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The R&D Spending Effects on the Manufacturing Firms' Productivity Evidence from Poland using the PSM and MDM Experiments

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أثر الإنفاق على البحث والتطوير على إنتاجية الشركات الصناعية أدلة من بولندا باستخدام تجارب مطابقة درجة الاحتمال (PSM) و مطابقة المسافة لـماهالانوبس (MDM)

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Abstract:
This research paper seeks to establish substantive evidence on the impact of R&D expenditures on productivity in SMEs in the formal private manufacturing sector in Poland, using the World Bank Enterprise Survey (WBES) 2025 data. Poland had been chosen as a case study principally due to the fact that it represents a major transitional economy in the Central Europe region, and a significant manufacturing hub in the European Union area.

The novelty of this paper is inspired by the argument made by (King and Nielsen, 2019). This is where they suggested that the Propensity Score Matching PSM, namely Nearest Neighbour matching, 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 developments in the matching methods suggested that the conclusions drawn from PSM analysis are best supported by a second estimator, such as Mahalanobis Distance Matching MDM, which has the property of double robustness, reduces imbalance, model dependence, and bias. Therefore, both the completely randomised experiment procedures by PSM, and the fully blocked randomised experiment by MDM are recommended for more confidence and reliability in the obtained results.

The findings show that there is statistically significant impact of R&D spending (*Treatment*) on firms' peroductivity as the (*Outcome*) variable using the Kernel-based matching and Mahalanobis distance matching, but the effects appeared to be statistically insignificant using the nearest neighbour matching procedure. These results suggest that Poland should adopt more effective strategies to promote R&D expenditures in the manufacturing sector owing to the positive impact of R&D spending on productivity in the firms operating in this important sector.

Keywords: Labour Productivity, Research and Development, Propensity Score Matching.

الملخص
تهدف هذه الورقة البحثية إلى تقديم دليل موضوعي حول أثر الإنفاق على البحث والتطوير (*R&D*) على مستوى الإنتاجية في الشركات الصغيرة والمتوسطة (*SMEs*) التابعة للقطاع الصناعي الخاص الرسمي في بولندا، وذلك بالاعتماد على بيانات مسح الشركات الصادر عن البنك الدولي (*WBES*) لعام 2025. وقد وقع الإختيار على بولندا كدراسة حالة نظراً لمكانتها كإقتصاد انتقالي محوري في منطقة وسط أوروبا، ومركز صناعي رئيسي ضمن اقتصادات الإتحاد الأوروبي.
تكمن المساهمة الأصيلة لهذه الدراسة في استنادها إلى الطرح النقدي الذي قدمه : (*King and Nielsen, 2019*) حيث جادلا بأن أسلوب المطابقة باستخدام درجة الإحتمال (*Propensity Score Matching PSM*) وتحديداً مطابقة أقرب مشاهدة مجاورة (*Nearest Neighbour*) قد تفتقر إلى القدرة على تصميم تجارب معملية ذات جودة عالية، وبالتالي قد تتسبب ضمناً في ضياع معلومات جوهرية دون الإستفادة منها وتوظيفها بكفاءة، مما يؤدي إلى ارتفاع نسبة عدم التوازن

وبناءً . (*Bias*) وبالتالي الوقوع في فخ التحيّز ، *Model Dependence* والإعتمادية المفرطة في النموذج *Imbalance* على هذه التطورات المنهجية، قامت هذه الدراسة اعتماداً على جدلية (*King and Nielsen, 2019*) بتعزيز النتائج المستمدة من تحليل (*PSM*) بمُقدِّر ثانٍ مثل المطابقة باستخدام مسافة ماهالانوبيس (*Mahalanobis Distance* *Matching MDM*)والتي تتمتع بخاصية المتانة المزدوجة (*Double Robustness*) وتساهم بفعالية في تقليل عدم التوازن والتحيز. لذا، تُوصي الدراسة بدمج إجراءات "التجربة العشوائية الكاملة" باستخدام منهجية (*PSM*) و"التجربة العشوائية المحجوبة بالكامل" باستخدام منهجية (*MDM*) لضمان أقصى درجات الموثوقية في النتائج.

تُشير النتائج العملية إلى وجود أثر ذي دلالة إحصائية للإنفاق على البحث والتطوير (كمتغير ثنائي للمعالجة) على إنتاجية الشركات (كمتغير تابع/ النتيجة) عند تطبيق منهجية (*Kernel-based matching*) والمطابقة باستخدام (*MDM*) في حين أظهرت النتائج عدم وجود أثر ذو دلالة إحصائية للإنفاق على البحث و التطوير على الإنتاجية عند استخدام مطابقة(*Nearest Neighbour*) . وبناء على هذه النتائج تحتاج بولندا إلى تبني إستراتيجيات أكثر نجاعة لتحفيز الإنفاق على البحث والتطوير في القطاع الصناعي، نظراً للدور الإيجابي الذي يلعبه هذا الإنفاق في رفع كفاءة وإنتاجية الشركات العاملة في هذا القطاع الحيوي.

