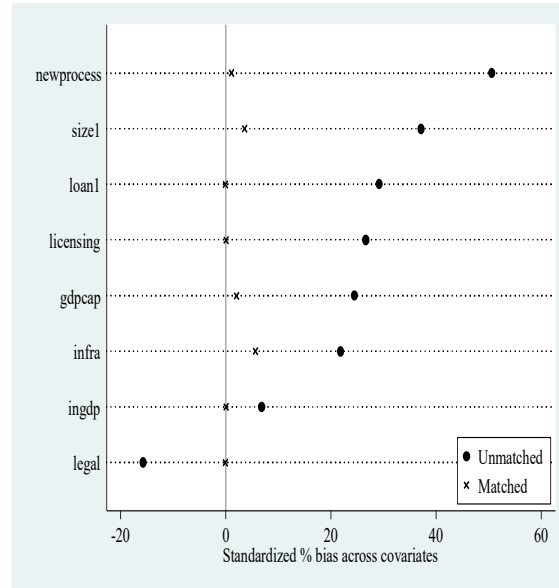


Figure 5.12 Mahalanobis Metric Matching, Graph



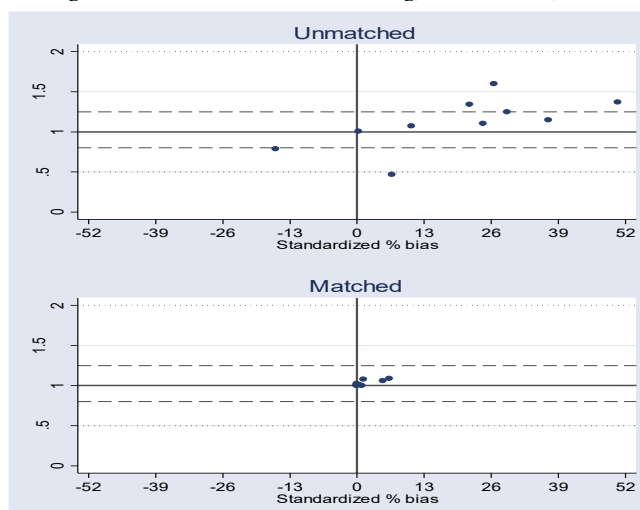
The significance of the training contribution to productivity, appears to be higher when including the propensity scores in the Mahalanobis matching, and the balancing of the explanatory variables is much better than in previous matching procedures, and without any loss in the matched sample as well.

Table 5.32 Augmented Mahalanobis Metric Matching, Score Included

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.3046874	9.81505012	.489637296	.043067817	11.37
	ATT	10.3046874	10.0852644	.219423042	.068935919	3.18

The confounding covariates are much better balanced in the augmented Mahalanobis metric matching, as shown in figure 5.13. This means bias has been reduced significantly well in comparison with previous matching suggestions.

Figure 5.13 Mahalanobis Metric Matching, Score included, scatter



5.3.1.8 Comparison between propensity score matching and Mahalanobis metric matching

From the table below, it can be seen from the comparison between the propensity score matching and Mahalanobis metric matching outcomes that, the bias reduction has gradually improved using the Mahalanobis and Augmented Mahalanobis matching. Note that, the figures which are shown in the table are in percentages (%) to demonstrate by how much the bias was reduced. This means that, the bigger the number, the better it is.

Table 5.33 Bias reduction percentage (%) in the confounding covariates using PSM&MDM

Variable	Propensity score matching with replacement and without a caliper	Propensity score matching with a 0.02 caliper	Propensity score matching without replacement and with a 0.02 caliper	Mahalanobis metric matching	Augmented Mahalanobis metric matching
World exports shares	75.1	76.4	76.4	98.7	98.7
National exports shares	96.5	95.6	95.6	96.5	94.7
Firm size	85.6	85.6	85.6	73.3	76.3
Infrastructure access	93.7	94.4	94.4	72.7	73.2
Loan	91.6	91.6	91.6	94.4	94.4
New production process	98.9	98.9	98.9	92.3	92.8
Licensed technology	85.5	85.5	85.5	98.7	99.3
GDP per capita	86.8	86.6	86.6	99.5	95.9
Legal rights index	62.9	62.9	62.9	76.3	87.2

For more details, see Appendix B, chapter 5 appendices, matching methods sub-section 2.

In conclusion, there is a stereotype about the ECA countries that in they enjoy a competitive advantage because of the low cost of labour in this region. This might have

important policy implications, where this reality might change over time, and these countries need to invest in their human resources skills to improve their firm level performance to compete in the international markets. Raising human capital optimisation and productivity, through improving and revamping education and specialised technical training (formal and informal), provides firms with employable skilled workers, to enhance the level of efficiency, in which they combine and integrate production factors.

Improving the bottom and middle firms' efficiency in ECA plays a pivotal role in catching the developments in technology and innovation in the frontier firms which gives them a chance to increase the quality of their production.

Almost all of the countries in this region have benefited from the training courses and technical assistance provided by the IMF and EBRD, which are to help these economies in their transition in many areas, both at the macroeconomic level and microeconomic level, in order to reform their economic policies and to ensure their ability in adopting and implementing the necessary frameworks for boosting skills and workers' adaptability. What might be needed is to encourage more of a transfer of that knowledge from the higher levels in the skills hierarchy to the lower levels.

5.4 Chapter Conclusions

This chapter was designed to examine and investigate the two main questions of this thesis.

1) What impact do workers with different levels of education have on technical efficiency on the manufacturing firms in ECA? 2) What are the effects of the formal training schemes on output per worker in ECA private manufacturing firms?

By way of a summary, this chapter's objective is to investigate and analyse the role of human capital composition at the micro-level, as measured by the employment shares of intermediate and highly-skilled labour in firm level efficiency across ECA countries. The results provide evidence that the higher the proportion of highly-educated human capital,

the lower is the regional inefficiency. This supports the assumption of the importance of a third level of education (university level) in enhancing productivity and growth.

The results suggest that skilled workers with a technical school and college level of education made a negative contribution in lowering the levels of inefficiency among firms in Eastern Europe and Central Asia. Higher levels of education are more crucial for innovation, so as to encourage growth in more developed economies, whereas secondary levels of education are more essential for imitation activities in order to foster growth in less developed economies. It has been noticed that observable tertiary education skills, embodied in a proportion of production workers, have a greater weight in interpreting the differences in productive efficiency across the enterprises subject to the study.

Moreover, it is also noted that, the average number of years of schooling associated with tertiary education workers, new organisational and management practices, research and development spending, and the spending on formal training, foreign ownership, and loans received from commercial banks, have all been shown to have a significant impact in minimising a firm's technical inefficiency, particularly, in the manufacturing sector. In addition, and unexpectedly, it is found that the relationship between a firm's age and its efficiency tends to be a positive and significant one.

In addition, the empirical results in this chapter suggest that the firms' size factor (micro, small, medium, or large) tends to play a role in thwarting firms from being more efficient, meaning that the larger the firm is, the less efficient it is anticipated to be.

In the light of other results, it is also found that, funds received from private commercial banks in the form of loans, and the percentage of foreign ownership in the firm – whether it is a complete or partial ownership – have their significant positive impact on firm level efficiency in this region.

To conclude, the obtained results in this chapter suggest that highly-skilled labour force seem to have played more important role in promoting efficiency at the firm-level in the manufacturing sector in the ECA region.

The results also suggest that manufacturing firms in ECA that have provided their permanent full-time workers with formal training have experienced higher levels of productivity. In this respect, it can be noted that firms with better access to finance, licensed technology, and operate in countries where the growth in GDP per capita is strong are more likely to offer their full-time workers better chance and access to formal training programs. Knowing that these programs are expected to be highly firms-specific.

Chapter 6: A Comparison between the Impact of Education and Formal Training on the Manufacturing Firms' Performance in the MENA and ECA Regions.

6.1 Introduction

This chapter is mainly designed to present a comparative analysis between the Middle East and North Africa region on the one hand, and the Eastern Europe and Central Asia region on the other, in terms of the different contributions of human capital composition to technical efficiency, and the impact of formal training programs on labour productivity at the micro level.

In this chapter, the research attempts to answer two main questions in respect of the different effects of education levels of technical efficiency in the MENA and ECA regions. It is also intended to seek some answers about the possible different effects on formal training on output per worker in the two regions.

It does not take much analysis to see that different levels of education differ considerably between developing and transition economies.

Given that the two pooled samples of the MENA and ECA countries are heterogenous, one would expect the effects of human capital stock (education and training) on efficiency and productivity respectively, to vary even within the region itself.

The effects of the share labour with university degree on technical efficiency is found to be positive in both regions MENA and ECA. The impact of the unskilled labour (low skilled workers) tends to differ between the two regions, this is where it is found to have positive

and significant impact on firms' efficiency in MENA. Whereas, it has insignificant effect on firms' efficiency in ECA.

The intermediate skilled labour impact of firms' efficiency seemed to be different between the two regions. In MENA this fraction of the total human capital stock had negative and significant impact on efficiency, whereas in ECA it had negative and insignificant effects on firms' efficiency.

6.2 Comparing the Impact of Education Levels on the Firms' Efficiency in the MENA and ECA Regions

Building on the results obtained from stochastic frontier models presented in chapters 4 & 5, and after dissecting the sample of the manufacturing firms in MENA and ECA, it appeared to be the case that higher percentage of low, medium, and highly skilled workers is employed in larger firms (the more efficient firms) in MENA. Conversely, lower percentage of low, medium, and highly skilled workers are employed in less efficient firms (small and medium ones).

