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The Productivity Potential of Automation Technologies

Issue briefing | September 29, 2025

Future Skills Centre | Centre des Compétences futures

The Future Skills Centre (FSC) is a forward-thinking centre for research and collaboration dedicated to driving innovation in skills development so that everyone in Canada can be prepared for the future of work. We partner with policymakers, researchers, practitioners, employers and labour, and post-secondary institutions to solve pressing labour market challenges and ensure that everyone can benefit from relevant lifelong learning opportunities. We are founded by a consortium whose members are Toronto Metropolitan University, Blueprint, and The Conference Board of Canada, and are funded by the Government of Canada's Future Skills Program.

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Key findings

- New automation technologies, including AI, have the potential to boost productivity across Canadian industries by an average of 13.8 per cent over the next 15 years.
- Potential gains are greatest in transportation and goods-producing industries, which could see annual productivity growth increase by as much as 1.2 percentage points above our baseline forecast.
- Industries less exposed to automation technologies could still benefit, with increases to productivity growth between 0.4 and 0.8 percentage points per year.
- Industries with the strongest potential productivity gains have greater exposure to multiple automation technologies.
- Across industries, exposure scores were highest for AI, followed by robotics. However, the dispersion between maximum and minimum exposure scores relative to the average is lowest for AI.

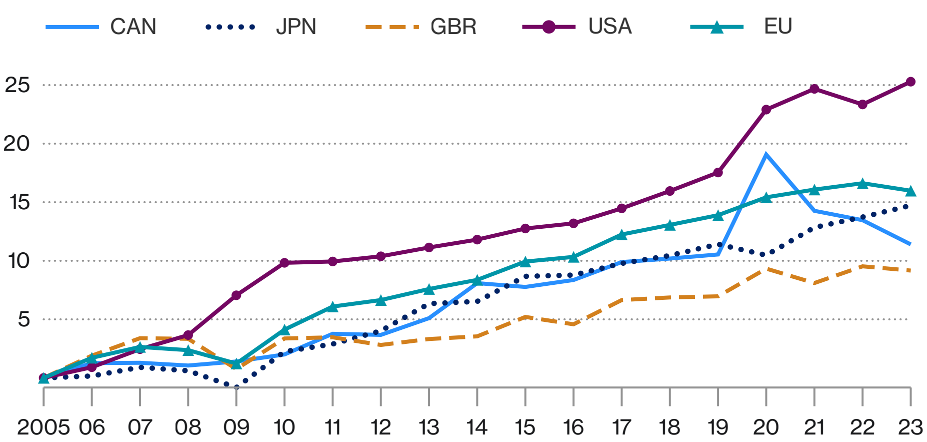
Automation technologies can strengthen Canada's economy

The Bank of Canada has declared that Canada is facing a "productivity emergency,"[1] but what does this actually mean? Productivity is the economic equivalent of a return on investment (ROI) – the net value we are getting given the inputs.

There are different ways to measure productivity, but the simplest is labour productivity, which is the output generated by individuals and businesses for each hour worked.[2] If, as a society, we are unable to increase productivity, our real income and standard of living will stagnate over time.

Over the past 20 years, Canada has faced stagnating productivity, and this is why we are now facing an "emergency." Since 2005, labour productivity in Canada, measured as GDP per hour worked, has managed to grow by only about 11 per cent, below the European Union (about 16 per cent) and Japan (approximately 15 per cent) and far behind the United States (about 25 per cent). (See Chart 1.) As of 2024, Canadian labour productivity is only 0.8 per cent above what it was in 2019.[3] This is one of the reasons so many people feel they are facing an affordability crisis.

Chart 1
Canada's labour productivity growth is lagging its peers
(cumulative growth in labour productivity, per cent)



Sources: The Conference Board of Canada, Organisation for Economic Co-operation and Development.

1 Rogers, "Time to break the glass."
2 Conference Board of Canada, The, *Cracking the Productivity Code: Charting a New Path to Prosperity.*
3 OECD, "Productivity levels."

Automation technologies such as artificial intelligence (AI), robotics, automated vehicles, virtual and augmented reality (VR/AR), and connected devices are changing the nature of work and the global economy. Harnessing these technologies is key to building a modern, resilient, and high-productivity economy in years to come.