الكلمات المفتاحية: إنتاجية العمل، البحث والتطوير، مطابقة درجة الاحتمال *PSM*.

1. Introduction

Several decades ago, the Schumpeterian and neoclassical growth theory confirmed the importance of the relationship between R&D expenditures output represented by innovation and economic growth at the macroeconomic level (Aghion & Howitt, 1996, Zabłocka-Abi &Tomaszewski, 2024). According to Statistics Poland report on Research and Development in Poland in 2024, business enterprises spent 34,288.7 million in local currency units (Polish Zloty; PLN) on research and development, and about 32,584.7 million PLN in 2023 and 2024 respectively (Statistics Poland; Central Statistics Office CSO, 2025).

The OECD, had defined 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, 2006).

Research and development claims its significance as being one of the firm's production determinants along with learning–by–doing and affects both its quantity and quality alike. 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 function, and it is "*disembodied*" because it is not linked physically with any particular production factor. Therefore, it can be siad that the interest in R&D is derived from its importance. This is where it is considered as one of the main drivers of economic growth, employment, and income, as it contributes to the improvements in humans' quality of life and nations' competitiveness. (Atkinson, Ezell, 2014).

This study attempts to quantify the impact of R&D expenditures on firms' productivity (proxied by labour productivity) in the private manufacturinfg sector in Poland. The importance of the manufacturing sector stems from its crucial role in the economy including; processing raw materials, transforming semi-finished goods into finished goods, creating more jobs, accelerating the urbanisation process in the country, motivating regional economic development, and by extension leading to the development of several interconnected sectors in the economy through intra and inter-sectoral linkages. (Roszko-Wójtowicz, et, al. 2019).

2. Literature Review

Generally, there are several studies that applied different models to analyse the relationship between firms' R&D, innovation, and performance, including those studies which applied the Crepon, Duguet, and Mairesse 1998 model (The CDM model). (Baum et al., 2017), (Lööf et al.,2017). These studies along with others found substantive evidence on the impact of R&D and innovation on firms' performance, and this relationship becomes more obvious in more developed economies. That is why it is of a vital importance for managers to understand the link between the value of R&D expenditures and firms' 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).

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 innovations resulted from the R&D activities are proved to have had significant positive effected of firms' performance, and the intensity of R&D activities also have positive impact on the firms' profitability.(Grabińska, Grabiński, 2018). It is also argued that firms that adopted R&D strategies as part of their operations have higher growth in productivity (Medda, Piga, 2014).

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 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.

3. 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).

3.1. 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:

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

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.

$$\mathbf{ATT = E(\Delta|D = 1) = E(y_1|x, D = 1) - E(y_0|x, D = 1)} \quad \textbf{Equation.2}$$

Alternatively,

$$\Delta_{\mathbf{ATT}} = \mathbf{E(\Delta|T = 1) = E(\ln OPW^1 | \, T = 1) - E(\ln OPW^0 \, |T = 1)} \quad \textbf{Equation.3}$$

The second term on the righ hand side of Equation.3 $[E(\ln OPW^0 \, |T = 1)]$ denotes for 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 (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, 2019).

3.2. Mahalanobis Distance Matching (MDM)

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, 2019). 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: $X_{FB} = M(X_{FB}|X_i = X_j)$, meaning that $I(X_{FB}) = 0$.

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: $I(X_{CR}) \geq 0$. 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, King and Stuart, 2008) (Imai, King and Nall, 2009) (King and Nielsen, 2019). 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: $\mathbf{X}_{\mathrm{EM}} = \mathrm{M}(\mathrm{X}|\mathrm{A}_{\mathrm{CEM}}, \delta = 0) = \mathrm{M}(\mathrm{X}|\mathrm{A}_{\mathrm{MDM}}, \delta = 0)$. 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: $\mathbf{X}_{\mathrm{EM}} \subseteq \mathrm{M}(\mathrm{X}|\mathrm{A}_{\mathrm{PSM}}, \delta = 0)$, 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).

4. Data Discussion

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 World Bank Enterprise Survey measures 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).

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 World Bank Enterprise Survey 2025 in Poland's sample, 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). Economically speaking, the manufacturing sector continues to play significant role in the development of national economies in Europe, Poland included, despite the growing importance of the services sector.

4.1. Data Sources

The dataset which is used for the estimation was taken from the World bank Enterprise Survey (WBES) implemented in 17 regions in Poland between April 2024 and April 2025, spanning more than 1700 private enterprises in Poland, 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.

In regard to R&D Spending data, more than 438 firms were included in the sample of interest, ranging from different manufacturing firms (low-tech, medium-tech, high-tech) with different sizes and ages. The aim in this analysis is to examine whether there is a statistically significant impact of R&D on firms' performance mainly labour productivity.

4.2. Variables for OLS Probit and Propensity Score Models

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 (productivity) in the OLS model had been ruled in the estimation process.

