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The impact of R&D expenditures on the small and medium firms' productivity in the formal private manufacturing sector in the Eastern Europe and Central Asia economies and in the Middle East and North Africa region

Salem Gheit *

ABSTRACT

This paper examines - through the lens of theory – the impact of R&D spending on productivity in small and medium enterprises SME's in the Middle East and North Africa & Eastern Europe and Central Asia nations, using the BEEPS 2013 database. The main contribution and novelty of this research is inspired by the argument of (King and Nielsen, 2016). This is where they suggested that the propensity score matching techniques, could approximate a low-standard experimental design, and could ignore much of the potentially useful information without efficient use, leaving us with higher imbalance, model dependence, and ultimately bias. Thus, these recent developments in the matching methods suggested that the conclusions drawn from PSM analysis are best supported by a second estimator, such as MDM, which has the property of double robustness, and reduces imbalance, model dependence, and bias. Therefore, both the completely randomised experiment procedures by propensity score matching, and the fully blocked randomised experiment by Mahalanobis distance matching are recommended for more confidence and reliability in the obtained results. The findings of this paper show that there is statistically significant impact of R&D spending (Treatment) on firms performance proxied by output per worker as the (Outcome) variable. Taking into account hetergeneity across countries and firms.

Keywords: Productivity, R&D Expenditures, Propensity score matching, Mahalanobis distance matching.

1.1 Introduction and Literature Review

It is widely acknowledged that a production unit can gain some degree of competitiveness; this is if it could raise its productivity and growth to a certain level through increasing its spending on research and development activities, along with other essential productivity-enhancing factors, (Chan, Lakonishok and Sougiannis, 2001).

The OECD defines Research and Development Activities (R&D) as: "….*creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications*", (Manual, 2003; Parham; Parham, 2006).

In the production function – which relates to the maximum level (quantity) of gross output (Y) that can be produced by all inputs, including the primary inputs (labour L, capital K), and intermediate inputs (principally materials M) – research and development incurs and claims its significance as being one of the determinants along with learning–by–doing. There is also the imitation of technological progress, which is thought to lead to improved production operations, both in terms of quantity and quality given that this disembodied technical change is captured by the parameter (A) in the above mentioned production

*Research Associate in Economics, Bournemouth University. U.K., Lecturer in Economics, Bani Walid University. Libya.
Email: i7695447@bournemouth.ac.uk
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function, and it is "*disembodied*" because it is not linked physically with any particular production factor.

It is also important for managers to understand the link between the value of R&D expenditures and firm's performance, (Zhu and Huang, 2012), especially in the technology producing corporations, which rely on their growth by the utilisation of innovative products, which in turn require more spending and investment in the R&D activities to achieve the aspired level of growth, (Lantz and Sahut, 2005).

Despite that, it is believed that expenditures on research and development, still stand at the boundary line between intermediate consumption and capital formation in the economic literature. There can be significant impact of such practices on productivity, even though they are seen as "*intangible*" assets for enterprises. However, managers sometimes seem to be disinclined to take risks, and prefer short term returns, and they might refrain from investing in more research and development activities for some reasons; (a) this is because expenditures on R&D are considered to be intangible investments, thereby, the probability of failure is arguably assumed to be greater than in the case of tangible investments. In addition, the long-term nature of R&D, as an investment, involves some risk before achieving the market-standard innovative products which can be outdated during the time they are preseneted, which implies considerable loss in the cost of this investment, which are – the costs – then irreversible; meaning that the firm will not be able to recover all of the invested money because the project will tend to be partly a firm specific one, and cannot be sold at the cost of acquisition, (Lantz and Sahut, 2005); (b) the R&D investors, in many cases, will not be able to fully appropriate the output of their inventions, and the latter are likely to have some of the public goods attributes, via the imitation activities, (Zhu and Huang, 2012).

In the main, the process of increasing the stock of knowledge is a process of transforming R&D inputs (the existing stock of knowledge, expertise and creative dexterity of individuals, capital assets, and intermediates) into R&D outputs (the increment and generation of new technologies, assimilation, and applications of existing and relevant knowledge), (Parham, 2006).

The key argument in this respect, is that although there is some fundamental importance of spending on R&D to heighten productivity, and expanding the prospects of production possibilites in the future, which is in a way that could parallel the investments in physical assests, such as machinery, buildings, equipment, etc., the beneficial assets resulting from these intermediate expenditures cannot be easily identified, quantified, or valued to be included in the balance sheet. Therefore, this class of spending is mostly regarded as being part of the intermediate consumption, (Corrado, Hulten and Sichel, 2009).

A growing body of empirical literature has sought to explore the rate of returns to research and development spneding at both the microeconomic and macroeconomic levels. It is therefore thought that both the rates of returns (private and social) to these activities are important for growth. However, it is also found that the social returns to research and development expenditures are believed to be significantly greater than the private, and given that the decisions at the firm level will be undertaken based on the private returns, a bigger role for governments is justifiable to fund and provide better assistance to this kind of investments on the grounds of its substantial social returns, (Griffith, 2000).

In theory, it has been emphasised that the accummulation of both human capital and research and development is important for economic growth, (Aghion and Howitt, 1992). This is where the private returns of R&D spending are measured via estimating the impact of the firm's R&D on its own output. That is, measuring the elasticity of output with respect to capital stock. The estimated elasticity, with respect to R&D expenditures, is found to be around 0.07 in the US firms. That is to say, an increase in R&D spending by around 10%, will yield an increase in output by around 0.7%, (Griliches, 1992). Most research of the impact of R&D has considered output as value added, and has treated capital and labour as inputs, (Dole, 1989), whereas some other studies used the industry gross output measures, (Scherer, 1982).

Equally important, is the fact that some other approaches have underlined that the impact of R&D on productivity is expected to be factor augmenting, meaning that it affects either labour or capital preponderantly but not equally, (Link, 1978).

Moreover, some have proposed that R&D could be included directly in the production function as an interactive additional input, rather than being just a multiplicative factor, and the results of this suggestion show that R&D has been influential, in terms of its effects on the demand for labour and capital, indicating some kind of complementarities between R&D and these two factors, (Nadiri and Bitros, 1980).

Another dimension of the estimated returns to R&D is related to the labour and capital allocated for R&D purposes, which are already included in the production factors (labour and capital), which suggests that the returns of R&D tend to be social, more than merely being private, and given that most measures of capital and labour at industry level already encompass the resources apportioned to R&D activities, then most returns are likely to be social considering the externalities of R&D with the estimated direct returns included, (Griliches, 1973).

The indirect returns to research and development activities is an additional trend, which has increased in the 1970s and 1980s; that is, the increase in productivity in the downstream industries is due to the higher quality in the capital and materials that they have acquired from the upstream industries, as a result of research-intensive industries through heavy research spending in the upstream industries.