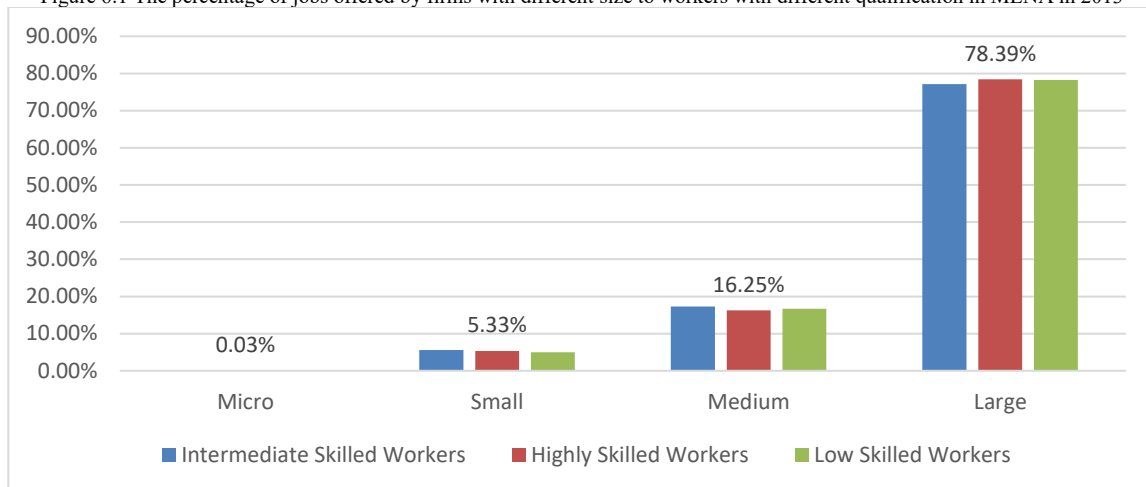
From an economic point of view, it should be marked that economies which are hugely endowed with a high proportion of skilled labour as a share of the total labour force, would need to take into consideration the high cost of the wage bill. In such economies, it is possible to find the optimal level of sophisticated technology which helps to enhance the level of efficiency of their resources of skilled labour and capital.

On the other hand, in those economies where the percentage of unskilled labour is relatively higher than the skilled labour in the total workforce, it is easier for them to deploy less advanced technology and lower level of capital accumulation.

In truth, the attractiveness of investing in skilled-biased technology depends on the supply of the factor that complements that technology. In other words, the larger numbers of skilled workers raise the incentives to invest in the technology which is expected to be used by skilled labour.

In the end, this is expected to raise the share of investment in the skilled-biased technology as opposed to the investments in the unskilled-biased technology. Therefore, the optimal combination of technology and capital is largely determined by the endowment of human capital.

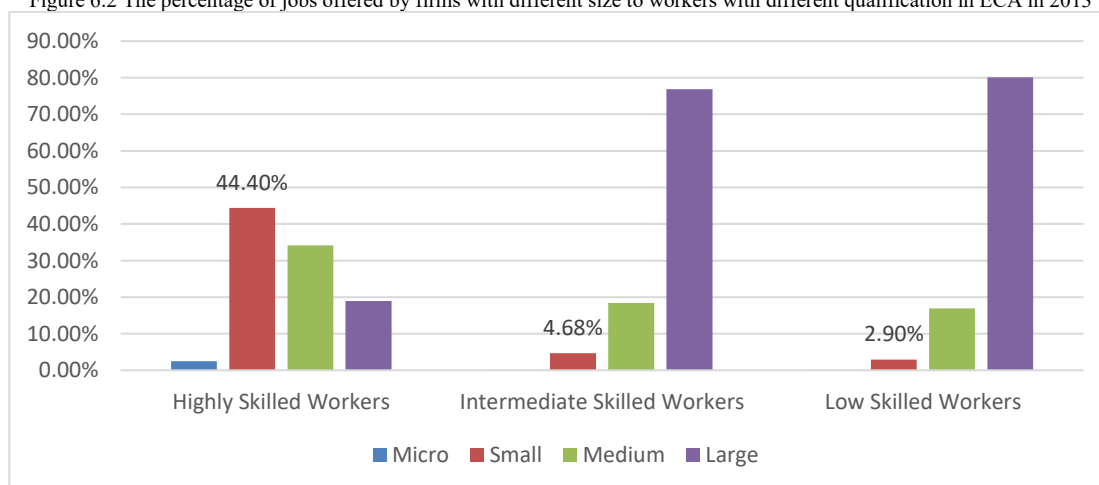
Figure 6.1 The percentage of jobs offered by firms with different size to workers with different qualification in MENA in 2013



Source: Author's calculations of the contribution of the private manufacturing firms to the job creation based on WB Survey dataset 2013.

In ECA, the picture differs dramatically. This is where higher percentage of highly skilled workers is employed in smaller firms (more efficient firms), whilst higher percentage of low and intermediate skilled workers is employed in medium and large firms (less efficient firms) in ECA.

Figure 6.2 The percentage of jobs offered by firms with different size to workers with different qualification in ECA in 2013



Source: Author's calculations based on WB Survey dataset 2013.

In ECA, there is marked difference in performance between the smaller and de novo on the one hand and privatised as well as larger firms on the other. Smaller firms appeared to be more efficient than larger firms. This can be justified by the fact that start-ups are driven mainly by profit motive and are required to make profit at the start, meanwhile this motive is already acquired in the larger and privatised enterprises, and their goals tend to be relevant to a combination of economic and social issues.

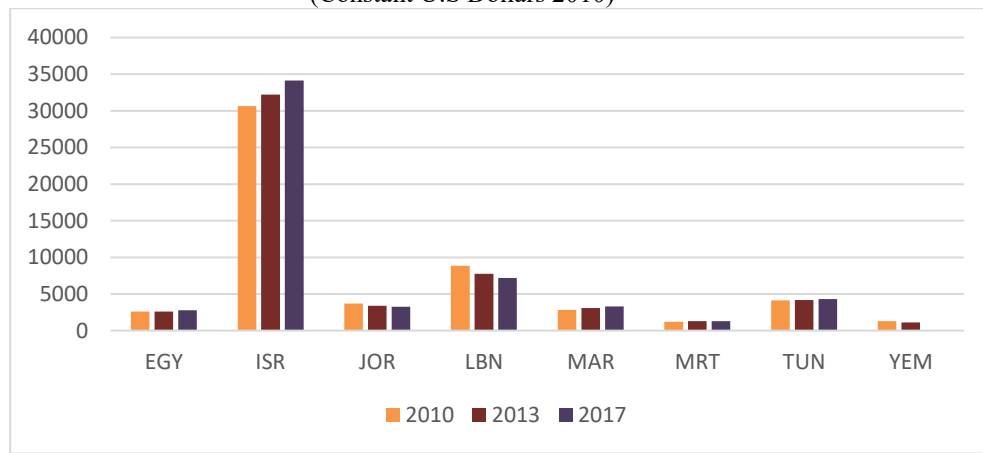
The new firms can play important role in promoting output by bringing new ideas into the mixture of firms which are already operating the marketplace. Market power makes it difficult for new small ventures to compete with the incumbent big businesses. The de novo enterprises are key players in the market in terms of their tendency to introduce new production techniques and new ideas. In addition, they are historically proven to be the job creation hitters, which drives job opportunities to grow especially for the low-skilled and less-educated labour force.

The start-ups might be more efficient in terms of using their capital, and may acquire better human resources and management, more optimal production structures. In the transition economies in ECA, the property rights are poorly protected, and the capital and financial markets are considerably under-developed, skilled workforce is not adequately available. Therefore, the weakness of the economy's institutions may hinder the larger and privatised plants to be re-structured in more effective manners within the appropriate timescale to grasp the business opportunities in the market economy.

Two fundamental factors may affect the ability of the larger privatised and smaller de novo firms alike to perform effectively under the new realities of the market economy are related to: the ways of doing business during the Soviet Union epoch, which will carry on affecting their current businesses despite that they are – the firms – either fully privatised or in the process of being privatised, and either they are privately-owned or government-owned. The other issue that might be of importance is relevant to the political and economic instability throughout many of these countries. This can be a serious obstacle which privatised firms might have to face and deal with when pursuing business advantages across the region.

In the two regions of MENA and ECA, it seems to be that there is an unequivocal relationship between the firms' efficiency and the economic performance. The effects of GDP per capita as a macro-level variable is proved to be positive on technical efficiency and statistically significant in both regions. In other words, manufacturing firms which operate in economies with higher GDP per capita, are expected to perform more efficiently than those firm operating in economies where GDP per capita is comparatively lower.

Figure 6.3 The Changes in GDP Per Capita in The MENA Region
(Constant U.S Dollars 2010)

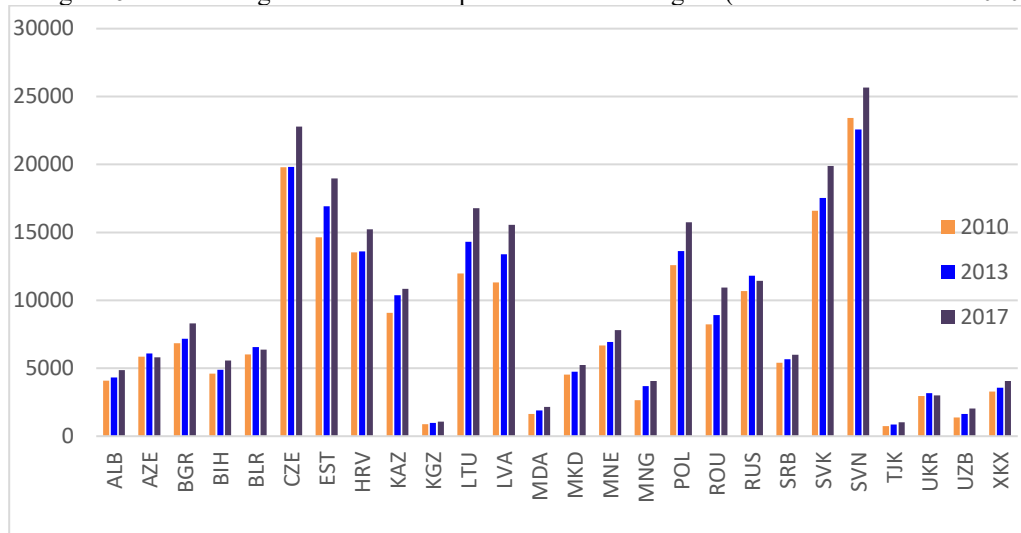


Source: The World Bank Group, World Bank Open Data 2018.