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. Research and Development Spending: represents whether the establishment allocated some of its financial resources to spend on research and development activities, either in-house or contracted with other companies, excluding market research surveys during the last complete fiscal year.
2. Size of firm: (small; 5-19 workers, medium; 20-99 workers, large; 100 or more workers).
3. External Financial Audit: represents whether the establishment has its annual financial statements checked and certified by an external auditor.
4. Foreign suppliers of inputs and finished goods: represents the percentage of this establishment's purchases of material inputs or supplies or finished goods and materials purchased to resell from a foreign supplier:
5. Direct international exports: represents the percentage of the establishment's sales that is exported directly outside Poland.
6. Social media website: represents whether the firm has a social media website to promote for its products.
7. Machinery and equipment replacement cost.
8. Annual cost of electricity.
9. Percentage of funds from internal sources such as retained annual earnings.
10. Percentage of funds from non-banking institutions such as microfinance institutions, credit cooperatives, credit unions, or finance companies.
11. The firm's main market: represents whether the main market of the firm is local, national, or international.
12. Percentage of input supplies from foreign sources.

5. Empirical results and discussion

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 Poland.

5.1. Ordinary least squares and probit models

From table (1) the effects of research and development activities on 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 firm-level productivity, and therefore, enhance the firms' efficiency and competitiveness. 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.

This research can trace out that the correlation between the R&D expenditures and productivity in the manufacturing firms in Poland 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 funds from internal sources, the international markets as the main market, the ercentage of input supplies from foreign sources as essential factors to invigorate performance and productivity. 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
2. Have a significant proportion of their exports targeted towards international markets.
3. They are also more likely to have contracted to purchase their material inputs from abroad.
4. They have a website on one of the social media platforms.

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 the null hypothesis which indicates that the model has no omitted variables is accepted. 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.

Table.1 The effects of R&D spending on productivity in Poland's manufacturing firms in 2025.

	OLS Model with Robust S.E	Probit Model
	Dependent Variable = Ln. productivity	**Treatment = R&D spending**
R&D spending [0,1]	.2440233***	-
	(.1080336)	-
Firm size [small, medium, large]	.128714***	.0671317***
	(.0611574)	(.0213559)
Percentage of direct international exports [%]	-	.0014222***
	-	(.0005653)
Machinery and equipment replacement cost [Total]	1.55e-09***	-9.93e-11
	(4.79e-10)	(1.16e-10)
External financial Audit [0,1]	.3581601***	.0468226
	(.094638)	(.0350924)
Percentage of funds from internal sources [%]	.0051112***	.0004909
	(.0019325)	(.0006864)
Percentage of funds from non-banking institutions [%]	.02071	-
	(.0144171)	-
Main market [local, national, international]	.1479051***	-
	(.0757617)	-
Social media website [0, 1]	.09411	.1044881**
	(.1105462)	(.0335909)
Percentage of input supplies from foreign sources [%]	.0070353***	.0010243*
	(.0017704)	(.0005979)
Cons	11.2072***	-
	(.2358858)	-
N	447	448
R^2	0.2573	Pseudo R2 = .1392
LR chi2 [5]	-	91.05
F [9, 437]	16.25	-
Prob > F	0.0000	-
Prob > chi2	-	0.0000
Diagnostic tests:		
1. Testing for Heteroscedasticity	chi2(1) = 0.00 Prob > chi2 = 0.9728	Presence of heteroscedasticity. Therefore, robust standard errors are used in the OLS model.
2. Omitted-Variable Test	F (3, 425) = 10.52 Prob > F = 0.0000	Ho: model has no omitted variables
3. Testing for Multicollinearity	Mean VIF = 1.18	Mean VIF < 10, No multicollinearity problem.
4. Joint Significance Test	F (9, 428) = 18.72 Prob > F = 0.0000	All independent variables have jointly significant impact on the dependent variable.
5. Normality Test	Skewness -.104709 Kurtosis 4.19813 Pr (Skewness) = 0.2524 Pr (Kurtosis) = 0.0000	Skewness = -0.11, p>0.001 Kurtosis = 4.11, p<0.001 If pr(skewness) value is above 0.05, then the null hypothesis that assumes that the distribution is normal cannot be rejected, meaning that the distribution is not skewed but exhibits kurtosis since the pr(kurtosis) is less than 0.05.

Robust standard errors S.E. in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2. Propensity score matching: Nearest neighbour matching, with replacement, without caliper

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. 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.

Table.2 Nearest neighbour matching, with replacement, without caliper.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Productivity	**Unmatched**	**13.0897244**	**12.5368421**	**.552882257**	**.124919295**	**4.43**
	ATT	**13.0897244**	**12.9095884**	**.180135958**	**.169126405**	**1.07**

The ATT estimation, reported in table 2, appears to be insignificant at 99%, 95%, and 90%, and the balancing needs to be checked before trusting the ATT estimation. See figure (1) below.