The main point is that the spillovers of expenditures that generated innovations stretch to promote productivity in industries that perform the research, which in turn positively contributes to the production processes in the downstream industries, (Terleckyj, 1974), (Scherer, 1982).

Further research, in this line, has shown some divergent results, where high returns for purchased capital have been reported in the regressions, but none have been found for purchased materials, (Sveikauskas, 1981); whereas, in some studies, the materials purchased from research-performing industries are found to have a significantly positive impact, (Scherer, 1982).

The fundamental argument in this regard is the lag (time slowdown) between the research spendings and its impact on productivity, which on average takes no less than half a year to be conducted and put into operation, (Mansfield, 1972). Several attempts have been undertaken in the agriculture sector to estimate and calculate this lag, and some concluded that the maximum effect can appear in a period between 5-8 years, with the total impact disappearing after 16 years, (Evenson, 1968), whilst in the industry sector this lag is thought to be 3 years for the private research and development based on some estimates, (Terleckyj, 1982), (Branch, 1974). In the meantime, others suggest that given the lag between the patent application and research expenditures in the first place, the estimated effect is around 1.6 years, (Pakes and Griliches, 1984a), (Pakes and Griliches, 1984b), and therefore, this lag can be from 4 to 6 years in the case of R&D spendings and the final profits of a firm, (Ravenscraft and Scherer, 1982).

Most economists recognise the critical importance of intangible assets into the innovative process in the modern-day economy. This is where in the U.S. some argue that investment in intangible assets, in recent years, was approximately equivalent to the investment in tangible assets. (Aizcorbe, Moylan and Robbins, 2009).

In part, the pursuance to identify the unexplained residual in the growth of output in the work of Solow has motivated the attention on the R&D, where, and as mentioned before, the growth in both labour and capital cannot only be used to interpret the whole growth in output, (Fixler, 2009).

According to (Schmookler, 1965; Kortum, 1997; Jones, 1995) the focus on R&D expenditure is drawn from the idea that firms (industries) tend to promote their products and processes' innovations through technical change. However, one of the principal objectives of the integration of R&D, as a capital into the national accounts, is to determine its contribution to the growth rate of real gross domestic product. Yet, limitations to the estimation process of R&D contribution still obstruct the attainment of a complete measure of its share in the output growth. More precisely, the national accounts focus only, and strictly on, the direct effects in determination of the different shares of inputs in gross domestic product.

1.2 *Methodology: Matching Methods*

The propensity score matching PSM and Mahalanobis distance matching MDM were integrated in this paper to provide broader understanding of the kind of causal effects that treatment variables such as research and development could have on labour productivity.

The propensity score matching can be defined as the probability of a group of participants receiving treatment based on observed characteristics. It allows scholars to reconstruct counterfactuals by making use of observational datasets. That 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).

The rationale for the matching methods choice is that matching can be 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, King and Stuart, 2008; Iacus, King and Porro, 2011), and therefore reduces the estimates inefficiency and bias.

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 sufficient number of observations. This happens when procedures like Coarsened exact matching CEM and caliper-based techniques are applied. (Rubin, 1973) and (Austin, 2011).

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), (Burgette, Griffin and McCaffrey, 2017).

1.2.1 Treatment Evaluation Definition and Propensity Score Matching PSM

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 (*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.

1. Treatment *D* is a binary variable that determines if the observation has the treatment or not.
2. *D=1* for treated observations and *D=0* for control observations.
3. The second step is to estimate a probit/logit model for the propensity of observations to be assigned into the treated group.
4. The x variables that could affect the likelihood of being assigned into the treated group are used in the model.
5. The propensity score model is a probit/logit model with D as the dependent (explained) variable and x as the independent variables (explanatory).

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

The propensity score model is the conditional (predicted) probability of receiving treatment given the pre-treatment attributes of x. The goal here is to find a match for each of treated observations not the control group

6. The next step is to calculate the treatment effect by comparing the outcome y between the treated and control observations, after matching the following

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

In order to account for a potential selectivity bias, the average treatment effect estimation is selected to compare the firms spending on R&D activities during the last three completed fiscal years and those that did not spend on R&D activities during the same period (Heckman, Ichimura and Todd, 1997) (Muehler, Beckmann and Schauenberg, 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 (R&D spending) or not (Blundell and Dias, 2002) (Caliendo and Hujer, 2006) (Muehler, Beckmann and Schauenberg, 2007).

In this case, the average treatment effect for the population (ATE) describes the difference in the expected output per worker (labour productivity) for firms that spent on R&D activities and those that did not spend on such activities, and this can be defined as:

$$\Delta_{\mathbf{ATE}} = \mathbf{E}(\Delta) = \mathbf{E}(\ln \mathbf{OPW^1}) - \mathbf{E}(\ln \mathbf{OPW^0})$$

Equation.1

Where;

$E(\ln OPW^1)$ is the expected log-output per worker for firms with R&D spending, and $E(\ln OPW^0)$ is the corresponding expected log-output per worker for firms with no R&D spending.

Consequently, the more appropriate evaluation parameter is the average treatment on the treated (ATT), which focuses on the productivity effect in these firms.

The ATT involves the difference between the expected output per worker with and without R&D spending programs.

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

Equation.2

Alternatively,

$$\Delta_{\mathbf{ATT}} = \mathbf{E(\Delta|T = 1) = E(\ln OPW^1|\ T = 1)} -$$

$\mathbf{E}(\ln \mathbf{OPW}^{0} \mid \mathbf{T}=\mathbf{1})$ **Equation.3**

The second term on the righ hand side of Equation.3 $[\mathrm{E}(\ln \mathrm{OPW}^{0} \mid \mathrm{T}=1)]$ denotes for a hypothetical outcome without treatment for individual who received the treatment and is not observable. Under the condition where $[\mathrm{E}(\ln \mathrm{OPW}^{0} \mid \mathrm{T}=1) = \mathrm{E}(\ln \mathrm{OPW}^{0} \mid \mathrm{T}=0)]$, the group of firms without treatment (R&D spending) is considered as an adequate control group.

For more details on propensity score matching procedures see (Austin, 2011). (Ho *et al.*, 2007), (King *et al.*, 2011), and (King and Nielsen, 2016).

1.2.2 Mahalanobis Distance 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 ignores 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, where 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: $\mathrm{X_{FB}} = \mathrm{M}(\mathrm{X_{FB}} | \mathrm{X_i} = \mathrm{X_j})$, meaning that $\mathrm{I}(\mathrm{X_{FB}}) = 0$.

Whereas in the case of 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: $\mathrm{I}(\mathrm{X_{CR}}) \geq 0$. 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, King and Stuart, 2008) (Imai, King and Nall, 2009) (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, King and Porro, 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, to obtain zero imbalance.

