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QUARTERLY REVIEW OF ACADEMIC LITERATURE ON THE ECONOMICS OF RESEARCH AND INNOVATION

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1. Low-Skill and High-Skill Automation

Acemoglu, D., Restrepo, P. (2018). Low-Skill and High-Skill Automation. Journal of Human Capital, 2018, vol. 12, no. 2.

- The study presents a theoretical model in which high- and low-skill workers compete against machines in the production of tasks and shows effects on displacement of jobs and productivity.
- The net impact of automation depends on the balance between job displacement and productivity effects in the long-term.
- The effects of automation on wages are potentially ambiguous, but it has an unambiguous impact on inequality: low-skill automation always increases wage inequality, whereas high-skill automation always reduces it.

The authors establish a task-based model, which highlights the increase in competition of workforce against machines on both sides of the skills spectrum. The presented framework incorporates both the more traditional automation of 'low-skilled' routine jobs, and the potentially transformative automation of highly-skilled jobs. The proposed model assumes a continuum of tasks, which can be performed by low-skill labour, high-skill labour, or capital. The high-skill automation represents the new element, based on the assumption that new developments in artificial intelligence allow capital to compete against high-skill labour in complex tasks. It shows that both types of automation lead to a displacement effect and a productivity effect. The displacement effect is taking away tasks from the directly affected factor, while the productivity effect tends to increase the wages of all factors. Such a displacement caused by automation also creates ripple effects whereby automation may reduce the wage of not just the factor it directly affects but of other imperfectly substitutable factors (of other workers) i.e. either type of automation can depress the real wage of both high-skill and low-skill labour.

Counteracting these forces, automation creates a positive productivity effect, pushing up the price of all factors. When the productivity effect is small (e.g. because capital is scarce), automation not only reduces low-skill wages but may even depress high-skill wages. Nevertheless, in the long-term, automation induces accumulation of capital and thus the productivity effect dominates. With this amplification of productivity effect, automation cannot reduce the wages of both types of labour simultaneously, but it can still depress the wage of the directly affected labour.

2. Skilled migration and innovation in European industries

Fassio, C., Montobbio, F., Venturini, (2018), "Skilled migration and innovation in European industries", Research Policy (forthcoming).

- The paper attempts to measure the impact of skilled immigration on innovation at the industry level and offers a direct comparison between the innovation effects of immigrant versus local population for each manufacturing sector.
- Immigrants have a stronger impact in sectors with high levels of foreign direct investment and in sectors more exposed to international trade. The positive impact increases in industries with high ethnic diversity.
- The key messages for policy makers are that innovation in Europe would benefit from policies favouring the entrance of potential workers with higher education and there is a case for innovation-oriented migration policy.

Since the patterns of skilled migration are unevenly distributed among different types of economic activities, the authors explore the sectoral perspective that allows for better measurement of the impacts of skilled migration on innovation. Skilled migrants are more likely to be employed in occupations that require a lower level of education and this over-education of skilled immigrants often weakens their contribution to firm productivity. Comparing the contributions to innovation between skilled migrants and the native workforce, the study examines the contribution of skilled immigrants in sectors characterised by low levels of education compared to the sectors with high levels. In a next step, the analysis looks into their contribution in sectors with high presence of foreign direct investment and in sectors with high levels of openness to trade. Finally, the focus shifts towards the contribution of skilled migrants to sectors with higher levels of cultural diversity.

The study estimates the impact of migrant workers on patent production in 16 manufacturing industries between 1994 and 2005 in France, Germany and the UK. By using patents, weighted by forward citations, applied at the European Patent Office; and measures of labour force in these three countries, the dataset allows to examine different characteristics of the labour force.

After showing that a highly educated workforce including both foreign and native workers has a positive impact on innovation, the findings suggest that the impact of skilled immigrants varies according to the characteristics of the sectors of their employment. Immigrants have a stronger impact in sectors with a high level of foreign direct investment and in sectors more active in international markets. The gathered evidence allows to conclude that innovation in Europe would benefit from policies that favour the entrance of potential workers with tertiary education or other type of advanced degrees. The study also highlights the need of a tailored migration policy that would be innovation-oriented and thus able to adjust to labour demand from industries with high levels of foreign direct investment and involvement in international trade. Considering the analysis of ethnic diversity in industries, the impact is increasing in industries with high ethnic diversity.