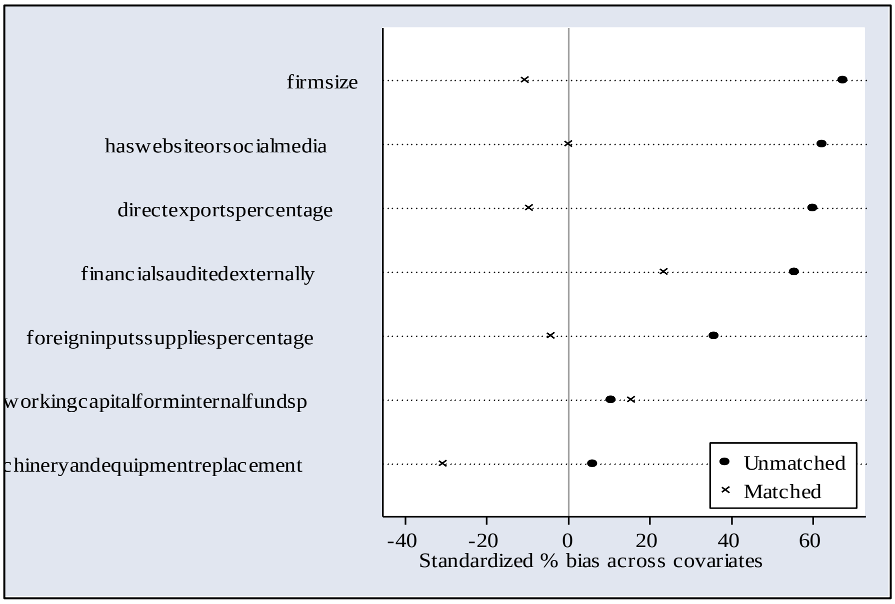

Figure (1) nearest neighbour matching with replacement, without caliper

When comparing the productivity means across firms, in tables 3 and 4, 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. But the ATT estimation is not statistically significant.

Table.3 Summary of Productivity If R&D Expenditures = 1 (R&D Expenditures)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Productivity	**66**	**13.08972**	**.777226**	**11.37939**	**15.203**

The mean of output per worker in those firms that spent on research and development over the last three complete fiscal years is 13.08972 – 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 12.90959 – table 4.

Table.4 Summary of Productivity If R&D Expenditures = 0 (R&D Expenditures)

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln Productivity	**66**	**12.90959**	**.8785299**	**11.01315**	**14.93065**

There is a reasonable level of common support as reported in table 5 with 66 treated observations included in the matching.

Table.5 Treatment Assignment.

Psmatch2: Treatment Assignment	Psmatch2: Common Support on Support	Total
Untreated	381	381
Treated	66	66
Total	447	447

5.3. Propensity score matching: Nearest neighbour matching, with replacement, with caliper (0.01) matching

The impact of firms' R&D expenditures in table 6, when imposing a (0.01) caliper with replacement, is found to be statistical insignificant at 99%, 95% and 90%, with 9 degrees of freedom.

Table.6 Nearest neighbour matching, with replacement, with caliper (0.01) matching.

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Productivity	Unmatched	13.0897244	12.5368421	.552882257	.124919295	4.43
	ATT	13.0955373	12.8708644	.224672847	.168711268	1.33

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 and untreated. In other words, this shows the region of common support right in the middle area between the two curves. The boxes in the right part of the figure show that the treated and untreated units of the matched sample are not very well aligned using 0.01 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 use Kernel-based matching to reduce bias, achieve low standard errore, stable estimates, and increase efficiency in the covariates.

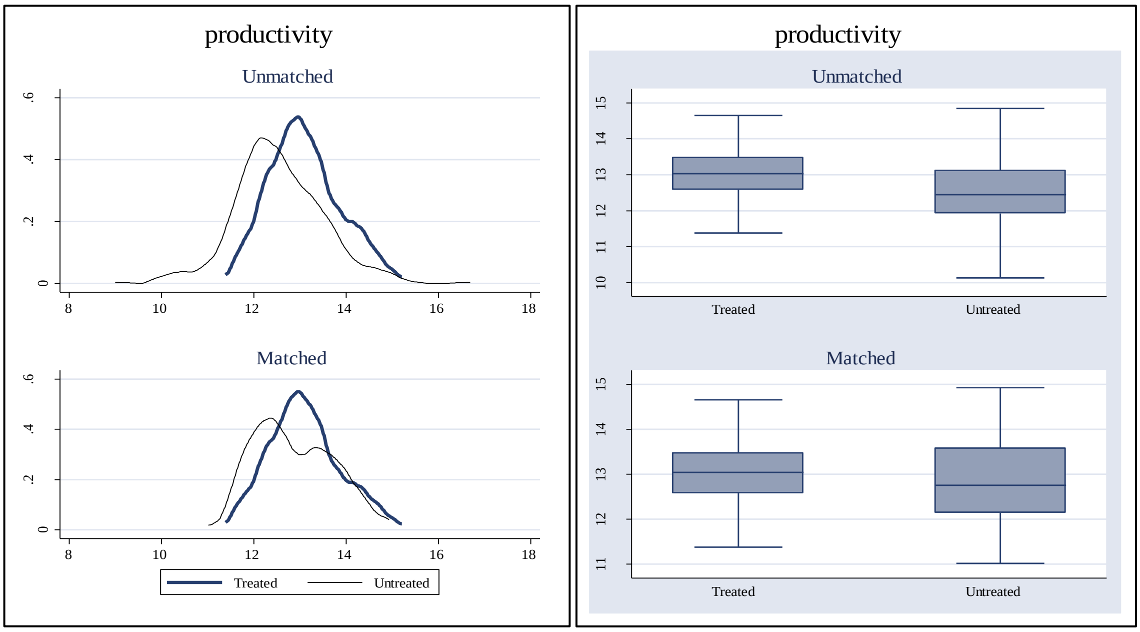

Figure (2) matching quality with replacement, with caliper (0.01).