However, the short- and long-term impacts of automation are still to be determined. The growth in traditional automation technologies like robotics has already been incredibly disruptive to manufacturing and utilities workers. Average employment in these occupations decreased by about 24 per cent between 2005 and 2020. Yet focusing on a single cluster like AI or robotics ignores the broader view of the interaction between these technologies. For example, modern robotics will be powered by AI and interact via connected devices. This research is one of the first to expand the analysis of productivity and labour market impacts beyond generative AI and take a wide variety of technologies into account.

There is often fear that new technologies will result in job losses through automation, but the productivity gains automation technologies can deliver may also increase employment. While these technologies reduce the number of workers needed to produce the same (or even more) output, they can support employing more workers as businesses scale up faster and produce more efficiently. Just because a job can be automated does not mean it will disappear, and firms may restructure their operations and increase employment in other areas. For example, the employment of data scientists, business systems specialists, and cybersecurity specialists has grown by between 400 and 800 per cent since 2005, highlighting the opportunities that new technologies can create.

Exposure is the first step to determining deployment

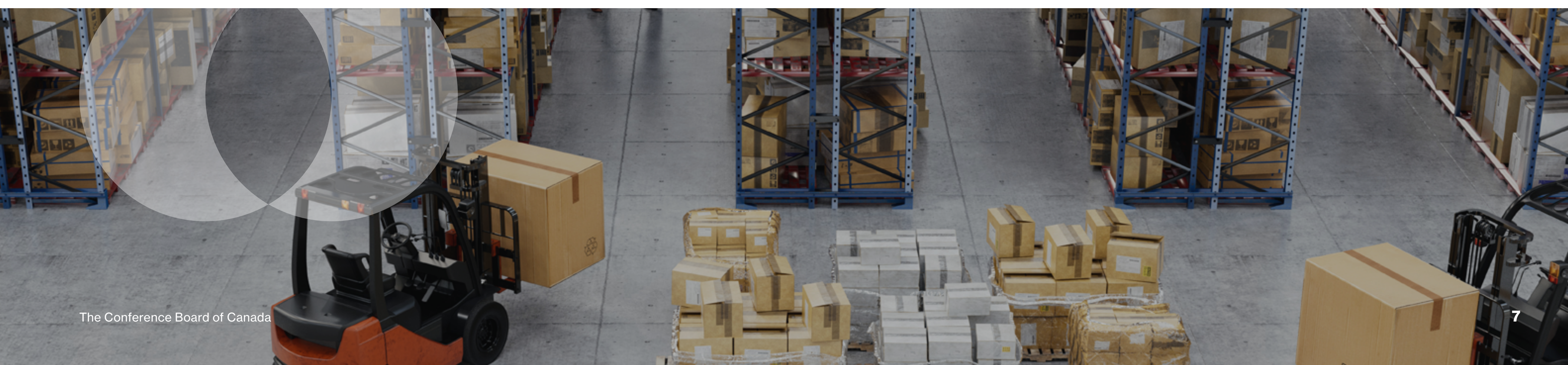
Our measure of job exposure to automation technology available. We measure the impacts of five clusters of automation technologies: AI, robotics, autonomous vehicles, VR/AR, and connected devices. We determine the share of occupation-specific tasks that can be performed by comparing them to over 80,000 patented technologies within each of these clusters, weighted by the technology's importance in that job. At the occupational level, the exposure score captures the intensity of task exposure—the concentration of patents to which the task is exposed—weighted by the importance of the task as well as the share of a job's tasks exposed to the technologies. See Appendix A for our detailed methodology.

At the industry level, the exposure score captures the average level of exposure of jobs making up that industry, weighted by each occupation's share of employment. Table 1 highlights the average exposure by industry to each technology cluster.