Based on this result and according to the World Bank statistics about the development in the levels of GDP per capita in MENA and ECA in recent years, this result suggests that firms which operate in Israel, Lebanon, Tunisia, and Jordan are expected to perform more efficiently than those in Morocco, Egypt, and the Yemen Republic.

In the Eastern Europe and Central Asia region, it is expected that firms in countries like, the Czech Republic, Slovenia, Slovakia, Poland, Estonia, Lithuania, and Latvia would perform more efficiently than other firms in other countries with lower levels of GDP per capita.

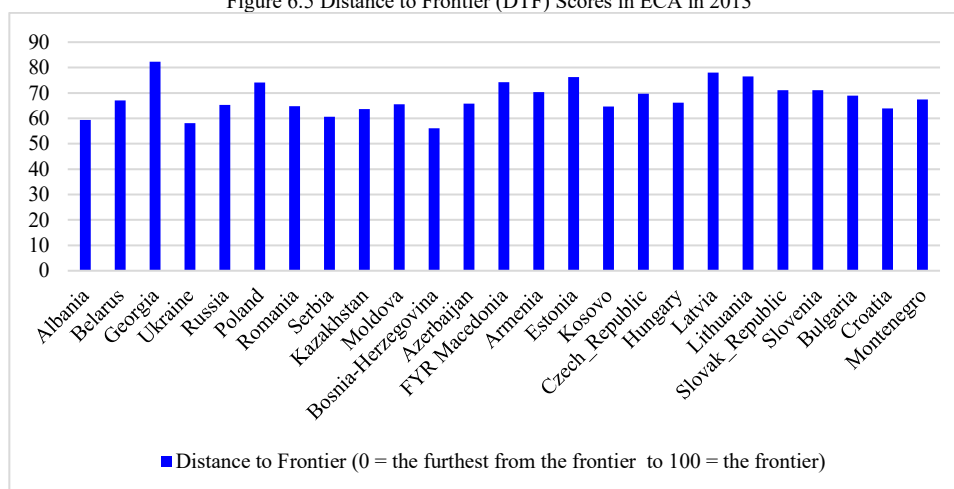
Figure 6.4 The Changes in GDP Per Capita in The ECA Region (Constant U.S Dollars 2010)



Source: The World Bank Group, World Bank Open Data 2018.

The index of the regulatory performance reflects two different stories in MENA and ECA. In the former, it appears that it is positively associated with the firms' efficiency in MENA, but its impact is found to be insignificant. On the minus side, in the latter, the firms' performance is negatively affected by the country's distance to the best observed performing nation in ECA.

Figure 6.5 Distance to Frontier (DTF) Scores in ECA in 2013



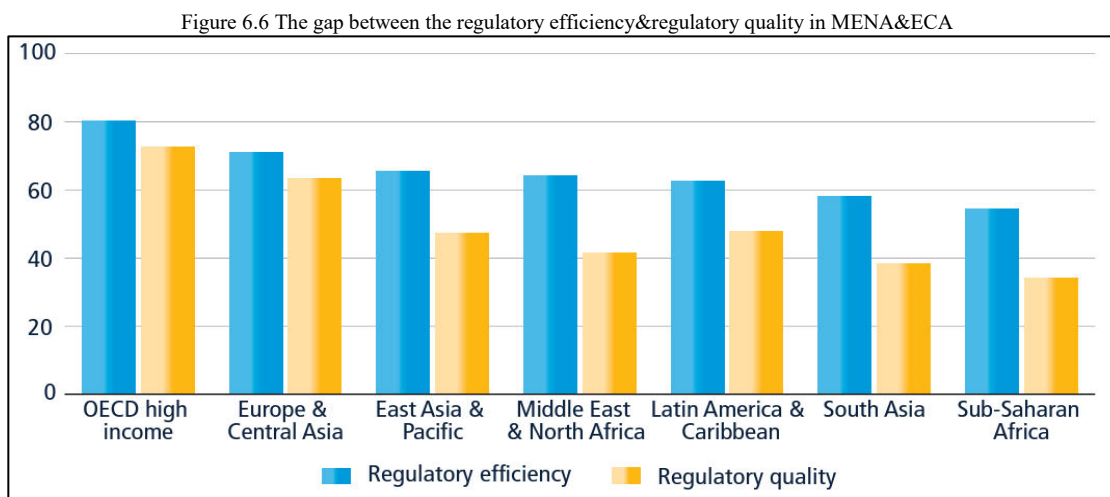
Source: World Bank, Doing Business Project

The results do not seem to be surprising given that businesses in poorer nations experience larger regulatory burdens, bureaucratic procedures, and weak property rights than other firms in relatively richer nations.

The evidence also shows that the relationship between the quality of regulations and the efficiency of regulations is strong. The quality analyses whether the regulatory infrastructure needed for a transaction to be successfully completed is in place.

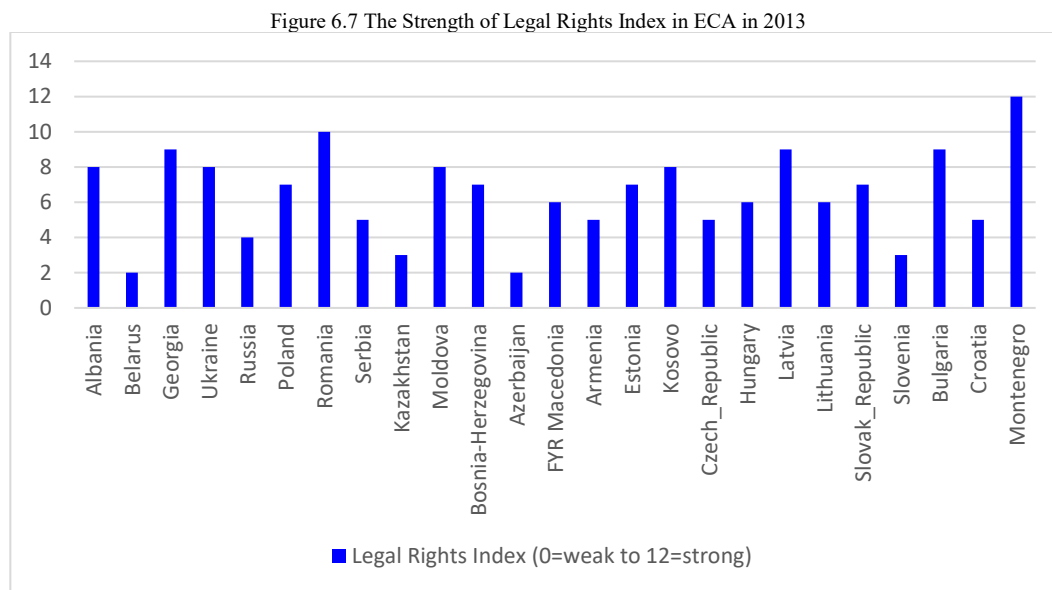
The distance to frontier score for regulatory efficiency is the aggregate score for the procedures, time, and cost indicators from starting a business, dealing with construction permits, registering property, paying taxes, trading across borders, etc. whereas the distance to frontier for the quality of regulations is the aggregate score for receiving credit, protecting minority investors, enforcing contracts and resolving insolvency.

Overall, it seems that economies that have efficient regulations processes appear to have good quality in their regulations. Some economies have managed to achieve the best of both the quality and efficiency of regulations.



Property protection rights are weak in the transition nations at large, and the regulations seem to be heavier in these countries in comparison with other regions. The key point in this respect is that, businesses need to spend more time to produce and save their energy for

marketing their products of goods and services in the hosting country. They are also expected to focus on allocating their financial resources in the best possible way in the production process. On the other hand, businesses need better and more flexible regulations and less complex bureaucratic procedures to grow and expand.