To illustrate the point: $\mathbf{X}_{\mathrm{EM}} = \mathrm{M}(\mathrm{X} | \mathrm{A_{CEM}}, \delta = 0) = \mathrm{M}(\mathrm{X} | \mathrm{A_{MDM}}, \delta = 0)$. 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: $\mathbf{X}_{\mathrm{EM}} \subseteq \mathrm{M}(\mathrm{X} | \mathrm{A_{PSM}}, \delta = 0)$, and hence, $\mathrm{I}(\mathbf{X}_{\mathrm{EM}}) \leq \mathrm{I}(\mathbf{X}_{\mathrm{PSM}})$, and it is strictly $\mathrm{I}(\mathbf{X}_{\mathrm{EM}}) < \mathrm{I}(\mathbf{X}_{\mathrm{PSM}})$, 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 $\mathrm{X_i}$ and $\mathrm{X_j}$ with the Mahalanobis distance,

$$\mathbf{M}(\mathbf{X_i}, \mathbf{X_j}) = \sqrt{(\mathbf{X_i} - \mathbf{X_j})' \mathbf{S^{-1}} (\mathbf{X_i} - \mathbf{X_j})} \qquad \textbf{Equation.4}$$

Where S represents the sample covariance matrix of X. (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 form the control units to which they were matched in the first step (Stuart and Rubin, 2008; Rosenbaum and Rubin, 1985), (Heinrich, Maffioli and Vazquez, 2010).

1.3 *Data Discussion*

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, Haltiwanger and Scarpetta, 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.

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 sector dummy variable (low, medium, and high technology industries) named as sector specific effects.

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 these 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 R&D spending in each region in comparison with the other.

1.3.1.1 Data from the Middle East and North Africa

The dataset which is used for the estimation was taken 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’s 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.

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).

In regard to R&D Spending 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.

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

1.3.1.2 Data from Eastern Europe and Central Asia

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 28 Eastern European and Central Asian nations.

The countries 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.

Regarding the R&D data in ECA, more than 4300 manufacturing firms from different economic activities with different sizes and ages reported whether they spent on R&D activities over the last three years prior to 2012.

1.3.1.3 Variables for OLS Probit and Propensity Score Models in MENA and ECA

For a start, one of the main differences between OLS models and Probit models lies in the fact that the former is widely used when dealing with (continuous dependent variables), whilst the latter is widely applied to deal with (binary dependent variables).

If the dependent variables is binary, the researcher can choose among OLS, logistic or probit regressions. Probit regression estimates the probability of an outcome. This is where events are coded as binary variables with a value of 1 representing the occurrence of a target outcome, and a value of zero representing its absence. OLS can also model binary variables using linear probability models. OLS may give predicted values beyond the range (0,1), but the analysis may still be useful for classification and hypothesis testing. The normal distribution and homogeneous error variance assumptions of OLS will likely be violated with a binary dependent variable, especially when the probability of the dependent event varies widely. Both models allow continuous, ordinal and/or categorical independent variables. (Menard, 2002).

The independent variables that appeared to be statistically insignificant in terms of their effects on the (continuous) dependent variable (output per worker) in the OLS model had been ruled out of the estimation process. At the same time, the same variables had been factored in the Probit model, because they had shown statistically significant impact on the treatment (binary) dependent variable (R&D expenditures).

Given that R&D expenditures are not the solely 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). Where 0= no impact, 1= minor impact, 2= moderate impact, 3= major impact, 4= severe impact. This categorisation applies for other similar inputs in the model.
3. Receiving fund from different sources in the form of loans (0, 1).
4. Size of 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 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).

11. The introduction of any new production methods over the last three years prior the survey (1,0).

12. Sector dummy variables are included to capture the specific effects of a high-tech, med-tech, or low-tech manufacturing plant.

13. 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.

14. Sector dummy variables are included to capture the specific effects of a high-tech, med-tech, or low-tech manufacturing plant.

15. 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 country specific effects on the firm's performance.

1.3.2 Empirical results and economic analysis for the MENA region.

The results in this section provide important empirical evidence on the positive and significant causal effects of research and development expenditures, international trade, firms size, new management practices, and funds in the form of loans on the firm-level productivity in MENA.

1.3.2.1 Ordinary least squares and probit models

From table (1) the effects of research and development activities on labour productivity were found to be significant and of positive contribution to firm's performance. This result mirrors a significant body the literature and previous empirical work in this field. This signifies the importance of spending on such activities to improve labour productivity, and therefore, enhance the firm's efficiency and competitiveness, overall, and in MENA specifically.

Despite the importance of R&D as a channel to human capital formation, and the role it plays in generating TFP via both innovation and technology transfer, the Middle East and North Africa economies are still far from being ideal in terms of the optimal level of R&D investment required to promote innovation and creation, and then a better performance to increase growth. Thus, there is a need for governments, alongside the private sector, to formulate appropriate and more persuasive policies that adopt more reforms to incentivise firms to embrace more efficient approaches in their financial resources allocation to enable more research and development activities, in order to bring forth private profits along with societal returns to the economy.

From table (1) this research can trace out that the correlation between the R&D expenditures and output per worker in the manufacturing firms in MENA is positive and statistically significant at $p = 0.05$ level.

The results also outline the importance of firm size as a determinant of productivity, and the share of direct international exports as an essential factor to invigorate performance and productivity.

The openness and trade integration with the global markets, within the Middle East and North Africa economies, has suffered from high tariff and non-tariff hurdles, which posed a considerable handicap.

The probit model estimates also reveal that firms, who are more likely to spend and allocated portion of their monetary resources for more research and development, are likely to:

1. Be larger and have better access to finance and

have received loans and subsidies to fund their production schemes.

2. Have a significant proportion of their exports targeted towards international markets.

3. Have applied new and improved specific management and marketing, as well as production practices and techniques, to improve their competitive positioning in the market.

