TECHNICAL NOTE ON THE MAIN INDICATORS EMPLOYED TO STUDY THE RELATIONSHIP BETWEEN AUTOMATION AND EMPLOYMENT.

Thirty years after Jeremy Rifkin's The End of Work, economists still debate technology's impact on employment. This note presents the indicators used by the most cited economic literature since 1995, studying automation's effects in adapting to labor shifts. It facilitates further research to shape policies mitigating automation's challenges and promoting sustainable growth.

ARTICLE	INDICATORS
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. Technological forecasting and social change, 114, 254-280.	**Probability of computerization**: P(z* | X*, D), where z* denotes the probability of computerization, X* represents the test features, and D consists of the training data used for prediction. These features include variables such as educational attainment, wage levels, and specific job attributes. On the other hand, D consists of the training data, which is used to train the Gaussian process classifier. This data would likely include historical information about occupations and their respective levels of computerization, serving as the basis for making predictions about new, unlabelled test data. In addition to that, they complementary use the **number of jobs at risk**, **relationship between an occupation's probability of computerization, wages, and educational attainment**.

ARTICLE	INDICATORS
Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of economic perspectives, 29(3), 3-30.	The **employment-to-population** ratio is a measure of the proportion of a country's population that is employed. The author likely used historical data on this ratio to assess trends in employment levels relative to the overall population. **Fluctuations in the unemployment rate** refer to changes in the percentage of the labor force that is unemployed. By analysing historical unemployment rate data, the author gains insights into the cyclical patterns of joblessness and assess the impact of automation on overall employment levels. **Technology investment data**, such as **private fixed investment in information processing equipment** and **software as a percentage of Gross Domestic Product (GDP)**, provide insights into the level of capital investment in technologies that may affect labor demand and productivity. **Business cycle effects** refer to the impact of economic cycles, such as recessions or expansions, on the labor market. By considering **how business cycles coincide with technological advancements**, the author assesses the influence of economic conditions on employment dynamics. **Global events**, specifically **the rise of import penetration from China**, is assessed using **trade data**, **import/export statistics**, and economic indicators to understand the impact of international trade on domestic labor markets. **Changes in occupational patterns** may involve analysing data on **job categories**, **wage trends**, and the **distribution of employment across industries and sectors** to identify **shifts in the types of jobs available** and **the skills in demand**. The complementarities between automation and labor that increase **productivity**, **raise earnings**, and augment **demand for labor** is supported by economic models, empirical studies, and analyses of specific industries or occupations to demonstrate the ways in which technology interacts with labor to enhance overall economic output and employment opportunities.

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Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. Economics Letters, 159, 157-160.	The indicators employed by the author for technological advancement include measures of **automation adoption rates**, **investment in digital technologies**, and **advancements in artificial intelligence and robotics**. For job displacement, the author uses indicators such as **layoffs due to automation**, **shifts in occupational employment**, and **retraining programs for displaced workers**. In terms of employment trends, the author looks at changes in **employment rates across different industries**, **shifts in the demand for specific skills in the labor market**, and the **development of new job categories as a result of technological advancements**.

ARTICLE	INDICATORS
Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. Futures, 90, 46-60.	Historical Trends in Technological Revolutions: These indicators involve examining historical data on the impact of past technological revolutions, such as the Industrial and Digital revolutions, on **employment patterns**, **economic restructuring**, and **wealth distribution**. This provides a basis for understanding the potential implications of the upcoming AI revolution. Susceptibility of Different Occupational Activities to be Replaced by Machines and Robots: The author utilizes studies and reports, such as those by McKinsey and other experts, that assess the **susceptibility of various occupational activities to automation**. This includes data on the **percentage of tasks within different professions that are highly susceptible, less susceptible, and least susceptible to automation**. Employment Statistics: The author incorporates quantitative data on **employment trends across different sectors, including agriculture, manufacturing, and services**. This includes information on the **decline in certain sectors and the growth in others**, providing insight into the shifting landscape of employment. Automation Projections: The author considers projections and estimates regarding the potential impact of AI and automation on jobs and industries. This involves data on the **expected rate of job displacement, the types of tasks that are likely to be automated, and the timeline for these changes**. Industry-Specific Data: The author likely examines industry-specific data to understand how AI technologies are being adopted and integrated across different sectors. This involves analysing trends in **AI investment, the development of AI applications in industries such as healthcare, finance, and manufacturing, and the potential effects on job roles within specific sectors**. Wealth Distribution: The author considers data related to **wealth distribution**, such as **income inequality trends**, **wealth accumulation among different demographic groups**, and the **potential impact of AI on wealth distribution patterns**. This involves referencing economic studies, reports, and **historical wealth distribution trends**.