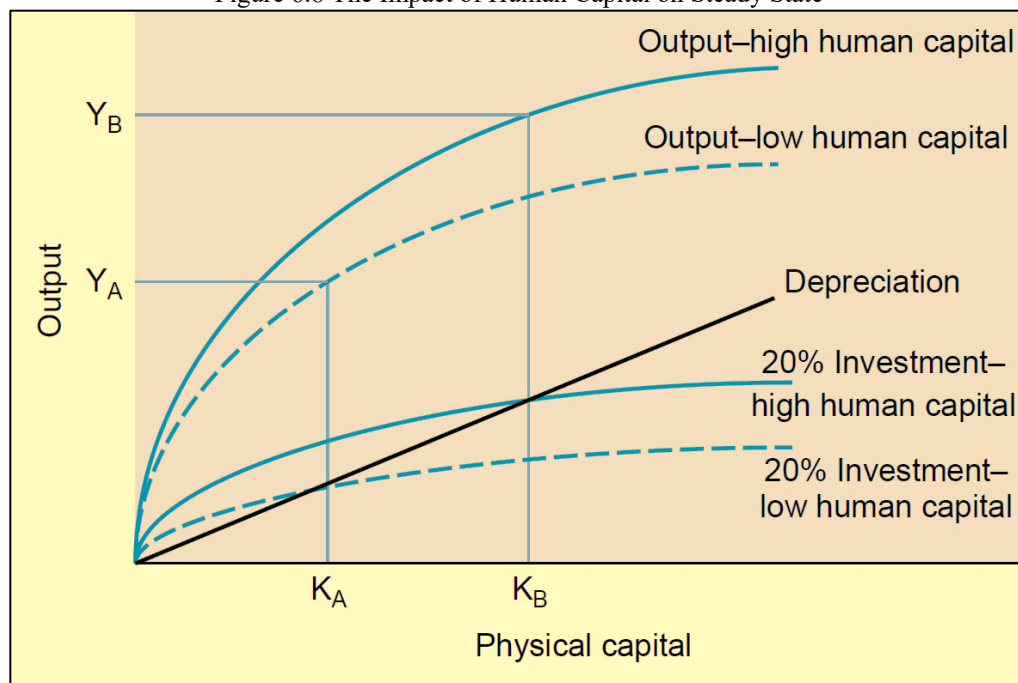
Source: World Bank, Doing Business Project

Governments in transitions economies and developing countries can spend more time and resources on providing basic social services to the society instead of only concentrating on setting more complicated regulations and inflating their bureaucratic systems.

By macroeconomics, the marginal product of the physical capital tends to increase with the increase in the amount of human capital in the country. This means that the more educated the workforce, the higher the marginal productivity of physical capital (MPK).

As shown in the figure below, higher human capital encourages more investment in physical capital. This implicitly means that the country can produce more output with a given amount of physical capital. In the steady state, and with holding the investment rate constant, this leads to more accumulation of physical capital stock (from K_A to K_B). In the end, this will be reflected in better standards of living (from Y_A to Y_B) in the country at large.

Figure 6.8 The Impact of Human Capital on Steady State



Source: David Miles, Andrew Scott (2008); Macroeconomics: Understanding the Wealth of Nations.

6.3 The Variance Parameter in the Stochastic Frontier Models

In MENA, the value of the variance parameter γ which lies between 0 and 1 is equal to .63562 when correcting for heteroscedasticity in u only, and it equals .61444 when correcting for heteroscedasticity in both u and v . It, therefore, confirms the presence of stochastic technical inefficiency and that it indicates to its relevance to obtaining the adequate representation of the data.

From this, if $\gamma = 0$, then the technical efficient capacity utilisation TECU value is expected to score 1 ($\sigma_u^2 = 0$), meaning that the deviations from the frontier can neither be ascribed to the presence of technical inefficiency nor to capacity underutilisation, and if $\gamma = 1$, where the value of $\text{TECU} = 0$, ($\sigma_v^2 = 0$), it will indicate that deviations from the frontier can be attributed to technical inefficiency and capacity underutilisation, (Pascoe et al., 2003). In case γ is larger than 0 and less than 1, then deviations can be explained by both technical efficient capacity utilisation and the random component, (Battese and Corra, 1977).

In addition, the production function inefficiency is calculated by the error term using the composite error term of the stochastic frontier model which is defined by $\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$. This is where it represents a measure of inefficiency level in the variance parameter which ranges from 0 to 1.

In the case of ECA, the value of the variance parameter γ is equal to .39660 when correcting for heteroscedasticity in u only, and it is equal to .41912 when correcting for heteroscedasticity in both u and v .

This indicates that the variance of the inefficiency effects is a significant term of the total composite error term variance, and therefore the deviations from the optimal level of output in the MENA manufacturing private firms subject to study is due to both the random exogenous factors and inefficiency existence in the production processes. In other words, this implies that the stochastic production frontier is significantly different from the deterministic frontier which does not comprise a random error.

6.4 Comparing the Effects of Formal Training on the Manufacturing Firms' Productivity in the MENA and ECA Regions

The firm-specific stock of human capital can be mainly obtained via training programs, which are designed particularly to meet the workers' need in terms of the skills they lack in the workplace.

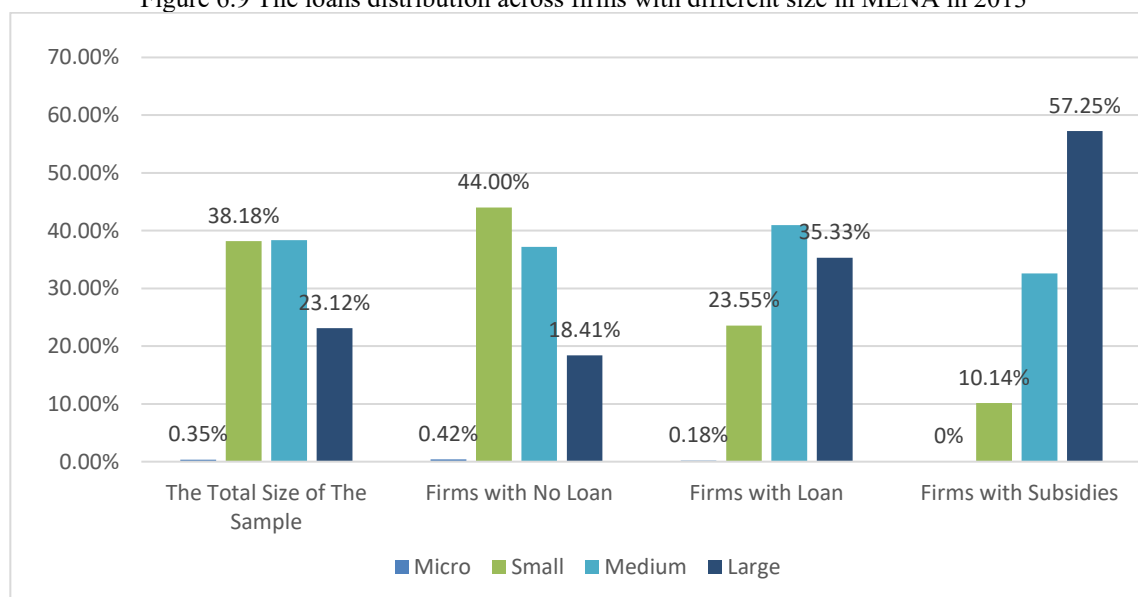
Firms with better access to finance in the form of loans are likely to export to the international markets, as they will be exposed to stronger competition, and they are more able to use more advanced and licensed technology than non-exporting firms.

This environment will partly be a good platform which provides the workers with the opportunity to develop their skill profile, grasp knowledge, and introduce new innovations and production methods.

The World Bank Enterprise Survey 2013 dataset reveals interesting pattern of fund distributed between firms with different size and characteristics. This is where larger firms dominate the loans and subsidies market with above 35% and 57% of the loans and subsidies granted and reported in this survey, despite they represent just over 23% of the total sample of manufacturing firms, whereas the smaller firms receive lower percentage of both loans and subsidies at 23% and 10% respectively, nonetheless they represented more than 38% of the total sample of manufacturing firms.

Larger firms are likely to be able to export, and in the same time they seem to be dominantly owned by state. In fact, they are in a favourable situation over smaller firms to receive fund and subsidies principally for two possible reasons: (a) the banking system in the middle east and north Africa is largely administered and to some degree owned by state. (b) larger firms' financial situation allows them to provide better risk profile, credit history, state of project profitability, and collateral when applying for loans from financial institutions.

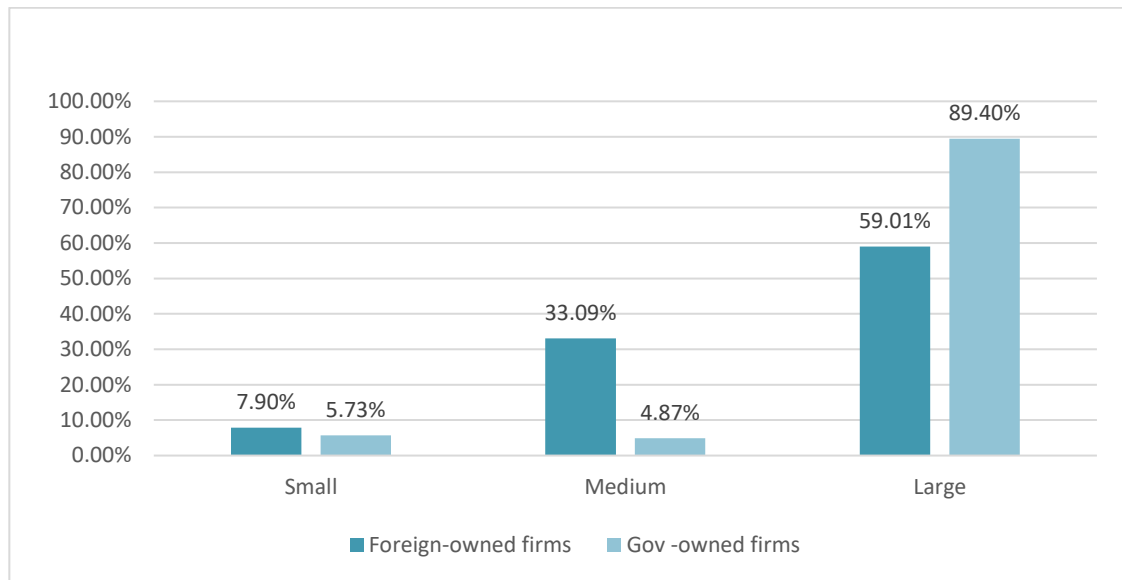
Figure 6.9 The loans distribution across firms with different size in MENA in 2013



Source: Author's calculations based on WB Survey dataset 2013.

Obviously large firms surpass small and medium-sized enterprises in terms of the percentage of exports of total sales to the global markets. This also evident especially in the case of the state-owned large firms.