3. The effect of immigration on innovation in Italy.

Bratti, M., Conti, C. (2018). The effect of immigration on innovation in Italy. Regional Studies, 52(7), 934-947.

- The study investigates the impact of immigration on innovation in the case of Italy, a country characterised by an inflow of low-skilled migrants.
- Findings do not support neither a positive nor a negative impact of immigration on innovation output at both the macro and firm level, and no differences arise for high- and low- skilled immigrants.
- The lack of effect of the low-skilled migrants can be explained by their "similitude" to the native workforce and the Italian productive structure specialised in traditional low-knowledge intensive activities.

The impact of immigration on innovation output has recently received increasing attention by the economic literature. While the potential positive effect of an inflow of high- skilled immigrants has been extensively investigated in the empirical literature, less has been done concerning low educated immigrants. Low-skilled immigration may hamper the innovative capacity of an economy by promoting the adoption of labour intensive and cost-saving technologies, reducing incentives to innovate for companies. The authors focus on the latter case by analysing the link between immigration and innovation in Italy. The country is a specific case because a large immigration wave has reached the country starting from the 2000s, tripling the population share of immigrants all over the country, and mainly in the richer North. Furthermore, the share of high-skilled immigrants is very low and low-tech and traditional activities dominate the Italian productive structure. Using both province (NUTS3) and firm level data, the authors analyse the impact of immigration on patents in 2000-2010 and 1995-2010 respectively, adopting an instrumental variables approach. Results reveal no significant impact of immigrants shares on innovation output, both overall and when distinguishing between low skilled and high skilled. Differently, the prevalence of traditional sectors is found to be a determining factor, negatively contributing to patent applications. From a policy perspective, this result confirms the difficulties of Italy to specialise in knowledge-intensive activities, to attract high-skilled immigrants and signals the risk of being trapped in a low- cost low- skilled productive structure.

4. Technology upgrading of middle income economies: A new approach and results

Radosevic, S., & Yoruk, E. (2018). Technology upgrading of middle income economies: A new approach and results. Technological Forecasting and Social Change, 129, 56-75.

- This paper presents a reflection on technology upgrading using a new conceptual and statistical framework that is multidimensional and encompasses dimensions of *intensity*, *breadth of technological upgrading*, and *technology and knowledge exchange*.
- The authors built a composite indicator of technology upgrading using 35 indicators that reflect *different patterns and drivers of technology upgrading,* and applied it to 42 countries ranging from lower middle income to upper high income.
- The findings suggest the existence of a middle-income trap in technology upgrading- *countries' technology upgrading activities are not reflected in their income levels*, though the magnitude varies according to the different dimensions present in the framework.

The paper starts by examining the current landscape of composite indicators that attempt to capture the performance of economies in terms of *growth, competitiveness and innovation* (e.g. Global Competitiveness Index, Global Innovation Index, World Competitiveness Report). The authors conclude that most of these indexes are similar in terms of their measurement outcomes as they aim at measuring the role of innovation to economic development. However, according to the authors, the drivers of growth and technological upgrading differ across income levels so their upgrading paths and stages of technological upgrading should be taken into account. The novelty of this approach is the creation of a multidimensional framework that not only includes R&D but also other dimensions that contribute to growth. This three-dimensional process includes i) a dimension of *intensity*, reflecting *the intensity of production, R&D and technology generation activities* in technological upgrading, ii) *breadth of technology upgrading,* to account for differentiated technological knowledge, physical infrastructure, human capital, and organizational capital of firms relevant for technological upgrading, iii) *knowledge inflows and outflows,* including measures of trade and FDI. Data were obtained from combining different sources for this information, namely World Bank, World Economic Forum Global Competitiveness Report, WIPO, UNESCO, UNComtrade, ISO, Thomson NSI, Forbes, and Barro-Lee dataset.

The results hint at a *robust and positive relationship between indexes of technology upgrading and income levels.* Moreover, results point towards a "threshold" from *the middle-income group to lower and upper high-income groups where the relationship between income level and technology upgrading changes dramatically into positive.* The authors conclude that a *middle-income trap* exists across the three dimensions they created for technology upgrading, though its importance changes depending on the dimension at stake. In particular, the findings suggest that it is highest for the dimension of interactions and knowledge exchange. The dimension of the breadth of technology upgrading comes next and finally the index of intensity of technology upgrading. It seems that *middle-income economies are not benefitting from being engaged in global technology and knowledge exchange as much as they should in comparison to other income groups.* Furthermore, the index of the intensity of technology upgrading mirrors cumulative technology capability while the dimension 'breadth of technology upgrading' captures the structure, infrastructure and organization of countries. At the same time, the latter are subject to market and system failures and may emerge from different non-technology related factors such as the political economy.