Table 1
Average exposure by industry to technology clusters
(exposure scores, per cent)

Industry	AI	Robotics	Autonomous vehicles and drones	Virtual and augmented reality	Connected devices	All technologies
Agriculture, forestry, fishing and hunting	10.4	8.9	1.2	1.7	0.6	27.7
Mining, quarrying, and oil and gas extraction	12.8	12.9	1.4	2.1	0.9	35.6
Utilities	12.6	8.0	0.8	1.7	1.0	28.7
Construction	10.4	10.7	1.1	1.9	0.7	29.6
Manufacturing	12.0	12.5	1.2	2.1	0.8	33.8
Wholesale and retail trade	10.4	5.3	0.6	1.7	0.5	21.9
Transportation and warehousing	12.7	12.5	2.7	2.4	1.0	37.9
Information, culture and recreation	10.9	3.5	0.4	1.3	0.6	19.8
Insurance, finance, real estate and leasing	10.4	1.8	0.2	1.0	0.4	16.0
Professional, scientific and technical services	12.4	2.8	0.3	1.2	0.5	19.9
Business, building and other support services	9.8	7.1	0.8	1.4	0.6	24.2
Educational services	7.6	2.2	0.2	0.8	0.2	13.1
Health care and social assistance	9.3	4.6	0.3	1.3	0.4	19.1
Accommodation and food services	7.7	4.3	0.4	1.1	0.4	16.7
Other services (except public administration)	9.6	7.4	0.8	1.4	0.5	24.1
Public administration	10.7	3.9	0.6	1.2	0.5	20.5

Sources: The Conference Board of Canada; OaSIS; USPTO; Statistics Canada.



Exposure to AI is high across all industries, ranging from a low of 7.6 in educational services to a high of 12.8 in mining and oil and gas. The broad-based exposure to AI aligns with the view that AI is a general-purpose technology with applications across a broad array of job functions.[4] On average, industries are most exposed to AI, followed by robotics. However, the difference between the maximum and minimum exposure scores relative to the mean is higher for robotics (1.6) than it is for AI (0.5).

Equally apparent is that goods-producing industries and transportation and warehousing have the largest exposure to non-AI types of technology, particularly robotics. Among goods-producing industries, mining, oil and gas, construction, and manufacturing are all slightly more exposed to robotics than to AI. Among service industries, administrative services and personal services stand out as having higher levels of non-AI exposure, similar in magnitude to utilities. Overall exposure to all automation technologies is higher than the sum across the individual clusters for all industries. This is because different clusters may be matched to the same task at the occupation level, reflecting the potential that the interaction between technologies magnifies the overall level of exposure for an industry. For example, exposure to autonomous vehicles and drones, VR/AR, and connected devices tends to be lower than exposure to the other two clusters. This may be due to these technologies primarily operating as an interface for other technologies, such as integrating AI into VR and AR applications for training simulations or enhanced data visualization and analysis. In this case, the patents specific to these clusters might result in fewer matches to specific occupational tasks but would still produce a high degree of complementarity with other technologies.

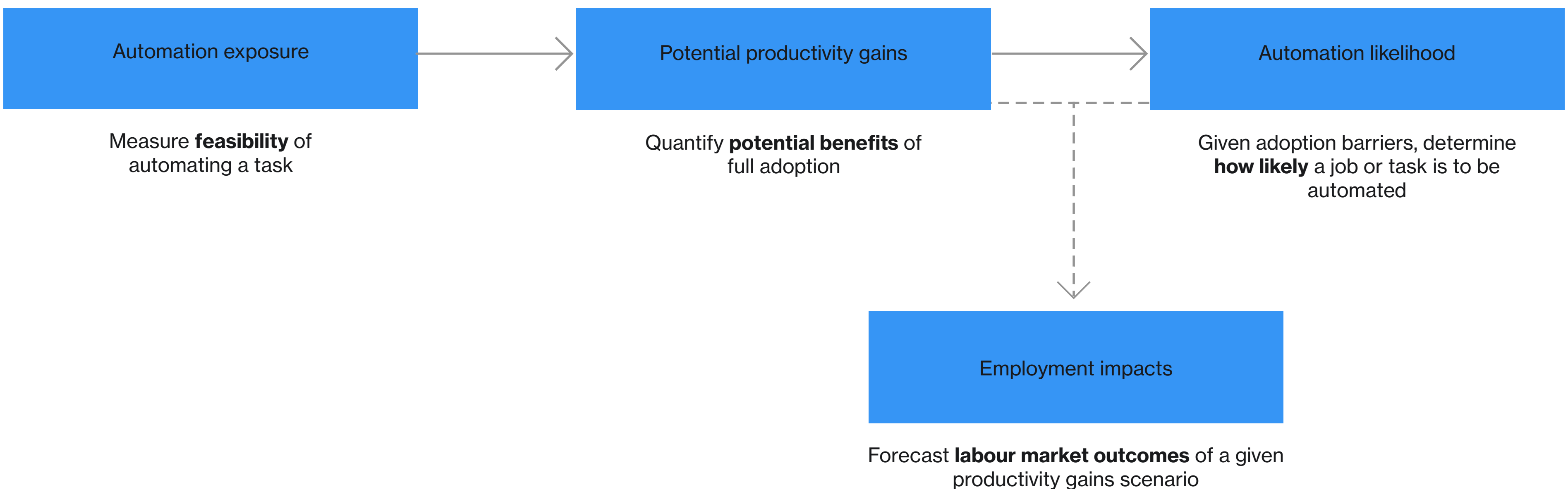
4 This is consistent with the findings in Eloundou and others, “GPTs are GPTs: Labor market impact potential of LLMs.” The authors find that large language models (LLMs) demonstrate the potential for widespread adoption, which satisfies a key requirement of being a “general-purpose technology.”