5.4. Kernel-based matching

The ATT estimation, reported in table 7, appears to be statistically significant at 90%, when using Kernel-based matching imposing a (0.01) bandwidth, and the balancing needs to be checked before trusting the ATT estimation. See figure (3) below.

Table.7 Kernel-based Matching

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Productivity	Unmatched	13.0897244	12.5368421	.552882257	.124919295	4.43
	ATT	13.0955373	12.8465786	.24895868	.129473655	1.92

The covariates are better balanced when imposing a (0.01) bandwidth, which indicates that the nearest neighbour matching procedure with and without a caliper performed poorly.

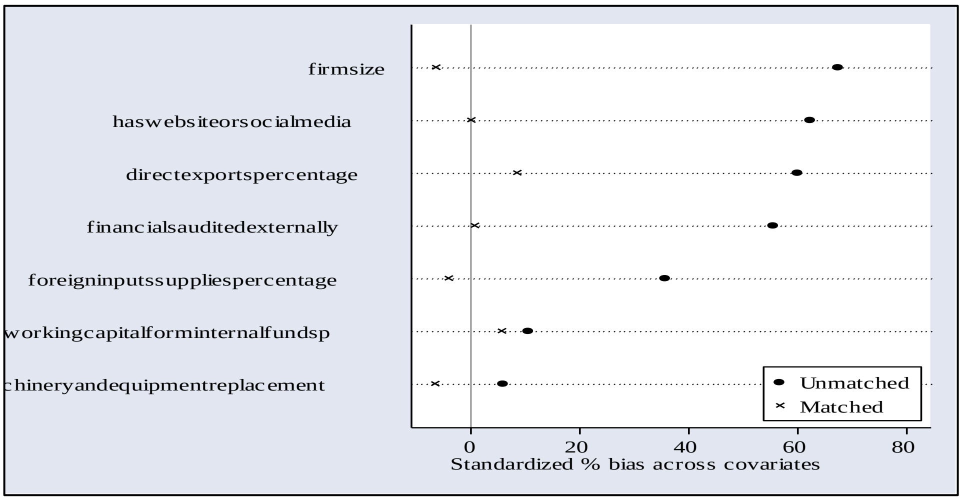

Figure (3) matching quality, Kernel-based matching with bandwidth (0.01)

5.5. Mahalanobis-distance matching results

In pursuit of better balancing and more bias reduction percentage for the confounders, the Mahalanobis distance matching is used. This is where the procedure is designed to reduce bias noticeably.

Table.8 Mahalanobis-Metric Matching

Variable	Sample	Treated	Controls	Differences	S. E	T-Test
Ln Productivity	**Unmatched**	**13.0897244**	**12.5368421**	**.552882257**	**.124919295**	**4.43**
	ATT	**13.0897244**	**12.8338571**	**.255867207**	**.138591176**	**1.85**

According to the matching results reported in table (8) 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 90% statistical confidence with 9 degrees of freedom. The difference in the ATT estimation – 0.255867207 – is positive and the t-stat suggests a statistically significant impact of the R&D spending on the logged value of the productivity of a firm. In addition, the balance of the confounding covariates in figure 4 is better than their balance in figure 3.