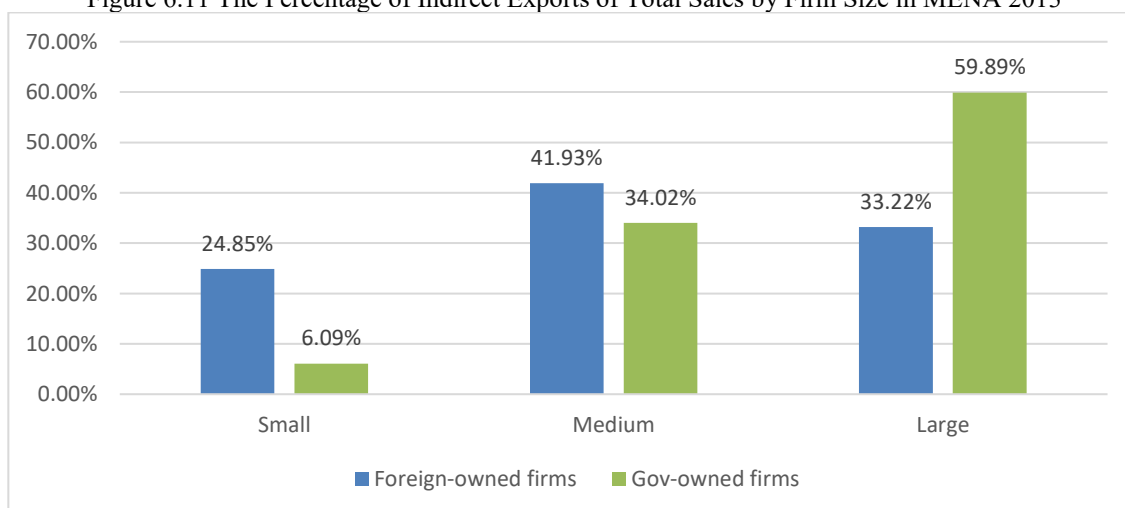
Figure 6.10 The Percentage of Direct Exports of Total Sales by Firm Size in MENA 2013



Source: Author's calculations based on WB Survey dataset 2013.

With respect to indirect exports as a percentage of total sales, the ratio of foreign-owned small and medium-sized firms improves noticeably compared to the state-owned small and medium-sized firms in this area.

Figure 6.11 The Percentage of Indirect Exports of Total Sales by Firm Size in MENA 2013

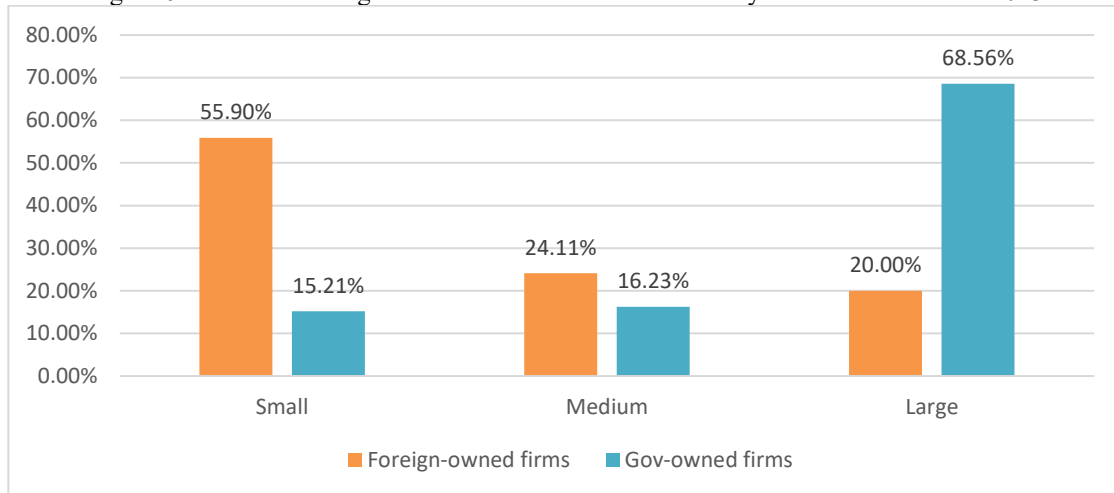


Source: Author's calculations based on WB Survey dataset 2013.

The foreign-owned small enterprises dominate the national sales as a percentage of their total sales in 2013 in MENA. Whereas, the foreign-owned medium and large firms'

national sales represented lower percentage of the total sales directed towards the local market.

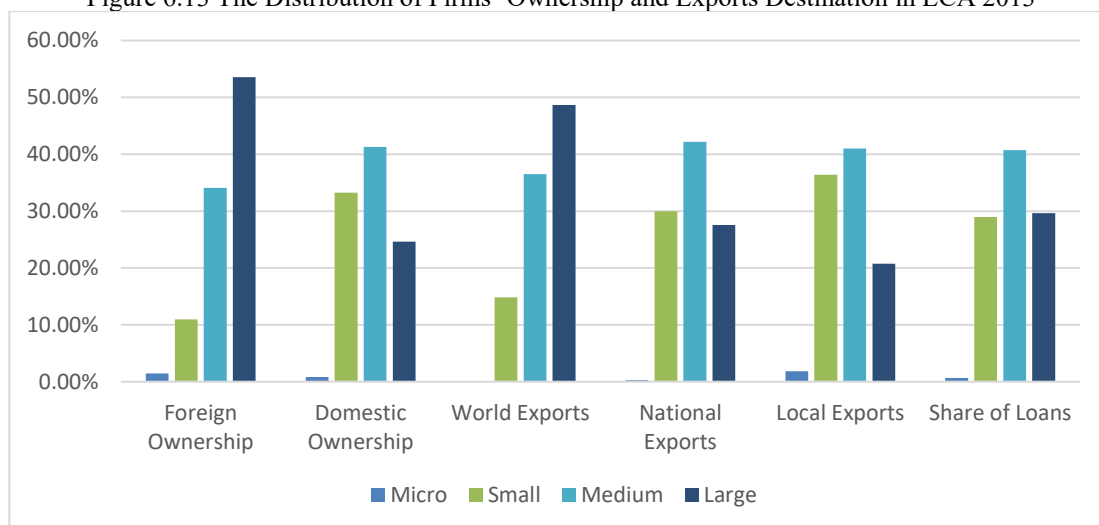
Figure 6.12 The Percentage of National Sales of Total Sales by Firm Size in MENA 2013



Source: Author's calculations based on WB Survey dataset 2013.

As for the foreign-owned firms, there appears that foreign investors are more interested in investing in larger firms by over 53% of the foreign shares is concentrated in the large firms, over 34% in the medium firms, and about 11% and 1.46% in the small and micro firms respectively.

Figure 6.13 The Distribution of Firms' Ownership and Exports Destination in ECA 2013



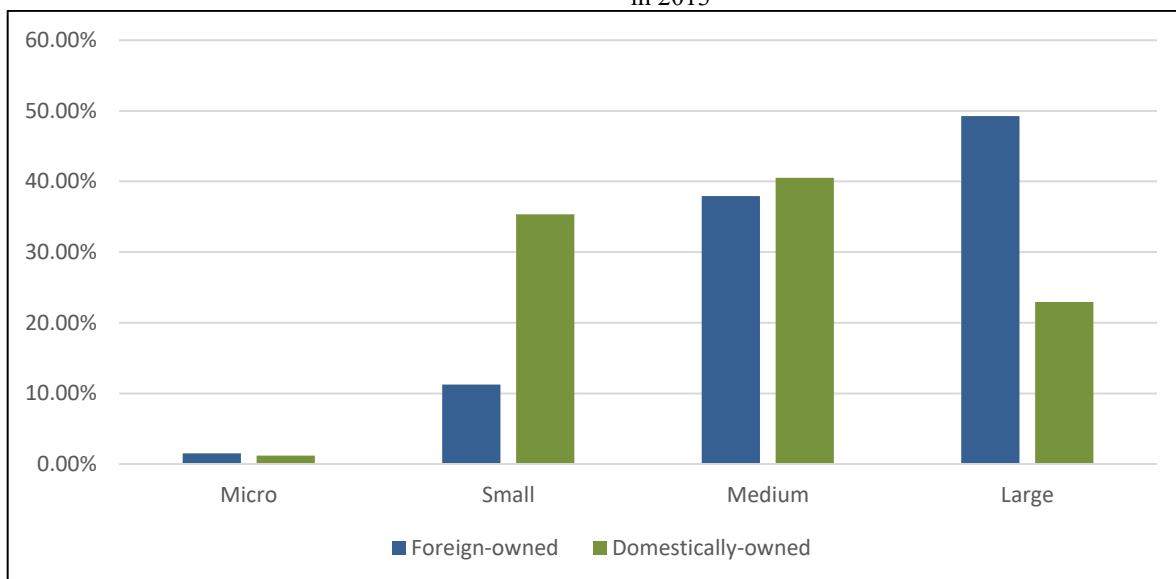
Source: Author's calculations based on WB Survey dataset 2013.

As regards exportation and trading with other partners in the global and local markets, it seems that larger enterprises in ECA outperform the small and medium firms in terms of the percentage of their sales in the global markets. In the meantime, small and medium enterprises outperform large firms concerning the percentage of their total sales in the local markets.

The distribution of firms which had received loans in ECA showed that the percentage of large foreign-owned firms was higher than the percentage of the domestically-owned large firms that had been granted loans.

In the case of small and medium size firms, the pattern of loans distribution changes dramatically. This is where the percentage of domestically-owned small and medium firms was higher than the percentage of the foreign-owned small and medium firms in terms of the loans received from different financial sources.