Understanding exposure scores

Exposure scores are distinct from the likelihood of a job or task being automated. The decision to adopt these technologies depends on both the *feasibility* (exposure) as well as the *expected gains* from adoption (potential productivity). (See Exhibit 1.) In isolation, measures of exposure highlight only the proportion of tasks that can be automated (i.e., performed by the technology); exposure does not tell us whether they *will* be automated.

Firms will decide whether to adopt these technologies based on the potential for returns on investments made. Individual firms will need to weigh the expected benefits from the productivity gains of automation against the costs of adoption. Here we focus only on the full potential of adoption. Barriers to adoption influencing predicted adoption rates will be the focus of our subsequent research on this topic.

Exhibit 1
Analytical framework for automation technologies and labour market impacts



Source: The Conference Board of Canada.

Transportation, goods-producing sectors hold most potential

We assume a "frictionless path of adoption," meaning that no barriers to adopting and deploying automation technologies exist over the next 15 years.[5] Under this scenario, we forecast that automation technologies could increase average Canadian productivity across industries by 13.8 per cent above baseline by 2040. This translates to an increase in annual productivity growth across industries of between 0.4 and 1.2 percentage points higher than our current (baseline) forecasts.[6] (See Chart 2.)

The three industries with the highest potential productivity gains (transportation and warehousing, mining and oil and gas, and manufacturing) benefit the most from automation technologies, with increases to annual productivity growth of between 1.1 and 1.2 percentage points above baseline. This translates into a total productivity increase by 2040 over our baseline forecast ranging from about 19 per cent in manufacturing to about 22 per cent in transportation. The productivity gains from automation are driven not only by AI but by the higher exposure of these industries to robotics and autonomous vehicles as compared to service-producing industries.[7]

5 Barriers can include anything that may prohibit or delay adoption, such as costs (i.e., how expensive it is to purchase a fleet of autonomous vehicles), policy uncertainty (i.e., uncertainty surrounding future policies regulating the use of AI), and social norms (i.e., public or political backlash to deploying robots in the production process).

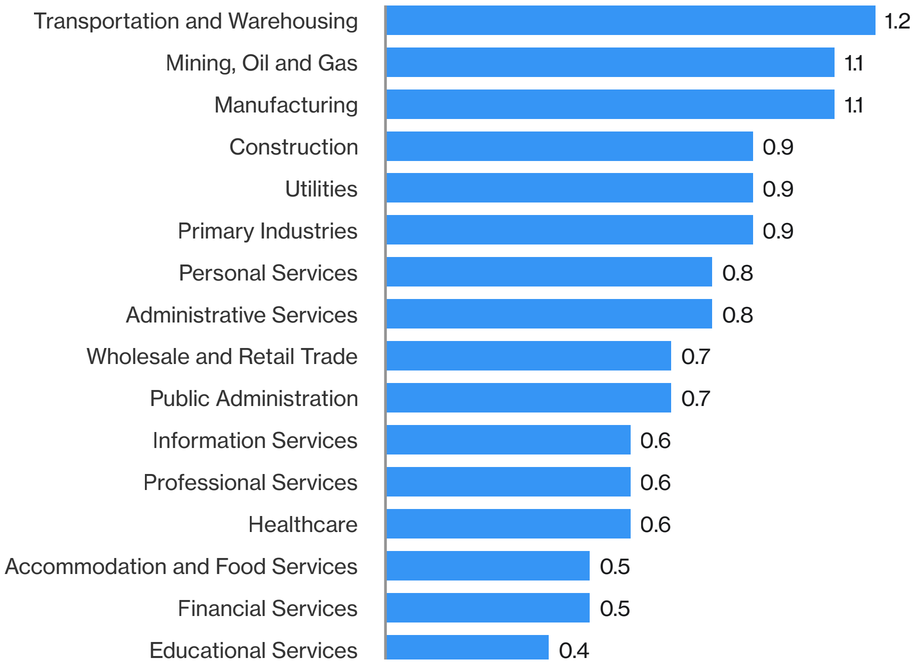
6 Our estimates are consistent with other existing forecasts, as summarized in Filippucci and others, "Macroeconomic productivity gains from Artificial Intelligence in G7 economies." A key distinction is that we consider a broader definition of automation technologies and do not restrict ourselves to focus solely on AI.