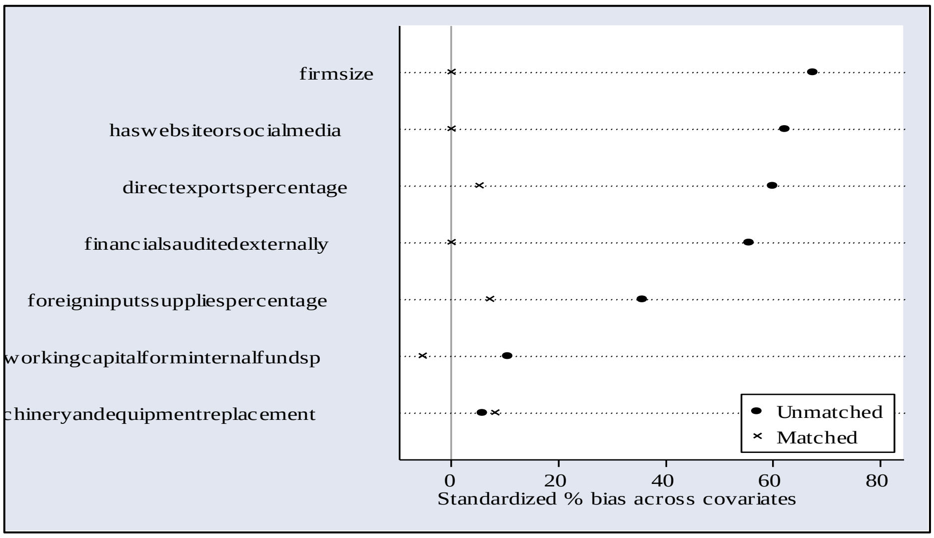

Figure (4) matching quality of Mahalanobis distance matching

5.6. Comparison between propensity score matching and Mahalanobis distance matching

The bias reduction has improved in the case of the effects of R&D on productivity, and the balance of the covariates has become much better with the Mahalanobis matching. As can be seen from the table (9), the bias has been reduced by a 100% in some regressors, which resulted in more robustness in the ATT estimation.

Table (9) comparison between bias reduction (%) using PSM and MDM

Variables	Bias reduction (%) using the Propensity Score Matching: Nearest neighbour matching with caliper (0.01)	Bias reduction (%) using the Mahalanobis Distance Matching
Firm size	84.2	100
Percentage of direct international exports	83.8	91.2
Machinery and equipment replacement cost	-421.7	-39
External financial Audit	58	100
Percentage of funds from internal sources	-45.1	50.2
Social media website	100	100
Percentage of input supplies from foreign sources	87.9	79.9

Knowledge creation and investing in the knowledge-based capital is to some extent a complex process, but it is regarded 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. 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 Poland to catch up with the technology leaders.

As for Poland, the IMF growth forecasts suggest that the country's economic growth will average around 3% per year in 2025 and 2026, compared to 1.5% per annum in the Eurozone during the same period. Meaning that Poland will remain the growth leader in Europe. The IMF and the Polish Economic Institute consider Poland as one of the most resilient economies in Central Europe. After slowing down to 0.2% in 2023, GDP grew by 2.9% in 2024, and this momentum is expected to continue in the coming years. There is a number of factor that supported the resilience of the Polish economy such as: the strong domestic demand and the growing household average incomes, the technological progress in the services sector in recent years, highly-skilled workforce that attracted foreign direct investments, the membership in the EU which facilitated the smooth access to the single market, the stability in the financial sector, the significant investments in the infrastructures sectors co-financed by both the government and the European Union, and most importantly, the increased spending on research and development activities and innovation.

Despite all of the above-mentioned factors, and according to the European Semester Report in 2024, the levels of R&D expenditures are still low, and the cooperation between science and businesses in Poland is still limited, which in turn affects Poland's innovation capacity. This is cemented by the data on the small and medium enterprises' limited ability to introduce product and business process innovations, which remain well below the EU average; at 43.1% and 47.5% of the EU average in 2024, respectively. Poland's low rate of innovative SMEs working with others reflects the country's challenges with collaboration. In addition, the country ranks third last among EU member states in terms of the number of public-private co-publications (56.6% of the EU average in 2024). Poland's companies have one of the lowest average shares of investment in intangible assets, according to the European Semester Report (2024). Poor connections between business and science are one of the root causes, which restricts the economy's ability to use research output. The Global Innovation Index (2023) states that Despite difficulties since 2017 (-16.8% points), Poland has demonstrated a great ability to export creative commodities, as evidenced by its impressive performance in design applications, placing third among EU Member States (at 151.0% of the EU average in 2024).

6. Conclusions

The Kernel-based matching and Mahalanobis mtaching results 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 Poland.

The empirical results appeared to well in line with the (King and Nielsen, 2019) argument. This is where the comparison between the results obtained from PSM and MDM, was meant to examine King and Nielsen 2019 assumption, and it turned out that the point King and Nielsen made in 2019 was valid in the sense that the imbalance and bias in the model was considerably reduced when applying MDM. In addition, a huge difference is found in the statistical significance of the R&D impact on firms' productivity in both the MDM and PSM models. Meaning that the ATT estimation using the nearest neighbour matching seemed to be insignificant, but the Kernel-based matching and Mahalanobis matching improved the statistical significance of the ATT notably.

The outcomes resulted from using both the PSM and MDM differed significantly 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 innovations. The application of Mahalanobis distance matching along with propensity score matching was meant to better allow for firm heterogeneity in the analysis. Which led to some interesting outcomes.

Compliance with ethical standards

Disclosure of conflict of interest

The author(s) declare that they have no conflict of interest.

7. References

Aghion, P. and Howitt, P. (1992) 'A model of growth through creative destruction', Econometrica, 60, pp. 323-351.

Aghion, P., & Howitt, P. (1996). Research and development in the growth process. Journal of Economic Growth, 1, 49–73. https://doi.org/10.1007/BF00163342.

Aizcorbe, M., Moylan, C. E. and Robbins, C. A. (2009) 'Toward better measurement of innovation and intangibles'.