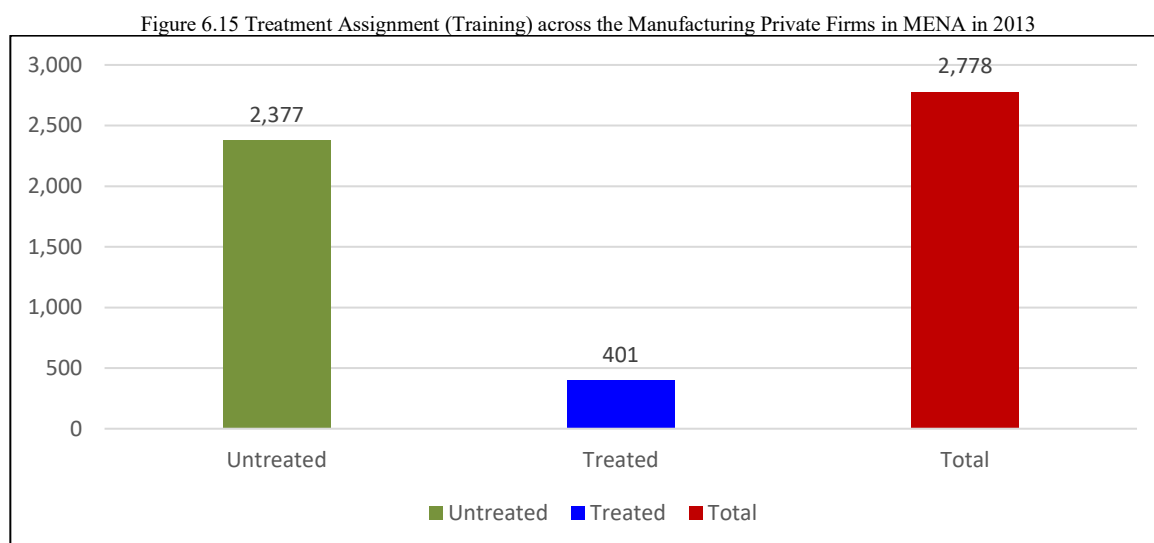
Figure 6.14 The Percentage of Foreign-Owned and Domestically-Owned Firms That Received Loans in ECA in 2013



Source: Author's calculations based on WB Survey dataset 2013.

The number of the treated firms (which offered training to their workers) in MENA is considerably less than the number of those untreated firms (which did not offer training). The results obtained from the propensity score matching and Mahalanobis metric matching methods do not tell a clear story about the possible reasons for the insignificant impact of training of firms' performance in MENA, but there can be several reasons for why the

share of the treated firms is markedly lower than the share of the untreated firms in this sample.



Source: The results are obtained from the matching methods applied in chapter 4.

The pattern of the training programs offered by firms, particularly those which have been granted fund in the form of loans, reveals an interesting narrative both in the MENA and ECA regions.

The selected sample was dissected in detail, and the analysis showed that small and medium manufacturing firms in MENA represented higher share of the total number of firms which did not provide their workers with formal training schemes. This is where 11%, and nearly 18% of the small and medium enterprises, respectively, did not offer training programs. In the same time, both small and medium-sized firms that did not provide training to their workers, received 0% of the granted loans.

Table 6.1 The distribution of formal training programs and received loans across the firms in MENA in 2013

Firm Size	Formal Training	Loan
Small	17.48%	25.85%
Did not (offer training / receive loan)	11.17%	0.00%
Did (offer training / receive loan)	5.95%	25.85%
Medium	35.32%	41.88%
Did not (offer training / receive loan)	17.84%	0.00%
Did (offer training / receive loan)	16.22%	41.88%
Large	47.21%	32.16%
Did not (offer training / receive loan)	19.46%	0.00%
Did (offer training / receive loan)	24.32%	32.16%
Grand Total	100.00%	100.00%

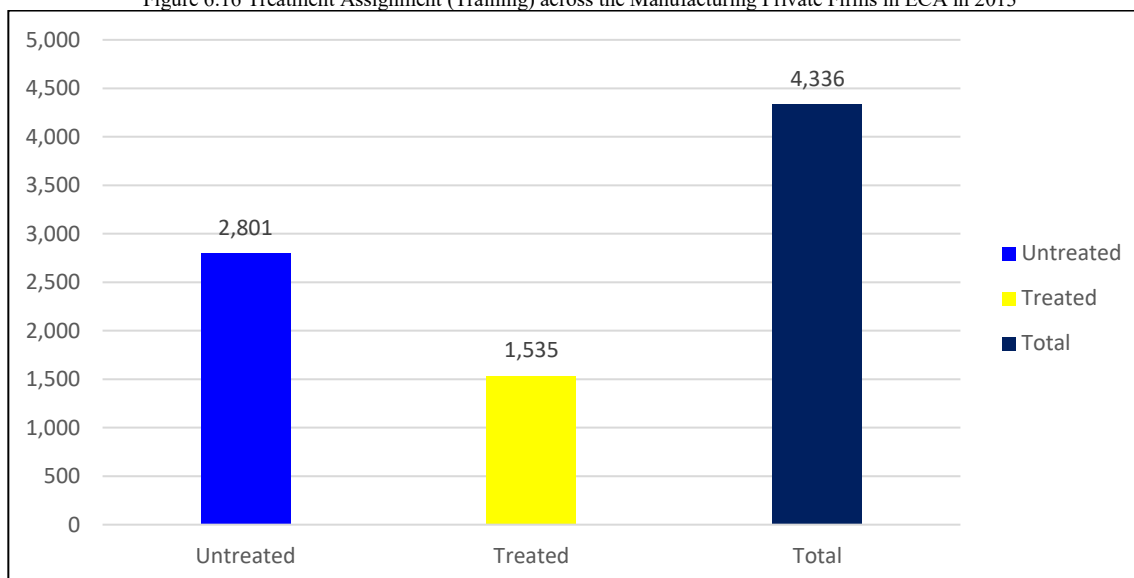
Source: Author's calculations based on WB Survey dataset 2013.

In the case of larger firms, the anecdote is different. This is where more than 24% of the large firms had offered their employees the opportunity to attend technical and vocational training to develop their skills. With knowing that 32% of these firms had received fund from different financial institutions.

In other words, it can be said that more efficient manufacturing firms – mainly the large enterprises – had been more able to provide the necessary requirement to receive loans, and by extension, allocate some of their financial resources to design and implement their training policy. The main goal of this policy is to improve their situation the international markets, by having their employees equipped with reasonable level of competitive skills.

The narrative in ECA tends to be divergent from that of MENA. On average, more firms offered formal training to their workers in ECA, in a sample of 4336 firms than in MENA, in a sample of 2778 firms in the manufacturing sector.

Figure 6.16 Treatment Assignment (Training) across the Manufacturing Private Firms in ECA in 2013



Source: The results are obtained from the matching methods applied in chapter 5.

By way of descriptive details, small firms which reported whether they offered formal training represented about 34% of the total sample spanned in ECA. Over 20 % of them did not offer any training programs to improve their workers' skill sets over the last three complete fiscal years, and they received no loans from any financial institution. About 13% of them reported that they had offered formal training, where almost 37% of this sample received loans from different sources.

Table 6.2 The distribution of formal training programs and received loans across the firms in ECA in 2013

Firm Size	Formal Training	Loan
Small	33.57%	36.88%
Did not (offer training / receive loan)	20.75%	0.00%
Did (offer training / receive loan)	12.82%	36.88%
Medium	39.63%	38.40%
Did not (offer training / receive loan)	22.74%	0.00%
Did (offer training / receive loan)	16.88%	38.40%
Large	24.03%	21.63%
Did not (offer training / receive loan)	11.15%	0.00%
Did (offer training / receive loan)	12.89%	21.63%
Grand Total	100.00%	100.00%

Source: Author's calculations based on WB Survey dataset 2013.

As for the medium-sized firm in this sample, 39% of the sample responded to the question whether they had plans for training programs over the last three complete fiscal years. Over 16% of them reported they had indeed offered training to their workers during this period. 38% of this sample was granted loans from commercial banks and other sources of fund.

The percentage of large firms that responded to the question related to whether the establishment had offered training plans is lower than that in the case of small and medium enterprises. This is where large firms represented only 24% of this sample, and only 12% on this percentage had provided their workers with the necessary training schemes to improve their skill profiles.

6.5 Chapter Conclusions

This chapter attempts to answer the questions on which this research is centred; 1) whether the education effects on firms' efficiency differ from one region to another, using the stochastic frontier methodology. The integration of heteroscedasticity into the stochastic frontier models applied in chapters 4 & 5 following (Caudill et al., 1995) and (Hadri, 1999) resulted in more accurate and robust measures of this relationship at the firm level in the two regions of MENA and ECA. 2) the second question involves whether the impact of training on labour productivity varies between MENA and ECA.

Regarding the first question, the maximum likelihood estimates showed considerable differences in the effects of the three levels of the skills embodied in the manufacturing workers across the two regions. In both regions, firms' technical efficiency appeared to have been associated with those workers with tertiary education and university degrees. Meanwhile, the link between firms' technical efficiency and those workers with lower educational attainment such as, secondary school and technical training schools was stronger in MENA than it is in ECA.

This suggests that improving access to education both in MENA and ECA must also rest on understanding the labour market demand for workers with college and non-college education.

The increase in the supply of secondary and post-secondary workers in these regions without considering the demand in the job market may not be a wise option from the policymakers' point of view. Allocating more resources to this level of education – given the stock of knowledge and the set of skills that this process imparts – needs to consider the possible fall or stagnation in the demand in the job market for this level of education.