4. They are also more likely to have contracted to purchase and use advanced and patented technology from abroad.

Table.1. The effects of R&D spending on output per worker in MENA manufacturing firms

	Model [1] OLS	**Model [2] Probit**
	Ln Output per worker	R&D spending
R&D spending [0,1]	0.189**	-
	(0.0824)	-
Firm size	0.123***	0.0127***
	(0.0254)	(0.0043)
Direct international exports ratio	0.360***	0.0189***
	(0.0421)	(0.006)
Loan [0,1]	0.562***	0.044***
	(0.0662)	(0.011)
New management practices [0,1]	0.287***	0.0685***
	(0.0768)	(0.016)
GDP per capita	0.0000791***	-
	(0.00000670)	
Life expectancy rate	0.0544***	-
	(0.0131)	
Strength of legal rights index	-0.270***	-
	(0.0376)	
Sector dummy [medium technology]	0.405***	-
	(0.0751)	
Sector dummy [high technology]	0.342***	-
	(0.0534)	
Government ownership shares	-	0.0001
		(0.0008)
New marketing approach [0,1]	-	0.0438***
		(0.013)
Subsidies [0,1]	-	0.0610***
		(0.023)
Training [0,1]	-	0.0698***
		(0.016)

	Model [1] OLS	**Model [2] Probit**
Licensed technology used [0,1]	-	0.0495***
		(0.018)
New production approach [0,1]	-	.2799***
		(0.023)
Cons	4.731***	-2.504***
	(0.910)	(0.123)
N	2846	3275
R^2	0.285	Pseudo R2 = .3707
LR chi2 [10]	-	942.84
F [10, 2835]	138.79	-
Prob > F	0.0000	-
Prob > chi2	-	0.0000
Diagnostic tests:		
1- Testing for Heteroscedasticity	chi2(1) = 35.06 Prob > chi2 = 0.0000	Presence of heteroscedasticity. Therefore, robust standard errors are used in the estimation.
2- Omitted-Variable Test	F (3, 4668) = 19.22 Prob > F = 0.0000	Some variables are not included in the model.
3- Testing for Multicollinearity	Mean VIF = 1.95	Mean VIF < 10, No multicollinearity problem.
4- Joint Significance Test	F (8, 4671) = 284.88 Prob > F = 0.0000	All independent variables have jointly significant impact on the dependent variable.

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Creating knowledge and investing in the knowledge-based capital is to some extent a complicated process, but it is acknowledged as an essential driver of economic performance.

However, it requires intensive efforts and a chain of innovative activities executed very often by highly qualified professionals and funded by principal research centres and public foundations, such as renowned universities and well-equipped laboratories. The research is usually based on everyday observations and experiences and through trial and error most of the time.

In developing countries, the key concern is about the readiness, as well as the adaptability of these countries' economic structures and institutional and economic regimes, to adjust to the new conditions of research and development prerequisites before making the crucial decision in relation to allocating some of their resources, which is to reflect their will to be engaged in this process.

Investment in knowledge, research, and education, can be partly affected by the regulatory and legislative systems, the competitive atmosphere, locally and internationally, the labour markets policies, and the financial markets, along with the governance environment. In some countries in MENA the climate to invest in research and development is not encouraging owing to over-regulation, control of information, and bureaucracy, especially in the public-sector activities which are fairly large in comparison with the private sector.

However, it appears as in table (1) that the legal rights index has had a negative impact on a firm's productivity.

There can be a feasible alternative for these countries that are placed way behind the technological frontier. That choice involves the adoption of the existing knowledge, which is created in advanced economies through R&D activities, to enhance productivity and growth. The foreign direct investments, and technological assistance agreements with the intellectual property rights owners, can be viable strategies to achieve this objective in the Middle East and North Africa to catch up with the technology leaders, given that MENA countries are in dire need of massive efforts and a timescale to establish themselves as proper candidates to be knowledge producers and as technological reverse engineering hubs in the future.

Based on the results, reported in table (1), access to licensed technology from a foreign owned company has a positive role in stimulating firms to allocate more funds for research and development, which turned out to be positively affecting workers' output.

Building on that it should be mentioned that the lack of technological capacity for MENA economies was a vital constraint to constant improvement in the economic performance and the sustainable creation of jobs in the domestic market.

In the context of accessing and mastering modern technologies, it seems that MENA economies can be categorised into four classes, starting with the technology developers, such as Israel, Turkey, and Iran, the technology users, including K.S.A, Qatar, U.A.E, Kuwait, and Bahrain, the integrated users, such as Egypt, Morocco, Tunisia, Jordan and Lebanon, and the isolated users, including Libya, Algeria, Iraq, Yemen, Syria, and the West Bank and Gaza.

The scale of international trade and the degree of openness in MENA economies is constrained and held back by their lack of ability to make practical and effective use of the advanced technologies, which prevents the spillovers of technology diffusion and positive influences of trade liberalisation on the momentum of economic performance.

Regarding the foreign direct investments in MENA, it seems to be that the investment climate needs more reforms, and there is the restrictive legal system that favours local companies and has placed some restrictions on foreign companies to own and invest in some sectors, such as the real estate and other activities.

Besides, there is the negative role that obstructive bureaucratic and administrative routines have played in impeding the businesses in general, and the foreign investors in particular, from making progress and achieving success, in relation to providing better knowledge and putting modern technologies into practice for better performance and productivity.

Despite the successful efforts made in the innovation and technology adoption field, the R&D still represents a low percentage of GDP due to the insufficient advancements that have been made to modernise telecommunications, as well as the information infrastructures to support the infant and emerging industries. The reshaping of the organising technological and managerial frameworks, to persuade foreign entrepreneurships to pour in more investments remains inadequate as well.

The performance of MENA economies in terms of providing an attractive and encouraging business environment for foreign investments was modest in comparison to other regions such as Eastern Europe and Central and South Asia. This is where FDI per capita was comparatively low, and in countries like Bahrain, Qatar, K.S.A, Tunisia, and the U.A.E the percentage of inward FDI’s was noticeably higher than that in Algeria and Syria (before the Arab Spring in 2011), but after the civil riots, all over the area, the climate for foreign businesses drastically deteriorated and the risk escalated to dangerously high levels.

Regarding the four diagnostic tests provided in table (1), in test (1) it appears that heteroscedasticity is present in the residuals distribution, therefore, in order to correct for this problem, the robust standard errors were included in the model as a remedial procedure in this case. Test (2) results suggest that some variable had been omitted form the model. This is true, first because some independent variables were rules out of the model as they were statistically insignificant, and to avoid any problem of multicollinearity between explanatory variables. Second, other important variables that may have significant impact on both dependent variables could not be included in the OLS and Probit models, simply because data unavailability in this specific dataset form the World Bank Enterprise Survey.

The results in test (3), are consistent with test (2) results. This is where they show that there is no multicollinearity issue in the models, and the value of VIF for all the explanatory factors are well below 10.

Test (4) usually referred to as the (F test, indicates that all independent variables have join significant effects on the dependent variables in the above OLS and Probit models.

In the normality test, if the residuals do not follow a normal pattern then omitted variables should be checked, model specifications, linearity, functional forms. In sum, it may be needed to reassess the model/theory. In practice, normality does not represent much of a problem when dealing with real big samples.

1.3.2.2 Propensity score matching: nearest neighbour matching

This is one of the easiest matching procedures, where a member of the comparison group is usually selected to serve as a match for a treated unit in terms of the closest propensity score, or in terms of the similarity in some observed features.