Atkinson R.D., Ezell S.J., (2014), Innovation Economics: The Race for Global Advantage, Yale University Press, New Haven.

Austin, P. C. (2009) 'Some Methods of Propensity-Score Matching had Superior Performance to Others: Results of an Empirical Investigation and Monte Carlo simulations', Biometrical journal, 51(1), pp. 171-184.

Austin, P. C. (2011) 'An introduction to propensity score methods for reducing the effects of confounding in observational studies', Multivariate behavioral research, 46(3), pp. 399-424.

Baum, C.F., Lööf, H., Nabavi, P., & Stephan, A. (2017). A new approach to estimation of the R&D–innovation–productivity relationship. Economics and Innovation and New Technology, 26(1–2), 121–133. https://doi.org/10.1080/10438599.2016.1202515.

Beck, T. and Demirguc-Kunt, A. (2006) 'Small and medium-size enterprises: Access to finance as a growth constraint', Journal of Banking & finance, 30(11), pp. 2931-2943.

Blundell, R. and Dias, M. C. (2002) 'Alternative approaches to evaluation in empirical microeconomics', Portuguese economic journal, 1(2), pp. 91-115.

Box, G. E. P. and William, G. Hunger and J. Stuart Hunter. 1978. Statistics for Experimenters. New York: Wiley-Interscience.

Branch, B. (1974) 'Research and development activity and profitability: a distributed lag analysis', Journal of Political Economy, 82(5), pp. 999-1011.

Burgette, L., Griffin, B. A. and McCaffrey, D. (2017) 'Propensity scores for multiple treatments: A tutorial for the mnps function in the twang package', R package. Rand Corporation.

Caliendo, M. and Hujer, R. (2006) '14 The Microeconometric Estimation of Treatment Effects-An Overview', Econometric Analysis, pp. 199.

Corrado, C., Hulten, C. and Sichel, D. (2009) 'Intangible capital and US economic growth', Review of income and wealth, 55(3), pp. 661-685.

Dole, E. 1989. The Impact of Research and Development on Productivity Growth. In: Norwood, J.L. (ed.). Department of Labor, United States of America.

European Innovation Scoreboard (2024) – Country profile Poland, EFIS Centre, Technopolis Group and OldContinent., European Commission Directorate-General for Research and Innovation.

Evenson, R. E. R. E. (1968) 'The Contribution of agricultural research and extension to agricultural production'.

Fixler, D. 'Accounting for R&D in the National Accounts'. ASSA meetings in San Francisco.

Grabińska, B., & Grabiński, K. (2018). Wpływ nakładów na badania i rozwój na rentowność przedsiębiorstw. Zeszyty Teoretyczne Rachunkowości, (96 (152), 43-62. (The original paper had been published in Polish; Abstract had been written in English).

Greevy, R., Lu, B., Silber, J. H. and Rosenbaum, P. (2004) 'Optimal multivariate matching before randomization', Biostatistics, 5(2), pp. 263-275.

Griffith, R. (2000) 'How important is business R&D for economic growth and should the government subsidise it?'.

Griliches, Z. (1973) 'Research expenditures and growth accounting', Science and technology in economic growth: Springer, pp. 59-95.

Griliches, Z. (1992) 'The Search for R&D Spillovers', Scandinavian Journal of Economics, 94, pp. S29-47.

Heckman, J. J., Ichimura, H. and Todd, P. E. (1997) 'Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme', The review of economic studies, 64(4), pp. 605-654.

Heinrich, C., Maffioli, A. and Vazquez, G. (2010) A primer for applying propensity-score matching: Inter-American Development Bank.

Ho, D. E., Imai, K., King, G. and Stuart, E. A. (2007) 'Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference', Political analysis, 15(3), pp. 199-236.

Iacus, S. M., King, G. and Porro, G. (2011) 'Multivariate matching methods that are monotonic imbalance bounding', Journal of the American Statistical Association, 106(493), pp. 345-361.

Imai, K., King, G. and Nall, C. (2009) 'The essential role of pair matching in cluster-randomized experiments, with application to the Mexican universal health insurance evaluation', Statistical Science, 24(1), pp. 29-53.

Imai, K., King, G. and Stuart, E. A. (2008) 'Misunderstandings between experimentalists and observationalists about causal inference', Journal of the royal statistical society: series A (statistics in society), 171(2), pp. 481-502.

Jones, C. I. (1995) 'R & D-based models of economic growth', Journal of political Economy, 103(4), pp. 759-784.

King, G., & Nielsen, R. (2019). Why propensity scores should not be used for matching. Political analysis, 27(4), 435-454.

King, G., Nielsen, R., Coberley, C., Pope, J. E. and Wells, A. (2011) 'Comparative effectiveness of matching methods for causal inference', Unpublished manuscript, 15.

Kortum, S. S. (1997) 'Research, patenting, and technological change', Econometrica: Journal of the Econometric Society, pp. 1389-1419.

Lantz, J.-S. and Sahut, J.-M. (2005) 'R&D investment and the financial performance of technological firms', International Journal of Business, 10(3), pp. 251.