In the same time, the expansion in university education in both regions appears to be a reasonable choice of policy. By economics the demand for university graduates and workers with tertiary education seem to be growing, and the more efficient firms in MENA and ECA dominate the labour market in terms of employing the more educated workers. By extension, it is also reasonable to think that the more educated workers receive considerably higher wages more than do poorly educated workers.

In MENA the stagnation in wages for years had caused the supply of more educated workers to decrease. At the same time, the firms' demand for more educated workers was growing but the rate of return to education has levelled off and maybe dropped in some countries in this region.

The cost of the mismatch between the skills supply and the employers demand can be high for the economy at large. That is mainly due to the underutilised fraction of human capital, and because of part of the workforce is under-schooled and not adequately equipped with knowledge and skills for the jobs available.

The bottom line, then, is that better wages and higher rates of return to higher education would encourage the individuals to invest in more time in schooling by enrolling in quality education institutions throughout the region and abroad. The ultimate objective is to grasp new knowledge, innovations, and skills to improve the chance of finding better jobs to earn higher wages and to secure better standards of living.

As for training, numerous studies in several countries revealed the fact that better trained workers, are more productive, and earn relatively higher wages. Presumably more training is expected to contribute to higher labour productivity.

In MENA, the impact of training on productivity is insignificant. The reasons for this are difficult to specify, but it could be ascribed to several factors including, the lack of adequate fund from the different financial institutions in the region, especially towards small enterprises. The loans and subsidies were mainly granted to larger firms. As a corollary, small firms could not provide training for their employees to enhance their skills and to improve their position in the market as potential competitors. The other factor is the effectiveness of the foreign management particularly in the small-sized firms. Given that small size firm represent a considerable share of the total sample at hand, their performance in MENA was found to be insignificant both in the stochastic frontier analysis and matching analysis, knowing that the variable of the foreign ownership shares was included in the OLS and probit models which were implemented in the MENA sample, but it was taken out because its impact was insignificant.

On-the-job-training – the skills that workers acquire while at work – is an important route to raise productivity, but the problem it is not as amenable as formal education. It is on the part of the private businesses to select how much training is needed for their employees, and how that training is going to be executed. There were various initiatives across the world with regard to the role which governments may play either in terms of running training programs or subsidies the training programs suggested and designed by the private sector, but thus far it seems that the outcomes have been rather mixed when it comes to the impact on firms' productivity.

Chapter 7: Conclusions and Policy Implications

7.1 Conclusions

This thesis contributes to the literature by providing empirical evidence using firm-level data from two different regions at different developmental stages. The contribution of this thesis lies in the following respects:

- 1- There are differences in the impact of human capital compositions on technical efficiency, and performance, across the selected sample of economies.

Controlling for heteroscedasticity in both error terms and heterogeneity in the stochastic frontier production functions, across the two regions, was important in the sense that it resulted in more accurate and robust measures of the impact of human capital on efficiency.

The results of the investigation indicate that the contribution of the shares of skilled and unskilled workers in the total labour force – distinguished via the three education stages – to efficiency vary significantly at firm level. They also differ between MENA region and ECA region according to each region's distance from the world technological frontier.

- 2- This thesis demonstrates that the reallocation of labour – high-skilled and low skilled – yields complementarity between human capital and a country's proximity to the technological frontier using the SFA methodology, with the correction for heteroscedasticity in the two error terms.

The effects of the three education levels including: the secondary school levels (unskilled/low skilled labour), the college or upper secondary school level (intermediate-skilled labour), and the university level (highly-skilled labour) are proved to vary widely across regions.

The addition of the average number of years of schooling of a full-time permanent worker – as an extra proxy for human capital stock – serves as another dimension to explore whether it has significant effects on efficiency in the private manufacturing firms. However, the findings of this research suggest that the impact of the average number of years of schooling on firms' technical efficiency seems to be insignificant. This result will be discussed in more detail as this chapter progresses.

- 3- The firm-level empirical evidence which is extrapolated from the formal private manufacturing sector, represent a reconciliation between the aggregate conclusions drawn from the macro-level analysis concerning the relationship between human capital and efficiency on one hand, and the conclusions obtained from micro-level analysis of this relationship on the other.

The study attempts to distinguish itself from previous macroeconomic analysis frameworks by offering substantive analysis of the association between human capital and efficiency. The analysis is executed by using different human capital components which are endogenously deployed by the manufacturing sector firms in the two regions.

There are various reasons for choosing these two regions, besides the panel firm-level data unavailability and inaccessibility for researchers in the human capital field in some regions.

The main reason for this choice is the different organisational structures and the dissimilarities between production functions across economies in different developmental phases, which can be a suitable platform for

analysing the distinctive effects of human capital composition in each region in comparison with the others.

- 4- The final contribution of this thesis is relevant to the different effects of training on the manufacturing firms' output per worker. This research examined this relationship and discovered that formal training programs – which had been offered in some enterprises – had significantly divergent effects on the productivity of full-time permanent employees in MENA and ECA. One of the key factors which appeared to have had played a crucial role in this relationship is the availability of the financial resources for the manufacturing firms with different sizes and characteristics.

Despite the wide range of studies which examined the effects of human capital on efficiency and productivity, and by extension, the effects on economic growth, it is difficult for an economic researcher to feel completely comfortable when comparing the macroeconomic with the microeconomic evidence, and reconciling the macro and micro evidence by combining data and results at different levels of aggregation (individual, firm, industry, and economy-wide) in order to draw a set of objective conclusions and to present substantive policy implications.

Building upon years of thought about human capital, and general attention to education in the more advanced economies, human capital formation is reasonably a synergistic and interactive process that begins very early in lifetime. The importance of adequate health and nutrition for building and developing the cognitive skills, the children readiness to start learning at school, and higher productivity in the adulthood stage, all have been documented in a large body of the literature.

Marketable skills can be crystallised and developed through the formal schooling and training from an early age and during adult life. The quality of family and school structures during different age stages are crucial to generate high level of skills and better individual performance.

The role of human capital as a growth-boosting factor and technology-diffusion facilitator is well documented throughout the developed economies. However, its contribution to growth in transition and developing economies – ECA and MENA included – have not been previously investigated thoroughly, especially at the firm-level, mainly due to data limitations. In fact, the relevant literature on the effects of human capital stock on productivity and growth is still in short supply, especially in MENA.

The probability of the different role which human capital might play at different developmental stages has not been thoroughly examined at the micro level in the growth literature.

(Krueger and Lindahl, 2001a) had found that the role of the initial levels of schooling was highly heterogeneous between high-income economies on the one hand, and middle and low-income economies on the other.

The surprising finding was that the role of this fraction of human capital seemed to be insignificant in the high-income economies (OECD members).

This thesis contributes to the literature by presenting important firm-level evidence about the importance of human capital across two different regions considering their distance to the world's technological frontier. The results suggested different roles of different levels of education on firms' performance represented by technical efficiency in MENA and ECA.

Since efficiency and labour productivity can be regarded as two indicators of competitiveness, this study investigated the way in which human capital composition increases firms' international competitiveness in MENA and ECA economies.

The data used in this thesis reveals an interesting narrative regarding the employment shares of workers with different levels of skills across different size firms with different shares of foreign and state ownership in the two regions of MENA and ECA in 2013.

The larger firms in MENA dominated the job market by offering more jobs than medium and small enterprises for low, medium, and highly educated individuals. Moreover, government ownership appears to be more concentrated in larger firms than in smaller and medium-sized enterprises which put the latter – small and medium enterprises – in a disadvantageous situation to compete in the domestic market let alone the international markets.

In ECA the picture slightly differs in terms of the pattern of workers distribution among different firms. Larger firms employed the largest share of workers with different skills, but the highly-skilled individuals are more concentrated in the small and medium firms. Whereas the low and intermediate skilled workers are more concentrated in large firms in this region. Furthermore, foreign ownership shares seem to be larger in large firms compared to small and medium-sized firms which are more domestic-owned.

The important issue is the mismatch between the quality of jobs offered in the labour market and the quality of skills embodied in human capital in MENA and ECA. This led to more labour force leakages from the formal sector toward the informal sector in MENA and resulted in workers with different skills to be entrapped in less efficient firms in ECA because of labour market rigidities and weak firm dynamism in this region.

This study was intended to examine the different contribution of skilled (college and university degree holders) and unskilled (non-college and high school level) human capital to efficiency and productivity across three middle and high-income regions; MENA, and ECA, using stochastic frontier analysis to meet this aim.

Given that the (Vandenbussche et al., 2006) model was not tested – to date – at the firm-level in the lower and upper-middle-income MENA and ECA economies – especially in the private manufacturing firms operating in the formal sector – this thesis findings provide important empirical evidence that supports the assumptions of this model.

This model assumes that adopting existing technology is not the only source of economic progress but also innovation is another major contributor to growth. In this respect, the type of human capital that is relatively abundant in a country is a crucial determinant either in the imitation activities or in innovation and creation activities.

Unskilled human capital is assumed – according to (Vandenbussche et al., 2006) – as more suitable for imitation efforts than for innovation activities according to the level of education, skills and knowledge stock embodied in workers. On the other hand, skilled human capital – highly-educated labour – is better suited to innovation and knowledge creation particularly in the technologically advanced economies (technological frontier economies).

The findings of this research are in line with this assumption. That is, unskilled human capital – low-skilled workers with a high school education – is found to be more important for firm-level efficiency and productivity growth in MENA – which is behind the technological frontier - than in ECA region. In other words, the results indicated that low and intermediate skilled labour in ECA do not seem to play significant role in promoting firm-level and industry-level efficiency in the manufacturing sector.