Table.2. Nearest Neighbour Matching with replacement, with caliper (0.02)

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Output Per Worker	**Unmatched**	10.6680357	9.74649024	.921545476	.086135317	10.70
	ATT	10.6680357	10.0480281	.620007646	.160019956	3.87

The procedure involves both options with and without replacement. In the with replacement option the untreated observation can be used as a match more than once, whereas in the without replacement choice the untreated unit in the comparison group can be allowed in the matching for one time only.

The ATT estimation, reported in table (2), appears to be significant at 99%, but the balancing needs to be checked before trusting the ATT estimation. See figure (1).

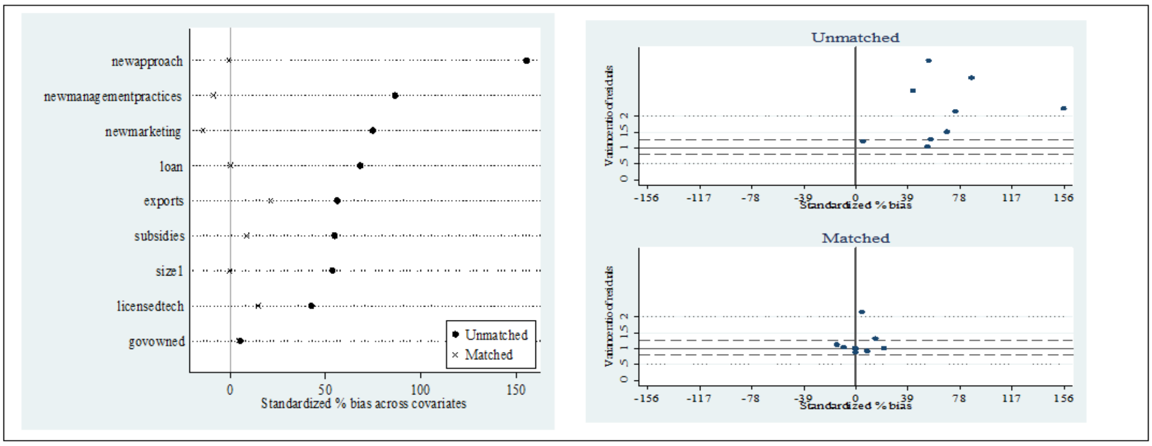

Figure.1 Nearest Neighbour Matching with replacement, with caliper (0.02)

The effect of firms' spending on R&D activities on worker's productivity, in the nearest neighbour matching procedure with replacement, is statistically significant. Where the cumulative student's t-distribution at F=10 is 1.372, 1.812, and 2.764 at n = 0.90, 0.95, and 0.99 respectively.

When comparing the output per worker means across firms, it can be noticed that the mean, if the firms are spending on research and development, is higher than in firms that did not spend on R&D activities.

Table. 3. Summary of Output Per Worker If R&D Expenditures = 1 (R&D Expenditures)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Output Per Worker	353	10.66804	1.571792	3.37115	17.97648

Summary of Output Per Worker If R&D Expenditures= 0 (No R&D Expenses)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Output Per Worker	353	10.04803	1.340488	6.184493	13.33578

The mean of output per worker in those firms that spent on research and development over the last three complete fiscal years is 10.66804 – table (3) – which is greater than the mean of output per worker in the firms that did not spend on research and development during the same period which equals 10.04803.

The impact of firms' R&D expenditures in when imposing a (0.02) caliper with replacement, is found to be statistically significant at 95% and 99% with 10 degrees of freedom.

The regressors are clustered around the centre in the lower part of the figure (1) but not very well balanced. It might be better to use the "without replacement" option to reduce the bias in the covariates.

The intersection between the two kernel density curves in figure (2) suggest that units that have the same features (X's) should have a positive probability of being either treated or untreated. In other words, this shows the region of common support right in the middle area between the two curves.

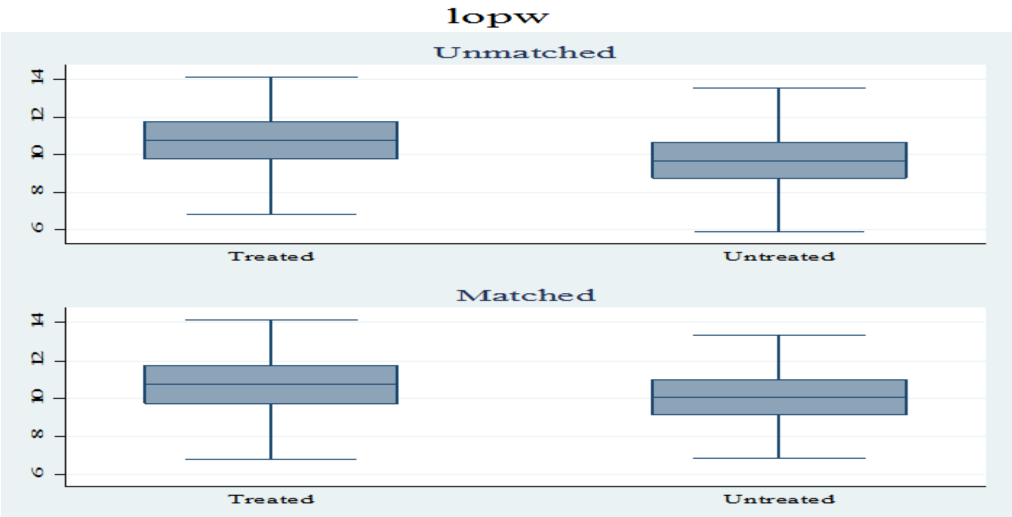

Figure.2. Matching Quality with replacement (Caliper = 0.02), output per worker

The boxes in figure (2) show that the treated and untreated units of the matched sample are not very well aligned using 0.02 caliper and allowing for each of the treated units to be used more than once in the matching process with the control units. Therefore, the next option is to restrict the multiple use of the treated units to be matched only once with only one unit of the control observations.

1.3.2.3 Mahalanobis-metric matching results

In pursuit of better balancing and more bias reduction percentage for the confounders, we use Mahalanobis and the augmented Mahalanobis matching. The two procedures reduce bias noticeably, especially with the inclusion of propensity scores in the augmented Mahalanobis.