7 Personal services and administrative services are comparable to utilities in terms of their exposure to robotics and autonomous vehicles.

Chart 2

Transportation and goods-producing sector have highest potential gains from automation technologies

(potential increase in annual productivity growth, percentage points)



Sources: The Conference Board of Canada; OaSIS; USPTO; Statistics Canada.

For service industries, potential productivity gains due to automation technologies are lower. Annual productivity gains due to automation in a frictionless scenario range from 0.4 to 0.8 percentage points above baseline forecasts per year. The three service industries with the highest productivity gains (personal services, administrative services, and wholesale and retail trade) generally have the highest exposure to non-AI types of technology relative to other service industries. In short, it is the combination of AI with other automation technologies that drives the largest productivity gains in service sectors.

Education services (0.4 percentage points per year), financial services (0.5 percentage points per year), and accommodation and food services (0.5 percentage points per year) are expected to see the lowest overall gains in this scenario. These industries are less exposed to automation technologies overall and are particularly limited in their exposure to non-AI types of automation technology.[8]

8 This could also partially reflect our choice of using patent data when innovation in education might instead be funded by public funds and non-profits.

Navigating uncertainty in technological adoption

Improving adoption and deployment of automation technologies would give Canadian productivity growth a much-needed boost. Canada has tended to lag on adopting promising new technologies, which has limited their productivity benefits.[9]

To maximize the potential benefits to Canadians, policymakers and businesses can work together to identify and reduce the most pressing barriers to adoption. Policies that encourage investment and reduce uncertainty and risk around adoption will ensure that these technologies can be deployed and help drive Canadian productivity.

The variance in potential productivity gains across industries is dependent on each industry's degree of technological exposure, with the highest gains concentrated in transportation, mining, and manufacturing. Prioritizing these sectors for investments in the short term would not only improve Canada's productivity performance but also ensure that they can grow and remain competitive globally.

While service industries are less exposed overall and have lower potential productivity gains, they can still benefit and unlock growth potential through these technologies. Firms would need to identify the technologies that deliver the highest return on investment and invest in skills training. Increasing private sector collaboration with post-secondary institutions will also help ensure that Canadians entering the workforce are equipped with the skills needed to maximize the potential gains and fill the emerging roles needed as the economy restructures. This will both ensure that displaced workers are able to reintegrate into the workforce rapidly and help policymakers deliver efficient and targeted supports.

Forecasts of potential productivity are not sufficient to fully characterize how the labour force will be impacted. There remains a tremendous amount of uncertainty surrounding the uptake rate, barriers to adoption, and deployment. Understanding these hindrances is essential to generate realistic outlooks for Canada's productivity growth and employment impacts from automation technologies.[10] The implications for employment and income depend on the structural changes that happen as the economy transitions.

In the next step of our analysis, we apply our industry-level potential productivity changes to our economic models to estimate changes in overall employment from full adoption and determine the likelihood of automation. Then, using our Model for Occupations, Skills and Technology (MOST), we dive deeper into the changing composition of jobs and skills. These results will enable us to uncover automation pathways and estimate job-specific automation probabilities. Overall, the impact on workers will depend on which firms decide to adopt new technologies, what the speed of that adoption is, and what new roles may be created or made redundant through that process.

9 In *Cracking the Productivity Code: Charting a New Path to Prosperity*, we examine the barriers that have held back productivity growth in Canada.