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Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different?. Journal of economic perspectives, 29(3), 31-50.	Labor Market Dynamics: This encompasses various aspects such as **trends in job creation**, **job destruction**, **labor force participation rates**, and **shifts in the composition of the workforce**. Monitoring these dynamics allows the authors to assess the impact of technological progress on employment patterns and the overall structure of the labor market. Income Inequality: Examining **trends in income distribution and disparities** within the labor force provides insights into how technological advancements may influence economic inequality, particularly in relation to the **potential displacement of certain workers or the creation of highly specialized, high-income roles**. Human Welfare: Measuring **human welfare indicators**, such as access to meaningful work, job security, and overall well-being, offers a holistic view of the societal impact of technological progress on individuals and communities, beyond purely economic considerations. Technological Unemployment: Tracking **instances of technological unemployment**, where individuals lose their jobs due to technological advances, provides a specific measure of the influence of technology on labor market dynamics and potential displacement of workers. Satisfaction and Meaning Derived from Work: Assessing subjective measures of **job satisfaction, fulfilment, and meaning in work** can offer insights into the human experience of employment and the potential effects of technological progress on the quality of work and life satisfaction. Qualitative Assessments of the Impact of Technology on the Nature of Employment: Utilizing qualitative research methods, the authors may capture firsthand accounts and **narratives that depict the evolving nature of work**, the challenges posed by technological advancements, and the broader implications for individuals and society.

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Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of political economy, 128(6), 2188-2244.	Exposure to robots: The authors construct a **measure of exposure to robots using data from the International Federation of Robotics (IFR)** on the increase in robot usage across industries. The exposure to robots measure is defined as **APRi**, the adjusted penetration of robots computed from European countries. They also exploit variation in industry-level adoption of robots in the US and European countries, such as the **adjusted penetration of robots between 1993 and 2007** to uncover the effects of the spread of robots on US labor markets. Robot usage across industries: The authors use counts of the **stock of robots by industry, country, and year from the International Federation of Robotics (IFR)** to measure robot usage across industries. This data allows them to examine the penetration and adoption of robots within specific sectors and analyse the relationship between robot usage and various labor market outcomes. Instrumental variable estimates and regression analyses: The authors employ instrumental variable (IV) estimates and regression analyses to quantify the **relationship between exposure to robots and its impact on employment and wages across commuting zones**. They use statistical methods to estimate the causal effect of robot exposure on labor market outcomes while addressing potential endogeneity and omitted variable biases. These methods involve specifying the relationships between exposure to robots and labor market variables, estimating the parameters of these relationships using statistical techniques, and **drawing inferences about the impact of robot exposure on employment and wages**.

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Gregory, T., Salomons, A., & Zierahn, U. (2016). Racing with or against the machine? Evidence from Europe. Evidence from Europe (July 15, 2016). ZEW-Centre for European Economic Research Discussion Paper, (16-053).	Labor Demand Effects of RRTC: The authors estimate the labor demand effects of routine-replacing technological change (RRTC) using a task framework of **regional labor demand in tradable and non-tradable industries**. They use empirical data for 238 European regions over the period 1999-2010 to quantify the impact of RRTC on labor demand. Direct Substitution of Capital for Labor in Task Production: The paper considers the **direct substitution of capital for labor in task production** as a channel through which technological change affects labor demand. This involves analysing how advancements in technology lead to a shift towards capital inputs in the production processes of firms. Compensating Effects Operating through Product Demand and Local Demand Spillovers: The authors also distinguish **compensating effects operating through product demand and local demand spillovers as additional channels through which technological change affects labor demand**. They model how declining capital costs incentivize firms to substitute capital for routine labor inputs and to restructure production processes towards routine task inputs, while also considering the increase in product demand and local labor demand resulting from these changes.