Table.4. Mahalanobis-Metric Matching and Augmented Mahalanobis-Metric Matching, (Score included)

Mahalanobis-Metric Matching						
Variable	**Sample**	**Treated**	**Controls**	**Differences**	**S. E**	**T-Test**
Ln Output Per Worker	**Unmatched**	10.6680357	9.74649024	.921545476	.086135317	10.70
	ATT	10.6680357	10.2804624	.387573354	.169517495	2.29
Augmented Mahalanobis-Metric Matching, (Score included)						
Variable	**Sample**	**Treated**	**Controls**	**Differences**	**S. E**	**T-Test**
Ln Output Per Worker	**Unmatched**	10.6680357	9.74649024	.921545476	.086135317	10.70
	ATT	10.6680357	10.2623569	.405678787	.171086918	2.37

According to the matching results reported in table (4) the causal effect of the research and development efforts on a firm's output per worker is found to be positive and significant at a 95% statistical confidence with 10 degrees of freedom. The difference in the ATT estimation – .405678 – is positive and the t-stat suggests a statistically significant impact of the R&D spending on the logged value of the output per worker of a firm.

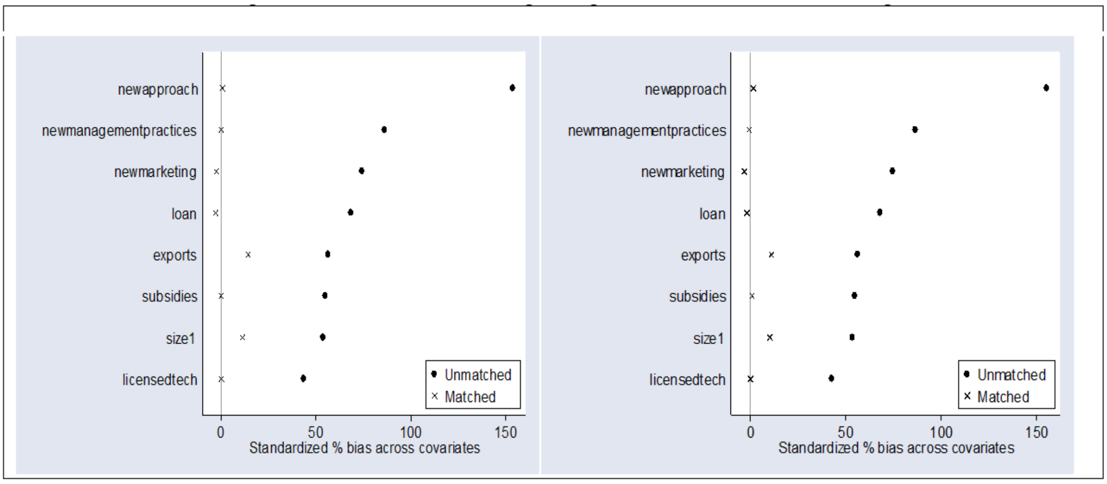

Figure.3. Mahalanobis-Metric Matching and augmented Mahalanobis-Metric Matching

The balance of the confounding covariates in figure (3) with the inclusion of the propensity scores is better than their balance in the MDM analysis without the inclusion of the propensity scores.

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

1.3.2.4 Comparison between propensity score matching and Mahalanobis metric matching

The balancing of the confounding covariates has improved extremely well with the use of the Mahalanobis and augmented Mahalanobis metric matching. This is where the bias was reduced by a 100% in some covariates.

Table.5. Comparison between bias reduction (%) using PSM and 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
Firms size	99.5	99.5	88.7	79.9	79.4
Government ownership	17.2	17.2	-17.6	52.2	53.2
Innovative marketing strategies	80.9	80.9	85.0	98.3	97.4
Subsidies	84.5	84.5	91.8	100.0	98.4
Licensed technology	65.8	65.8	94.7	100.0	100.0
International exports	62.3	62.3	68.0	72.1	78.2
Loan	100.0	100.0	100.0	97.3	99.1
New management practices	89.6	89.6	93.6	98.4	99.2
New production approaches	99.5	99.5	97.5	98.6	98.1

The contents of this table are taken from the estimation appendices which are not attached in this document.

1.3.3 Empirical results and economic analysis for the ECA region

1.3.3.1 OLS and probit models estimates

Table 6 highlights the OLS estimates of the causal effects of a vector of explanatory variables on output per worker as a measure of firm's productivity including the effects of R&D expenditures.

The results indicate the positive impact of R&D spending as a determinant of firm level productivity in ECA along with other factors such as the share of foreign ownership in the firm, the firm's level of technology, and the receipt of loans as a means to fund the firm's economic activities.

The OLS results suggest that if a firm increases its spending on R&D activities by 1 percentage point, the increase in productivity tends to be about 0.3%.

The probit model suggests that the firm's R&D activities can be determined by several factors such as the percentage of foreign shareholders, accessibility to finance, and the ratio of domestic ownership. It can also be affected by the firm's size and level of technology, and the prevalent bureaucratic framework.

Table.6. The impact of R&D on labour productivity in the ECA manufacturing firms

	OLS Model	Probit Model
	Ln Output Per Worker	**R&D expenditures**
R&D expenditures	0.259***	
	(0.0510)	
Foreign ownership shares	0.00584***	0.00193*
	(0.000911)	(0.000990)
Finance accessibility	-0.0314*	
	(0.0138)	
World exports	0.193**	0.271*
	(0.0646)	(0.134)
National exports	0.385***	0.406***
	(0.0407)	(0.0558)
Firm size		0.143***
		(0.0322)
Loan	0.327***	0.177***
	(0.0397)	(0.0503)
Bureaucracy		0.218***
		(0.0311)
Domestic ownership shares		-0.00325*
		(0.00151)
GDP per capita	0.0000969***	0.0000248***
	(0.00000362)	(0.00000437)
Legal rights index	0.0375***	
	(0.00870)	
Sector dummy Med Tech	0.249***	0.201**
	(0.0511)	(0.0664)
Sector dummy High Tech	0.179***	0.256***
	(0.0420)	(0.0559)
_cons	8.367***	-1.890***
	(0.0797)	(0.175)

	OLS Model	**Probit Model**
N	4280	4324
R^2	0.234	Pseudo R2 =0.087
F(10, 4270)	128.70	
Prob > F	0.0000	
LR Chi2(10)		324.43
Prob > Chi2		0.0000
Diagnostic tests:		
1. Testing for Heteroscedasticity	chi2(1) = 0.00 Prob > chi2 = 0.9649	Presence of heteroscedasticity. Therefore, robust standard errors are used in the estimation.
2. Omitted-Variable Test	F(3, 4242) = 10.04 Prob > F = 0.0000	Some variables are omitted as they had no statistically significant impact in the model.
3. Testing for Multicollinearity	Mean VIF = 1.34	Mean VIF < 10, No multicollinearity problem.
4. Joint Significance Test	F(11, 4245) = 114.37 Prob > F = 0.0000	All independent variables have jointly significant impact on the dependent variable.

Robust Standard Errors in Parentheses

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

However, the reported results in table 6 reveal the negative impact of domestic ownership on the firms' decision about allocating some financial and human resources for certain research and development activities over the last complete fiscal years.