10 In 2025, KPMG found that Canada ranked 44th out of 47 countries in AI literacy and 42nd in measures of trust in AI systems. (KPMG, "Study shows Canada among least AI literate nations.")

Appendix A

Methodology

Exposure scores

Our exposure scores are computed using natural language processing to compare occupation descriptions in OaSIS with U.S. Patent Office patents from the first quarter of 2005 through the first quarter of 2025 to determine the percentage of tasks of a given occupation that can be performed by automation technologies. Specifically, we combine two OaSIS data sets to define tasks: (1) the main duties data set, which records the tasks that are specific to a given occupation, and (2) the work activities data set, which ranks all occupations according to their importance. We use more than 4,700 unique task and duty descriptions from OaSIS and compare their similarity to over 80,000 patents, resulting in 388 million pair-wise comparisons.

Since the main duties are occupation specific, we give them a weight similar to the highest importance score a task can receive (i.e., five out of five).

Each task in the OaSIS database is compared to descriptive U.S. patent titles to determine the similarity between the task and the technology. A cosine similarity score, bounded between –1 and +1, is used to determine how similar the task is to the technology.

Undertaking this measure produces nearly 390 million task-by-patent similarity scores. To make the results tractable, we classify the technology patents into five mutually exclusive technology clusters. When the same patent falls into more than one technology cluster, it is assigned to the group it is closest to. For a task to be deemed exposed, we retained a threshold of 0.4 or above. This threshold was decided by testing different values and examining patents just above and below the threshold. The 0.4 threshold appeared as the least likely to exclude true positives and most likely to exclude false positives.

Task-level exposure is aggregated for each occupation at the five-digit NOC level using a formula that combines two key elements: (1) the intensity of innovation, and (2) the extensiveness of the tasks exposed weighted by the importance of the task to the overall occupation. The intensity of innovation is expressed as the ratio of the total number of patents matching a specific task over the largest total number of matches across all tasks and technology clusters weighted by their importance. Thus, the higher the number of matches and the closer to the maximum across occupations, the higher the intensity component of exposure for this task. These intensity metrics are aggregated to the seven-digit OaSIS occupation level by taking their weighted average, using the importance of the task for the occupation. The extensiveness component of exposure is measured as the importance-weighted share of tasks in each seven-digit OaSIS occupation that are exposed to at least one patent. Exposure is then calculated as the product of these two elements. Finally, the resulting exposure scores are aggregated to the five-digit NOC level for further analysis.

The resulting occupational exposure score is a number between zero and one and can be interpreted as a percentage of the share of tasks at risk of being automated, where values closer to one indicate a larger number of tasks being more intensively exposed to innovation.[1]

For example, suppose Occupation A has three tasks. Tasks a, b, and c have a weighted importance score of 0.5, 0.3, and 0.2, respectively.[2] The extensiveness of exposed tasks is defined as the number of tasks exposed to at least one patent. Weighting these exposures by importance yields the following extensive exposure:

$$e_{A,extensive} = \underbrace{[0.5 \times \mathbf{1}(\boldsymbol{Exposed} = \boldsymbol{true})]}_{\text{Task a}} + \underbrace{[0.3 \times \mathbf{1}(\boldsymbol{Exposed} = \boldsymbol{true})]}_{\text{Task b}} + \underbrace{[0.2 \times \mathbf{1}(\boldsymbol{Exposed} = \boldsymbol{false})]}_{\text{Task c}}$$

$$e_{A,extensive} = \underbrace{[0.5 \times \mathbf{1}]}_{\text{Task a}} + \underbrace{[0.3 \times \mathbf{1}]}_{\text{Task b}} + \underbrace{[0.2 \times \mathbf{0}]}_{\text{Task c}} = \mathbf{0.8}$$

1 Note that given our definition, for an occupation to receive an exposure score of one, it would first need to have all its tasks exposed to at least one patent, and the number of patents matching these tasks would have to be the highest among all other occupations.

2 Weights are normalized so that they add up to one. In this example, the importance scores are, respectively, 5, 3, and 2. Conversely, if the three tasks had a score of 2, their corresponding weight would be one-third each. This normalization pre- or post-calculation is required to have extensive values bounded between zero and one.