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Autor, D., & Salomons, A. (2017, June). Robocalypse now: Does productivity growth threaten employment. In Proceedings of the ECB Forum on Central Banking: Investment and Growth in Advanced Economie (pp. 45-118).	Data on Employment: The author employs measures such as the **number of employed workers and the ratio of employed workers to the working-age population to capture the level of employment across different industries and countries**. This data helps in understanding the dynamics of workforce participation and the impact of productivity growth on overall employment levels. Labor Productivity: This is measured as **real output per worker**, capturing the efficiency of labor in various industries. The author analyses how changes in labor productivity relate to changes in employment, particularly examining **whether productivity growth leads to job losses or job gains**. Value-added Growth: The study considers indicators of **value-added per worker** as well as the impact of total factor **productivity** on value-added growth. This helps in understanding the added value generated by each worker and the overall efficiency of production processes in different sectors. Relationship between Productivity Growth and Employment Growth: The author investigates the **relationship between productivity growth and employment growth**, examining how changes in productivity levels correspond to changes in overall employment. This analysis allows for the assessment of whether productivity gains have led to job creation or job displacement. Spillover Effects of Productivity Growth: The study explores how **productivity growth in one sector can influence employment growth in other sectors**, capturing the spillover effects of technological advancements. This analysis helps in understanding how changes in productivity in one industry can have wider implications for employment across the economy. Changes in Workforce Skills: The author considers how changes in the **skill composition of the workforce**, particularly in response to technological diffusion, influence the employment implications of productivity advancements. This includes examining the **demand for high-, middle-, and low-educated workers** in the context of changing productivity levels. Technological Diffusion: The study investigates how the **spread of technology across sectors** influences the employment implications of productivity advancements. This helps in understanding how technological advancements impact job opportunities and skills requirements across different industries.

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Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. Economics Letters, 159, 157-160.	The paper employs specific **task analyses within occupations** by examining detailed task data to understand the specific activities and responsibilities that make up different jobs. This allows the researchers to assess the variation in tasks within occupations and how they contribute to the overall automation potential. Technological feasibility studies involve evaluating the current and potential **technological capabilities related to automating specific tasks within occupations**. This assessment helps determine which tasks are more susceptible to automation based on the existing technological landscape. Assessments of the **adaptability of tasks to automation** involve considering how easily certain tasks within occupations could be replaced by automated technologies. This analysis considers factors such as the complexity of tasks, the potential for technological advancements, and the potential for workers to adapt to changes in task requirements.
Borland, J., & Coelli, M. (2017). Are robots taking our jobs?. Australian Economic Review, 50(4), 377-397.	Total work available: The author likely used measures of **aggregate hours of work** to assess whether the total amount of work available has decreased following the introduction of computer-based technologies. These measures would provide insight into the overall volume of work in the labor market. Pace of structural change and job turnover: The authors have utilised data on **job churning rates, industry composition changes, and the frequency of job turnover** to evaluate the pace of structural change and job turnover in the labor market. These indicators would help assess whether the application of computer-based technologies has accelerated these dynamics. Impact of computer-based technologies on employment: The author reviewed recent studies and employed **empirical evidence to evaluate the specific impact of computer-based technologies on employment**. This assessment involves considering various job categories, sectors, and skill levels to understand the nuanced effects of technology adoption on employment dynamics. **Historical data on technological advancements and their effects on employment**: To provide a comprehensive analysis, the authors have examined historical trends in technological advancements and their impact on employment. This historical perspective would contribute to understanding the long-term patterns and precedents in labor market adjustments to technological changes.

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Klenert, D., Fernandez-Macias, E., & Antón, J. I. (2023). Do robots really destroy jobs? Evidence from Europe. Economic and Industrial Democracy, 44(1), 280-316.	Industry-level data on employment by skill type: This indicator involves **data that categorises employment within industries by skill type**, which allows for the analysis of how the adoption of robots affects different skill levels within the workforce. Data on robot adoption: This refers to quantitative measures of the **adoption and deployment of industrial robots within various industries and sectors in Europe**, providing insight into the prevalence and impact of robotic technologies. Different sets of fixed-effects techniques: Fixed-effects techniques are used to control for unobserved heterogeneity and are essential in panel data analysis. The authors employ various **fixed-effects models to account for specific assumptions**, indicators, and parameters and to identify the specific factors driving their results. Capital/labor ratios: These ratios provide insights into the **capital intensity of production processes** and are likely employed to understand how changes in robot adoption may relate to the relative use of capital and labor in different sectors. Capital formation: This indicator typically refers to the process of increasing the **amount of capital within a country's economy** by engaging in activities such as investment in machinery and equipment. The authors employ this as a control variable to account for broader economic and technological trends that are independent of robot adoption.

About the author

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