Despite the proven importance of R&D in promoting firm's performance, businesses in ECA still lagging behind in this respect, and their investments in technology development are very low in comparison with businesses in other regions. A jump-start is needed to revamp and boost the prevailing sluggish system of investments in research and development. Governments can stimulate firms to participate along with universities and other R&D institutions to pour more financial capital into this area.

Openness represented by world market exports and national market exports and foreign ownership represented by the percentage of foreign shareholders are found to play vital roles in both enhancing firms' productivity and encouraging firms to spend on R&D activities. Stronger competition in the world markets drives firms to adapt and adopt and spend more of new technologies and research in production in order to both improve the quality of their goods and to be able to absorb more sophisticated innovations within their production structures and benefit from them over the longer run.

As regards the four diagnostic tests that are included in table (6), the same analysis for similar tests shown in table (1) approximately applies for the results added in table (6).

The ATT reported in the nearest neighbour matching results in table (7) demonstrates the positive and significant impact of firm's R&D investments on the level of productivity. The comparison between the means of output per worker as a measure of performance shows that the mean of output per worker in firms that spent on research and development activities over the last complete fiscal years is greater the mean of output per worker in firms that did not invest in research and development during the same period.

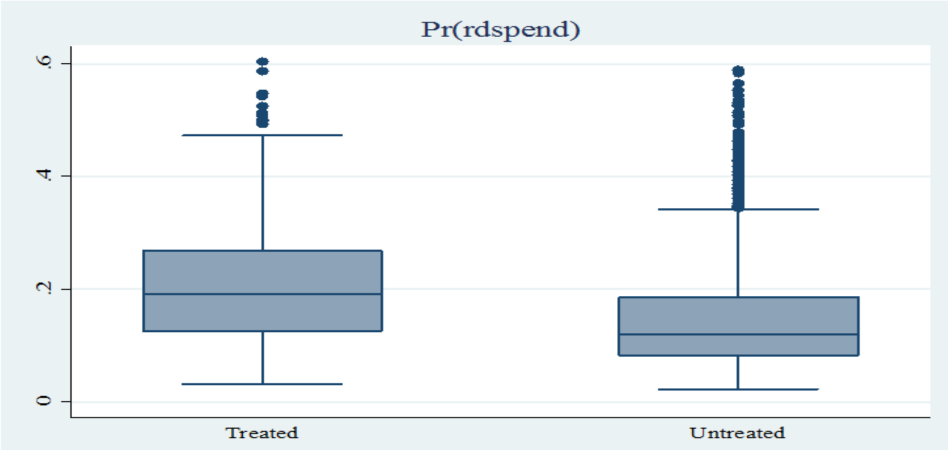

Figure.4. Propensity scores (Treated, untreated)

To assess the efficacy of this estimation we need to look at the balance of the matched confounding covariates resulted from the matching. The matching with replacement and without caliper achieved good balancing, and this balancing can be improved by imposing some forms of common support via calipers.

1.3.3.2 Nearest neighbour matching

Table.7. Nearest neighbour matching, with replacement, no caliper

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.5117948	9.89843835	.613356439	.057023973	10.76
	ATT	10.5117948	10.0740833	.437711504	.089949569	4.87

The differences between the output per worker means reported in table (8) indicate that the productivity mean in the matched group of firms that spent on research and development is greater than the productivity mean in firms that did not allocated some resources for research and development activities.

Table.8. Summary of output per worker if R&D expenditures = 1 and if R&D expenditures = 0

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln output per worker	668	10.51179	1.307031	4.400592	15.94088
Summary of Output Per Worker If R&D expenditures = 0					
Variable	Obs	Mean	Std. Dev.	Min	Max
Ln output per worker	668	10.07408	1.488507	4.506105	17.11672

The ATT estimation after imposing a caliper (0.02) shows the same significant impact on firms' productivity and the balancing of the covariates does not differ from the previous balancing when the matching was performed without caliper.

Table.9. Nearest neighbour matching, with replacement, caliper (0.02)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.5117948	9.89843835	.613356439	.057023973	10.76
	ATT	10.5117948	10.0740833	.437711504	.089949569	4.87

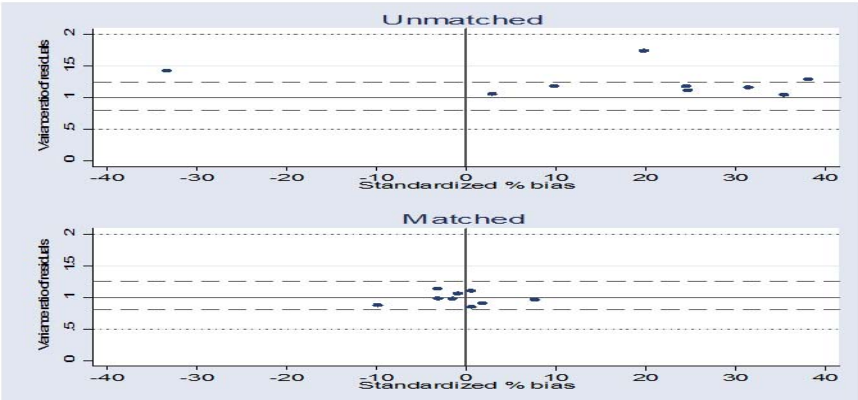

Figure 5. Nearest neighbour matching, caliper 0.02, scatter

1.3.3.3 Mahalanobis-metric matching results

The Mahalanobis metric matching was applied in pursuance of producing more robust and consistent estimates as well as obtaining better balance for the covariates in the matched sample.

Table.10. Mahalanobis-metric matching and augmented Mahalanobis-metric matching, scores included

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Mahalanobis-metric matching						
Ln output per worker	Unmatched	10.5117948	9.89843835	.613356439	.057023973	10.76
	ATT	10.5117948	10.1584367	.353358137	.082530654	4.28
Mahalanobis-metric matching, scores included						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Ln output per worker	Unmatched	10.5117948	9.89843835	.613356439	.057023973	10.76
	ATT	10.5117948	10.1884648	.323329988	.083076581	3.89

The causal effects of internal R&D on productivity are positive and statistically significant. Figure (6) provides similar balancing for the covariates.

The in-house research and development expenditures is key for the firm's performance. Its importance emanates from the fact that internal R&D activities increase the firm's capacity to absorb and benefit from the ideas and innovations generated through the outsourced external R&D activities carried out by other enterprises in the market.

To put it another way, the firm can make use of the knowledge generated by other firms (e.g. frontier firms) with less cost than the knowledge economic value, also the firm can buy a product where in the new knowledge is supposed to be imbedded in it.