5. Path of technology upgrading in the BRICS economies

Lacasa, I. D., Jindra, B., Radosevic, S., Shubbak, M. (2018). Paths of technology upgrading in the BRICS economies. Research Policy.

- The study analyses innovation trends in BRICS economies between 1980 and 2015, investigating the intensity and direction of the upgrade of their technological production.
- Technological upgrading is measured using the rise in the production of frontier technologies, the intensification of knowledge intensive activities and the increase in global interaction.
- Findings suggest that each country experiences its specific path, depending on its capacity to produce frontier or incremental knowledge and adopting technology produced abroad.
- China emerges as the country being able to reduce the gap with high-income countries, increasing its capacity to produce both incremental and frontier knowledge and diversifying its economic structure the most.

In a world characterised by an accelerating pace of innovation production, emerging economies have been changing their positioning in the global production of knowledge, while the economic centre of gravity has been moving towards the East and the South. The paper analyses the trend of technological upgrading of the so-called BRICS economies (Brazil, Russia, India, China and South Africa), focusing on how their integration in the global knowledge generation process has changed. Technological upgrade is defined as the i) capability to produce frontier knowledge, ii) the degree of diversification of the economy towards a larger number of knowledge intensive activities and iii) the interaction with foreign economies. Using patent data from 1980 to 2015, the authors map the evolution of the BRICS and compare their performance with the EU, the United States and Japan.

The gathered evidence reveals an overall increased capacity to produce knowledge at the frontier and to engage in frontier technological activities. China stands out as the country most capable to reduce the gap with the world leading economies, increasing the knowledge intensity of its economy and successfully diversifying its technological content. However, the country still engages in incremental innovation activities, while still lagging behind in terms of international co-generation of frontier knowledge, differently from India which is more globally integrated despite a lower intensity of frontier technology production.

6. Persistent heterogeneity of R&D intensities within sectors: Evidence and policy implications

Coad, A. (2018). Persistent heterogeneity of R&D intensities within sectors: Evidence and policy implications. Research Policy.

- The paper investigates the existence of convergence in R&D intensities within European industries, drawing on a panel of top R&D investors from the EU Industrial R&D Investment Scoreboard.
- Results reveal an absolute convergence process, i.e. companies with R&D intensity lower than the average have been increasing it overtime.
- There is no evidence of companies converging to a common R&D intensity and, on the opposite, heterogeneity persists and increases overtime

Since knowledge intensive sectors are characterised by higher R&D investments, an increased specialisation of economies in these activities will contribute to increasing the overall R&D intensity of an economy. While the above is true, heterogeneity in firms' behaviour within sectors implies that different companies will achieve different R&D intensities, independently from the sector in which they operate. As the evolutionary literature on economics of innovation suggests, R&D investment patterns depend on different factors and decisions are characterised by routines, rather than optimisation choices. As a consequence, the shift of economic output towards more knowledge intensive sectors may not be sufficient to increase the overall R&D intensity, and policies aiming at promoting innovative investments in less knowledge intensive sectors should be considered. To support the latter argument, the paper analyses the trends in R&D intensity for a sample of world top R&D investors drawn from the EU Industrial R&D Investment Scoreboard, covering the period 2000-2015. The methodology relies on convergence analysis techniques, aimed at identifying i) the emergence of a catching-up process by companies with lower initial R&D intensity and ii) the evolution of the R&D distribution. Results reveal an upwards trend: companies whose R&D intensity was below the sample average in 2000 have increased their investment faster than those firms with higher intensities, suggesting a catching-up process. However, no convergence towards a common R&D intensity level is found. Differently, the dispersion of the sample persists and increases overtime, supporting heterogeneity in companies' strategies, routines or research or managing capabilities.

7. Artificial Intelligence in Service

Huang, Ming-Hui, Rust, R.T., "Artificial Intelligence in Service", Journal of Service Research (2018), Vol. 21(2), 155-172.