Per the above calculation, 80 per cent of the work activities and duties of Occupation A are thus exposed to at least one patent. To compute the intensity of exposure, we take the average number of patents matching each task weighted by their importance and normalize this number by the highest weighted average across all occupations. For example, suppose that Occupation A is exposed to 100 patents for Task a and to 30 patents for Task b. (Task c is not exposed to any patent.) Then the weighted average of the number of matched patents is as follows:

$$AverageCount_A = 100 \times 0.5 + 30 \times 0.3 = 59.$$

To get the intensity, we normalize this number by the value that is the highest among all occupations. Suppose this value is 295 for some other occupation in our data set. Then the exposure intensity is given by the following:

$$e_{A,intensive} = \frac{\mathbf{59}}{\mathbf{295}} = \mathbf{0.2}$$

The exposure score of Occupation A is then the product of these two components:

$$exposure_A = \underbrace{0.2}_{e_{A,intensive}} \times \underbrace{0.8}_{e_{A,extensive}} = \mathbf{16\%}$$

This means that 16 per cent of tasks for Occupation A are exposed on average when accounting for the share of tasks being exposed, their importance, and the degree of patent intensity.

At the industry level, we aggregate occupation-level exposures across all occupations within an industry (and within a province) at the NAICS three- or four-digit level, weighted by each occupation's share of employment within an industry. For a given industry *i* within province *p*, the exposure score is computed as follows:

$$c_{i,p} = \sum_{a \in NOC} e_a \times \frac{Employment_{a,i,p}}{\sum_{j \in NOC} Employment_{j,i,p}}$$

Thus, if Industry X in Ontario is composed of one worker from Occupation A with an exposure score of 0.2 and two workers from Occupation B with an exposure score of 0.6, the resulting exposure score is as follows:

$$c_{X,ON} = \left(0.2 \times \frac{1}{3}\right) + \left(0.6 \times \frac{2}{3}\right) = 0.47$$

We aggregate by industry and province for two reasons. First, it allows us to control for province-specific factors that affect the estimation of productivity growth. Second, it allows for differences in the occupational composition of industries across provinces. So, while we do not assume a difference exists in the level of exposure between "data scientists" in any industry or province, we do allow for the possibility that data scientists may account for a greater proportion of employment within a given industry in Ontario than in Alberta, which affects the relative exposure scores computed.

Productivity gains

To determine productivity gains, we employ a standard production function used in the economics literature to estimate the relationship between real value-added growth within an industry (three- or four-digit NAICS) and province between 2005 and 2020 and exposure scores, controlling for changes in hours worked, province, and sector (two-digit NAICS). We use Statistics Canada Tables 3610040201 and 3610048901.

This structure assumes that by controlling for changes in inputs (hours worked) and long-run changes in the economic environment (by controlling for province and industry), the impact of exposure scores is interpreted as the contribution to productivity growth. By using real value added, we avoid confounding changes in prices with changes in productivity.

For the estimation on historical data, we restrict our sample of patents to those dated between 2005 and 2020 to avoid adding unnecessary statistical errors due to patents from outside the sample years.

We employ a weighted least squares regression using the following functional specification:

$$\log \Delta GDP_{i,p} = \beta_0 + \beta_1 c_{i,p} + \beta_2 \log \Delta Hours_{i,p} + \delta_s + \delta_p + \epsilon_{i,p}$$

where $\log\Delta\mathrm{GDP}_{i,p}$ is the log change of GDP (value added) of industry *i* in province *p* between 2005 and 2020, $c_{i,p}$ is the exposure score of industry *i* in province *p*, $\log\Delta\mathrm{HOURS}_{i,p}$ is the log change of hours worked in industry *i* in province *p* between 2005 and 2020, and δ_S and δ_p are controls for two-digit industry codes for sector *s* and for province *p*. Observations are weighted by industry and province employment shares.

The resulting estimates β_1 are then adjusted with the estimated standard errors. Larger standard errors, which reflect less precise estimates, lead us to lower the expected impact proportionally to their size so as not to overstate the true effect.

To give us our forecast of 15year productivity growth, we compute $(\beta_1)\,\tilde{c}_{i,p}$, where $\tilde{c}_{i,p}$ is the exposure score derived using patent data from 2005 to 2025 to incorporate the most recent technological innovations in our estimates. We apply our productivity estimates β_1 to the most aggregated industry-level exposure scores.

Appendix B

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