These spillovers of knowledge can be received from other research and development activities funded by government or they could be imported from other firms in the same industry or even from overseas due to the fact that knowledge spread cannot be limited within a country's geographical borders. Especially if the firm is open to external competition in the global markets and developed robust trade relationships with other parties in other nations. Openness to external markets and openness to knowledge and technology diffusion is pivotal for firms to grow and develop their productivity and increase their gross sales.

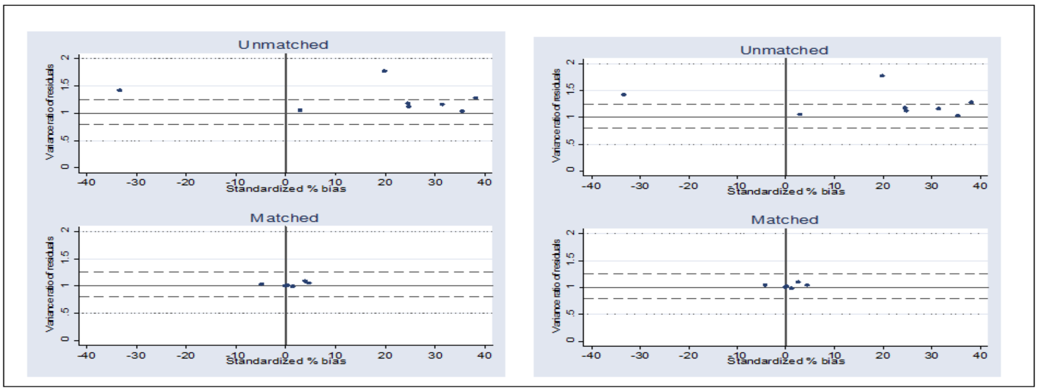

Figure. 6. Mahalanobis-metric matching and augmented Mahalanobis-metric matching, scores included

1.3.3.4 Comparison between propensity score matching and Mahalanobis metric matching

The bias reduction has improved in the case of the effects of R&D on performance, and the balance of the covariates has become much better with the Mahalanobis matching. As can be seen from the table (11), the bias has been reduced by a 100% in some regressors, which results in more robustness in the ATT estimation.

Table 11. Comparison between bias reduction (%) using PSM and 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
Foreign ownership shares	61.1	61.1	61.1	93.2	93.6
World exports shares	95.3	95.3	95.3	100.0	100.0
National exports shares	93.5	93.5	93.5	98.9	100.0
Firm size	98.2	98.2	98.2	99.4	98.8
Loan	79.9	79.9	79.9	98.7	98.7
bueaurucracy	88.3	88.3	88.3	78.3	82.2
Domestic ownership shares	99.0	99.0	99.0	95.8	96.9
GDP per capita	88.1	88.1	88.1	83.0	88.9
Medium technology firms	-12.7	-12.7	-12.7	100.0	87.5
High technology firms	87.6	87.6	87.6	100.0	100.0

The contents of this table are taken from the estimation appendices which are not attached in this document.

1.4 *Concluding Remarks*

The results of this analysis suggest that allocating more financial resources for research and development activities will have positive and significant effects on firms' productivity in the formal private manufacturing sector in the pooled sample of firms from both the MENA and ECA regions.

To a great extent, the (King and Nielsen, 2016) argument is proved to be true. This is where the outcomes resulted from using both the PSM and MDM differed in terms of the existing imbalance in the confounding covariates, which appeared to be extremely lower, and the bias reduction reached 100% in some covariates in the MDM outcomes compared to the PSM results.

Economically speaking, better productivity will result in better firms' competitiveness both in the local and global markets, better ability to expand towards new markets, higher percentage of exports, and higher revenues, which by extension, means more fund will be available to improve the firms' performance through better resources allocation in the R&D activities and new production approaches and new management ideas.

The application of Mahalanobis distance matching along with propensity score matching was meant to better allow for firm heterogeneity in the analysis. Which yielded some interesting outcomes.

This is where the comparison between the results obtained from PSM and MDM, was meant to examine King and Nielsen 2016 assumption, and it turned out that the point King and Nielsen made in 2016 was valid in the sense that the imbalance and bias in the model was considerably reduced when applying MDM. Yet, no huge difference is found in the statistical significance of the R&D impact on firms' productivity in both the MDM and PSM models.

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أثر الإنفاق على البحث والتطوير على إنتاجية الشركات الصغيرة والمتوسطة في قطاع التصنيع الخاص الرسمي في أوروبا الشرقية واقتصادات آسيا الوسطى وفي منطقة الشرق الأوسط وشمال إفريقيا

سالم غيت *

ملخص

تبحث هذه الورقة تأثير الإنفاق على البحث والتطوير على الإنتاجية في المؤسسات الصغيرة والمتوسطة في الشرق الأوسط وشمال إفريقيا وأوروبا الشرقية وآسيا الوسطى، باستخدام قاعدة بيانات (BEEPS) 2013. تتبع المساهمة الرئيسية والأصيلة لهذا البحث من فرضية وحجة King and Nielsen عام 2016. اللذين اقترحا أن استخدام أسلوب Propensity Score Matching للمماثلة والمطابقة وتقدير تأثير مجموعة من المتغيرات المستقلة على المتغير التابع قد يؤدي إلى الحصول على نتائج غير متينة يمكن الاستناد إليها في التحليل السببي للعلاقات بين المتغيرات، كما أن هذا الأسلوب قد يتجاهل الكثير من المعلومات والبيانات المهمة حول المتغيرات أثناء القيام بعملية المماثلة مما يؤدي إلى اختلال النماذج المقدّرة والتحيّز في تقديرات المعلمات .لذلك فقد اقترحا حلاً عملياً فعالاً لهذه المشكلة وذلك باستخدام Mahalanobis Distance Matching كإستراتيجية داعمة للأسلوب السابق PSM ، حيث أن نتائج تقديرات MDM تعتبر أكثر دقةً ومتانةً وموثوقية. كما أن النماذج المُقدّرة بهذا الأسلوب لاتعاني من تحيز في تقديرات المعلمات ولا تعاني من الاختلال الإحصائي والقياسي. وقد اتضحت صحة هذه الفرضية في هذا البحث بعد إجراء التقدير بالأسلوبين المذكورين أعلاه وكانت النتائج متوافقة تماماً مع ما افترضه King and Nielsen عام 2016. من الناحية القياسية أظهرت نتائج البحث وجود علاقة سببية ذات دلالة إحصائية وتأثير إيجابي للإنفاق على البحث والتطوير على الانتاجية والآداء في المؤسسات الصغيرة والمتوسطة في الإقليمين موضوع الدراسة والمذكورين أعلاه.

الكلمات الدالة: الانتاجية، الإنفاق على البحث والتطوير.

*أستاذ مشارك،جامعة بورنموث ، بريطانيا؛جامعة بني وليد، ليبيا

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