- This paper explores the way artificial intelligence (AI) could reshape services, suggesting that at a certain stage, an advanced AI could perform nearly all service tasks.
- The progression of task replacement by AI depends on four intelligences required for service tasks: mechanical, analytical, intuitive and empathetic. Firms will have to consider these when taking decisions about substituting human labour.
- A key implication is that as AI takes over more analytical tasks, analytical skills will become less important, giving more importance to the "softer" intuitive and empathetic skills of service employees.

The article aims to answer the questions of when, how, and to what extent should services be provided by artificial intelligence, and how this deployment of AI will reshape service provision and the job skills required of employees. The authors developed a theory of AI job replacement, describing the replacement of tasks and jobs and its implications on the service sector. Focusing on specific tasks, the authors assume that job replacement begins first for mechanical tasks, then for analytical tasks, followed by intuitive tasks and empathetic tasks. After the initial mechanical tasks' replacement, a transition period should lead to further task replacement, up to a stage where AI is performing equally to humans in all four intelligence areas. Such a development could eventually lead to replacement of human labour by AI or a complete integration of AI with human workers. This would have repercussions on the decision-making process within firms choosing replacement strategies and profound changes on service jobs market. This advanced tasks replacement level leads the authors to suggest the need for improved methods of training and strategies for the workforce, presenting additional issues for researchers and policy makers to consider. The authors warn against an oversupply of analytical skills in the current education, as these could rather soon become a comparative advantage of machines. They suggest that interpretation and decision-making based on analytical results together with creative thinking will become the most valuable assets for highly skilled service workers.

8. BIG data-BIG gains? Understanding the link between big data analytics and innovation.

Niebel, T., Rasel, F., & Viete, S. (2018). BIG data–BIG gains? Understanding the link between big data analytics and innovation. Economics of Innovation and New Technology, 1-21.

- The authors use firm-level data encompassing 4,400 German firms based on the 2015 wave of the ZEW ICT survey and EUROSTAT's Community Innovation Survey (CIS).
- Overall, firms that use big data analytics exhibit a higher propensity to innovate and higher innovation intensity. This holds for both the manufacturing and the services sector.
- IT-specific knowledge and skills are key to ensure that the use of big data by the firm leads to innovation, while the same is not true for general human capital.

Big data analytics make use of vast and speedily increasing amounts of data to better support decision-making and firms' strategies. However, most of these data is typically unstructured and heterogeneous, which poses some technical challenges to firms to master its true potential to derive adequate insights from patterns in such large volumes of data. The authors alert us to the fact that these limitations hamper the 'Big gains' from big data on firm performance as big data analytics may not guarantee sustainable and positive effects on firm performance. Moreover, the authors mention other types of barriers that may impact the value companies get from big data analytics which include bad internet connection and an unclear regulatory environment. Focusing on its benefits, the paper stresses that big data analytics can improve the efficiency of the R&D process in firms and ultimately business innovation through the creation of new products and/or services, process innovation and the elaboration or redefinition of business models. However, the “big data hype” and its impact on firm performance is somehow lacking empirical evidence to have a more complete and substantiated picture of the power of this technology in supporting business decisions and innovation outputs. The analysis uses firm-level data for about 4,400 German firms in both the manufacturing and services sector from the ZEW ICT Survey. 22% of the firms surveyed reported that they are using big data to support their decisions. The two most common big data-based practices in firms include the provision of digital assistance systems for employees and automated information exchange with suppliers and customers. The authors define two main innovation outcomes as the dependent variables- the propensity to innovate and the intensity of innovation here defined as the share of sales from the new product developed. The control variables include a set of firm characteristics such as business R&D intensity (i.e. share of R&D expenditures in total sales), ICT intensity (proxied by the share of employees who mainly work with personal computers and the share of employees with access to the Internet in the workplace), the share of highly skilled employees (i.e. workers with degrees from universities and technical colleges), and the age and size of the firm, among others. The results indicate that practices based on big data analytics are associated with a higher propensity to innovate, as well as a higher innovation intensity. The magnitude of the effect is similar in the manufacturing and services sector. Furthermore, the likelihood of the firm innovating is found not contingent on general human capital, while it is contingent on firms’ investment in IT-specific knowledge and skills.

9. Data Analytics skills, innovation and firm productivity

Wu, L., Hitt, L., & Lou, B. (2017). Data Analytics Skills, Innovation and Firm Productivity. The Wharton School Research Paper No. 86,

- The study investigates the relationship between data analytics skills, innovation and productivity for a panel of US firms between 1987 and 2010.
- Results reveal that data analytics capabilities are relevant for incremental innovation processes that recombine existing information, while no relationship is found for novel innovation output.
- Data analytics skills are also positively related to firms' economic performance, but only when used for process innovation process, suggesting complementarities between data analytics and process improvement practices.