Link, A. N. (1978) 'Rates of induced technology from Investments in research and development', Southern Economic Journal, pp. 370-379.

Lööf, H., Mairesse, J., & Mohnen, P. (2017). CDM 20 years after. Economics of Innovation and New Technology, 26(1–2), 1–5. https://doi.org/10.1080/10438599.2016.1202522.

Mansfield, E. (1972) Research and innovation in the modern corporation. Springer.

Manual, O. F. 2003. Proposed Standard Practice for Surveys on Research and Experimental Development. OECD Publishing.

McCaffrey, D. F., Griffin, B. A., Almirall, D., Slaughter, M. E., Ramchand, R. and Burgette, L. F. (2013) 'A tutorial on propensity score estimation for multiple treatments using generalized boosted models', Statistics in medicine, 32(19), pp. 3388-3414.

Medda G., Piga C., (2014), Technological Spillovers and Productivity in Italian Manufacturing Firms, "Journal of Productivity Analysis", 41 (3), DOI: 10.1007/s11123-013-0351-1.

Menard, S. (2002) Applied logistic regression analysis. Sage.

Morgan, S. L. and Winship, C. (2014) Counterfactuals and causal inference. Cambridge University Press.

Muehler, G., Beckmann, M. and Schauenberg, B. (2007) 'The returns to continuous training in Germany: new evidence from propensity score matching estimators', Review of Managerial Science, 1(3), pp. 209-235.

Nadiri, M. I. and Bitros, G. C. (1980) 'Research and development expenditures and labor productivity at the firm level: A dynamic model', New Developments in Productivity Measurement: University of Chicago Press, pp. 387-418.

Pakes, A. and Griliches, Z. (1984a) 'Estimating distributed lags in short panels with an application to the specification of depreciation patterns and capital stock constructs', The Review of Economic Studies, 51(2), pp. 243-262.
Pakes, A. and Griliches, Z. (1984b) 'Patents and R&D at the firm level: a first look', R&D, patents, and productivity: University of Chicago Press, pp. 55-72.
Parham, D.(2006) 'Empirical analysis of the effects of R&D on productivity: Implications for productivity measurement'. 16-18.
Ravenscraft, D. and Scherer, F. M. (1982) 'The lag structure of returns to research and development', Applied economics, 14(6), pp. 603-620.
Rosenbaum, P. R. and Rubin, D. B. (1985) 'Constructing a control group using multivariate matched sampling methods that incorporate the propensity score', The American Statistician, 39(1), pp. 33-38.
Roszko-Wójtowicz, E., Grzelak, M. M., & Laskowska, I. (2019). The impact of R&D expenditure on productivity in the manufacturing industry in Poland. Econometrics. Ekonometria. Advances in Applied Data Analytics, 23(4), 112-138.
Rubin, D. B. (1973) 'Matching to remove bias in observational studies', Biometrics, pp. 159-183.
Rubin, D. B. (1976) 'Inference and missing data', Biometrika, 63(3), pp. 581-592.
Rubin, D. B. and Stuart, E. A. (2006) 'Affinely invariant matching methods with discriminant mixtures of proportional ellipsoidally symmetric distributions', The Annals of Statistics, pp. 1814-1826.
Rubin, D. B. and Thomas, N. (2000) 'Combining propensity score matching with additional adjustments for prognostic covariates', Journal of the American Statistical Association, 95(450), pp. 573-585.
Scherer, F. M. (1982) 'Inter-industry technology flows and productivity growth', The review of economics and statistics, pp. 627-634.
Schmookler, J. (1965) 'Technological change and economic theory', The American Economic Review, 55(1/2), pp. 333-341.
Statistics Poland; Central Statistics Office. (2025), Research and experimental development in Poland in 2024. Released on 23.10.2025.
Stuart, E. A. (2010) 'Matching methods for causal inference: A review and a look forward', Statistical science: a review journal of the Institute of Mathematical Statistics, 25(1), pp. 1.
Stuart, E. A. and Rubin, D. B. (2008) 'Best practices in quasi-experimental designs', Best practices in quantitative methods, pp. 155-176.
Sveikauskas, L. (1981) 'Technological inputs and multifactor productivity growth', The Review of Economics and Statistics, pp. 275-282.
Terleckyj, N. E. (1974) Effects of R&D on the productivity growth of industries: an exploratory study. National Planning Association.
Terleckyj, N. E. (1982) 'R&D and US Industrial Productivity in the 1970s in The Transfer and Utilization of Technical Knowledge edited by D', Sahal. Lexington, MA: Lexington Books.
Zabłocka-Abi Yaghi, A., & Tomaszewski, T. (2024). The interdependence of R&D, innovations, and productivity: case of Polish manufacturing companies. Ekonomia i Prawo. Economics and Law, 23(1), 195-212.
Zhu, Z. and Huang, F. (2012) 'The Effect of R&D Investment on Firms' Financial Performance: Evidence from the Chinese Listed IT Firms', Modern Economy, 3(08), pp. 915.