Integrating human capital in the inefficiency function in the stochastic frontier production model suggests that human capital affects growth through technical efficiency and does not enter directly as a production factor. This assumption is line with (Benhabib and Spiegel, 1994) who suggested that human capital can directly affect total factor productivity – the efficiency in which production factors are used – and is also consistent with (Romer, 1990c) who proposed that human capital increases the country's capacity to innovate and generate new technologies which are suited to production structures in this country.

However, this result chimes with the conclusions of Krueger and Lindahl (2001) about the positive association between the low levels of education and growth only in the underdeveloped economies.

On the other hand, highly skilled human capital – workers with a university degree and above – appeared to have played a significant role in enhancing efficiency growth in the two – MENA, and ECA – regions subject to study. This result compares well with (Vandenbussche et al., 2006) assumptions, especially in ECA. Although their hypotheses suggest the insignificant role of skilled labour in driving growth and more important role for low skilled labour in enhancing growth in less developed regions such as MENA. This result is also consistent with (Corvers, 1997) who suggested that the effect of human capital on manufacturing sector performance in the European Union is only significant for highly-skilled workers.

Another important finding in this research is relevant to the independent impact of the average years of education – as a measure of school attainment – which is found to have no significant impact on firm-level technical efficiency in the two regions of MENA and ECA based on the obtained maximum likelihood estimates suggesting that human capital quality – tacit knowledge and cognitive skills acquired throughout the years of education and in the workplace – is what matters for efficiency more than human capital quantity – the number of years spent in school and college – which chimes with previous studies in the literature such as (Aghion et al., 2009) and (Hanushek, 2013).

This conclusion sheds some light on the cogency of years of schooling as an adequate proxy for human capital stock and this mirrors the conclusions of (Hanushek and Kim, 1995) who suggested that cognitive skills – measured by international test scores across nations – is more crucial for average annual real growth rates than the growth in average years of education. (Eric A. Hanushek and Wößmann, 2007) also suggested that average years of education as a measure of educational attainment is not flawless and it does not consider the qualitative differences in individuals' knowledge either

between education stages or across countries in terms of education systems efficiency, and learning environment quality.

The discussion of education quality inevitably leads to casting some light on the policy impact on quality. Putting more resources into the schooling system by spending more on classes environment and quality through more training for teachers does not necessarily result in improved educational attainment students.

The issue from a policy aspect is that the quality differences are closely related to the employed different sets of instruments of a certain policy. However, the evidence on the educational quality – throughout the literature – suggests that for the developing countries the economic impact of higher educational quality comes in part from better school attainment. The focal point is that the contribution of human capital to growth hugely hinges on the efficiency with which the various resources are allocated to the different levels of education in the different countries.

Some results that are emerging from research suggest that there is evidence that education is productivity-enhancing, and it is not just a devices that is used to signal the individuals' ability to their employers. (Sianesi and Reenen, 2003) suggested that the effects of primary and secondary schooling appear not only statistically significant but also larger in magnitude for less developed economies. They added that the impact of increases in various levels of education greatly vary across nations based on the economy's level of development.

This makes clear that primary and secondary schooling is more related to growth in the poorer and intermediate developing economies respectively, whereas tertiary skills are more associated with growth in the OECD economies.

7.2 Some Policy Implications

The findings of this thesis have a number of important policy implications. They confirm the results of earlier research in this field showing that high skilled labour matter for efficiency and growth. In high-income economies such as some of the Eastern and Central Europe nations, there is a tendency to invest more in higher education to grow faster depending on high-quality human capital to innovate.

In the same time, there seems to be underinvestment in primary and intermediate levels of education in terms of the quality of tacit knowledge required for the available job opportunities that are offered in the markets in the ECA countries.

Higher education is crucial for these countries and for their innovation activities. In the more developed economies, the capacity to continue to grow, depends largely on new ideas, new advanced technologies, and innovations which are captured by TFP. Tertiary education is also essential for ECA growing economies to adapt and accommodate the advanced innovations to boost their growth and converge with the technological frontier.

In the Middle East, and according to the World Bank, education in broader terms and tertiary education specifically, has faced consistent challenges for many decades. The region comparatively falls behind other regions in terms of the education quality for several years.

The associated issues to the low quality of education, such as high rates of unemployment among the university graduates is one of the important indications of the dire need of reforming the education systems in MENA as a whole, and in the poorer countries in this region.

Despite the growth in the number of higher education institutions, degrees, choice of programs, female participation shares, and enrolment rates in the Middle East and North Africa, the quality of the available options either from the students' point of view or the employers' side is still low.

Students' reality fell short their expectations when it comes to the pace of progress in capturing the skills needed most in the job markets in this region. Employers on the other hand fail consistently to find the calibre of graduates to reach the capacity they continuously seek. The gap is widening between what the job market looks for, and what the graduates have to offer in the form of knowledge and skills.

In spite of the high percentage of government spending on education, and the percentage of GDP in the MENA countries in comparison with some countries in other regions, the outcomes and the effects of education differ widely between nations.

In addition, this thesis investigated the impact of two cross-border activities, foreign direct investments and international trade, on the firm-level efficiency and productivity in MENA and ECA using a stochastic frontier analysis methodology and a matching methodology to examine the efficiency and productivity externalities of foreign ownership and international exports of firms. The results suggest the positive impact of firms' international exports in the two regions – MENA and ECA – However, foreign ownership appeared to be playing a more significant role in ECA than in MENA.

The macroeconomic stabilisation policy is an important constituent for the ECA economies to feed off the transition process and make it more successful. Additionally, establishing market-supporting institutional frameworks, and setting some standards for property and contract laws, as well as effective accounting systems are fundamental to ensure the continuation of the process. They need to deregulate and liberalise the price system and trade, develop and support the new private internal industries, increase the scale of the privatisation process of small and medium enterprises, and design a more responsive labour market and unemployment policies.

In MENA economies, the aim of human capital investment needs to give priority to building the skills required to leverage technology adoption and progress in the coming years along with the primary objective of closing the skill gap in the region. In this region, there needs to a much more concreted endeavor to reconcile the growth theory and the findings of several micro-studies in order to establish a connection between innovations and human capital.

The private and public sectors in the Middle East and North Africa region are required to work and collaborate in order to reform and strengthen the labour force structure, expand the talent pool, and re-design the appropriate labour markets policies. This will help several economies in this region to close the skills gap, the gender gap, and ensure higher level of human capital optimization.

The main issue which most economies in MENA face lies in the high exposure to the Fourth Industrial Revolution emerging trends and the low capacity of their labour force to adapt. A few economies in this region – Jordan included – are prepared to this high exposure measured by the impact of the latest technologies, economic diversification, and worker productivity. Whereas, Egypt and Morocco have comparatively lower levels of exposure and lower level of adaptation by their labour force.

Governments in MENA need to consider serious movements to adopt more knowledge-intensive and value-added investments and more persuasive production strategies. The growth of the private sector needs to be a priority for the foreseeable future. It needs to be supported to expand and burgeon in a more encouraging business environment which is essentially required to attract foreign investments, and to increase the chance for firms to be exposed to more advanced technologies along with the flows of FDI.

Universities in MENA, and other higher education institutions, as basic places for research and innovation are advised to modernise their educational schemes and teaching plans to provide students with better technical and cognitive skills, in order to be better suited to the job opportunities in the labour markets across the region.

To pre-empt any consequential effects of any new wave of political upheaval or economic turbulence, new ways of thinking are urgently needed in MENA economies, as the levels of dissatisfaction and frustration among the educated youth in this region have already reached an unprecedented height in recent years. Thus, governments and policymakers should respond faster with important economic corrections, and make choices and determine priorities, to guarantee the alleviation of most of the binding constraints in the investment climate, and direct their efforts and resources towards a more dynamic rehabilitation of the public sector.

It is also found that the percentage of foreign ownership of the firm (whether it is a complete or partial ownership) do not seem to have significant influences on efficiency. Finally, it is noted that the openness to external competition in the international markets promotes both a firm's efficiency and productivity where exporting firms are expected to gain more benefits from trading with more developed countries, and learn about the new technology and production know-how, which allows for innovation to be diffused and adopted at a larger scale in these firm's local business environment, which will raise the level of competition internally as well.

There is still much effort to be done to improve the value chains across MENA – where value being added to a commodity or a service by firms located in different nations – and FDI attraction in the advanced manufacturing industries, as well as leveraging trade opportunities by introducing better policy regimes to increase the export production.

In practice, several policy regimes need to be drastically addressed to make the market environment more competitive, reduce the high cost of transactions and to alleviate the rising levels of uncertainty in the economy partly due to political factors in the region.

By way of summary, the empirical evidence in this research is consistent with the endogenous growth theory in several respects. This is where the stochastic frontier analysis results suggest that as a country – region – lags behind the technological frontier, it becomes more dependent on technology imitation activities, in order to

converge and catch up with the frontier, and this implies reallocating the labour force – highly-skilled and low-skilled – between the economic activities based on the economy's proximity to the global technological frontier. This is to some extent true, especially in the manufacturing firms in MENA. This where workers with high school level – unskilled or low-skilled labour – appeared to play more significant role in promoting efficiency than in ECA.

On the other hand, workers with tertiary education and a university degree are found to be crucial for enhancing efficiency in ECA. Therefore, to drive some policy implications, highly skilled human capital is strongly associated with high growth rates especially in the more developed economies.

By way of conclusion, the research summarised in this chapter suggests that a more competitive business climate, in which firms have better access to highly-skilled labour, advanced technology, and finance in different forms, will have higher chance to grow and flourish rapidly. On the other hand, workers in this environment with better access to high quality training programs, better opportunity to have better jobs which match their skills and education levels, are likely to perform better, their marginal productivity will grow faster, and they are likely to have better impact on firms' technical efficiency and by extension growth.

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