The increased availability of data, due to the digitisation of physical processes and business activities, provides firms with the possibility to analyse a huge wealth of information to make informed decisions concerning production and organisational choices. The paper investigates to what extent the availability of data analytics skills is relevant to innovative processes and economic performance of companies, and whether this relevance varies across types of activities and innovations. Using a panel of US companies between 1987 and 2010, the paper tests the hypothesis that data analytics skills and incremental innovations or innovative outputs based on recombination of knowledge are complements. Furthermore, the analysis assesses the complementarity between analytical capacity and other process/organisational practices in affecting firms’ performance. Adopting natural language processing techniques to identify analytical skills of employees and the novelty of patent application, fixed effects, instrumental variables and General Method of Moments models are estimated to verify the validity of the hypothesis. Results confirm that the analytical capability endowment of company is indeed relevant for activities relying mainly on the use of existing information to produce incremental innovations. Differently, no or negative relation is found for those firms engaged in the production of novel innovations, i.e. engaged in exploratory innovative strategies. Consistently, data analytics skills are positively correlated to firms’ sales when complementary organisational practices aimed to process improvements are put in place within the company, suggesting that complementarity holds.

10. The impact of machine learning on economics

Athey, S. (2018). The impact of machine learning on economics. In The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

- This paper provides a reflection on the work developed so far to apply machine learning (ML) in the field of economics, while it also adopts a forward-looking approach to establish a set of predictions on the future impact of machine learning on economics.
- The author distinguishes between traditional approaches and machine learning approaches to estimate the impact of counterfactual policies in economics including a review of early use cases of applications of machine learning to economics.
- The author concludes that the added value from using ML techniques in economics problems comes from i) its flexibility to choose functional forms, ii) the use of algorithms that are data-driven and enable comparisons between alternative models instead of choosing a priori the model. Overall, ML is expected to bring new policy questions, more interdisciplinary collaboration and an extension of the role of the economist in the engineering and implementation of policies.

The definition of ML in the literature is not consensual as some define it more narrowly and others more broadly (e.g. as a collection of subfields of computer science). According to the narrow definition applied to the field of economics, ML is a field that develops algorithms designed to be applied to datasets, with the main areas of focus being prediction (regression), classification and clustering. ML has two main branches, notably unsupervised ML and supervised ML. The first branch does not impose any "labels" *a priori* to the analysis which helps the initial phase of finding patterns or similarities in e.g. potentially related products. Moreover, unsupervised ML can be very handy to reduce potential issues with spurious correlations because it does not require the use of outcome data. On the other hand, supervised ML typically entails using a set of explanatory variables to predict an outcome. The author then elaborates on the difference between ML methods and the traditional econometric and statistical techniques: ML methods tend to use data-driven model selection which means that the functional form that is to be used is not pre-determined by the researcher and instead the algorithm performs a maximisation exercise to select among alternative models. Moreover, *ML is likely to help make estimation methods more credible, while maintaining the identifying assumptions.* ML models are also useful in *anomaly detection (of outliers or unusual behavior)*, as well as fraud situations or *system failures.* The author also presents some examples of ML prediction methods in policy analysis. For example, ML models are used in credit scoring, to better allocate resources in cities and reduce code violations, and combined with images from satellites and street maps, it can *predict poverty and safety.* The author also stresses the contribution of ML to making analysis more fair and non-discriminatory, as *algorithms can absorb and use a lot more information than humans* which makes them *less likely than humans to rely on stereotypes.* ML and causal inference literature refer some problems that can be addressed with ML, such as the choice of instrumental variables, difference-in-difference approaches, and randomized assignments. Finally, the paper makes some predictions about the future impact of ML on Economics. These include i) use of ML methods for prediction, clustering, and textual analysis, ii) *development of new econometric methods based on ML to solve traditional social science estimation tasks,* iii) increased model robustness thanks to ML, iv) *increase in interdisciplinary research*, v) extension of the role of the economist *engaging with firms, governments* to engineer, *design and implement policies in digital environment, vi)* more research to assess the impact of AI and ML on the economy, vii) *research on developing high-quality metrics that can be measured quickly*, to enable incremental innovation and policy experimentation, etc.