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Digitalization: Labour Markets

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Overview

The impact of digitalization on the economic and financial well-being of Canadians is intrinsically linked to the impact of new technologies on labour market outcomes. This paper, which is part of the Digitalization Overview series, provides a comprehensive overview of the channels and mechanisms that govern this relationship. We set the stage by discussing historical episodes of rapid technological change and highlight lessons for the current era of digitalization. History shows that digitalization affects both labour demand and labour supply, and we explore both of these facets in this paper. On the demand side, the firm-level adoption of digital technologies affects the labour demanded at adopting firms and in the economy. On the supply side, many characteristics of the Canadian labour supply stand the economy in good stead when looking to a future with increased digitalization. The interaction of digitalization effects on labour supply and demand culminates in the wage effects. Research generally shows that benefits of digitalization have not been shared equally, and we highlight the implications of digitalization for inequality and inclusion. We then discuss the trends in digitalization during the COVID-19 era and the role of the pandemic in accelerating digitalization and changing the nature of work. We close the paper by highlighting emerging trends and opportunities for future contributions to research.

Key messages

- The adoption of digital technologies has disrupted labour markets, resulting in the reallocation of workers across firms, sectors and occupations.
- Several supply-side characteristics of the Canadian labour market are complementary to digitalization, notably the high level of post-secondary educational attainment and an immigration policy that attracts high-skilled immigrants.
- Recent waves of automation have contributed to the decline in the labour share of national income and the increase in income inequality.
- No consensus exists on the effects of digitalization on aggregate wages. Empirical research is mixed, and theoretical models are ambiguous as to the predicted effects.
- Labour market reallocations and implications for the inequality of future technologies may differ from the trends associated with those of recent waves of automation. In particular, high-skilled workers may be increasingly vulnerable to digital technologies such as artificial intelligence (AI). This differs from the information and communications technology era, when codifiable routine tasks in the middle of the skills distribution were more likely to be automated.

1. Historical lessons

1.1 The long-run benefits and costs of new technologies

Concerns about a future where a large part of the labour market is permanently displaced by new technologies in the workplace date back to at least the Luddite movement of the 19th century. At that time, workers opposed the increased use of machinery in the textile industry. However, **analysis of historical episodes of rapid technological change reveals a nuanced relationship between the adoption of new technologies and the welfare of workers.**

History suggests that automation leads to employment growth in some industries and declines in others. Using historical data from the 19th and 20th centuries, Bessen (2019) shows that employment growth in the United States was robust in the textiles and primary steel industries during a time of rapid technological change and automation. He argues that as production ramped up and markets became saturated, a declining elasticity of demand eventually led to a downturn in employment in these industries.

More generally, Autor (2015) notes that **three main factors determine the effect of technological change on workers:**

- **Complementarity and substitutability of skills.** The introduction of robots in a manufacturing plant could provide a career boost for an information technology (IT) specialist with relevant expertise, but it could also result in layoffs for assembly line workers whose tasks can be completed by the new robot. In this way, technology benefits workers with complementary skills but not those whose tasks can be performed by the new technology.
- **Elasticity of labour supply.** High-skilled workers are in limited supply. Because of this, they are more likely than low-skilled workers to enjoy wage increases when a new technology raises the demand for the complementary tasks they perform. Yet, some technologies involve complementary tasks that can be performed by workers without advanced training: for example, self-checkout kiosks need attendants to guide customers through the checkout process. However, these workers are less likely to enjoy wage gains from digitalization. This is because the supply of low-skilled workers is typically very elastic, with an adequate number of prospective workers to fill the vacancies created by a new technology. Furthermore, to the extent that self-checkouts are a substitute for the tasks done by workers in related jobs (e.g., cashiers), this technology may also result in less employment for low-skilled workers.
- **Elasticity of demand.** When textile plants were automated during the 19th and 20th centuries, typical North American households had far fewer clothes in their wardrobe than they do today. Despite the fact that a mechanized textile plant required fewer workers to produce the same amount of cloth, the pent-up demand for cheap clothing resulted in increased production of textiles. This meant that demand for complementary labour skills increased alongside automation (Bessen 2019). As this example shows, product innovation can stimulate consumption and hence labour demand, particularly for products where demand is highly responsive to lower prices or higher levels of consumer income.

Technology adoption affects aggregate labour market outcomes through various channels. Autor and Salomons (2018) find that automation reduces employment and the labour share of value added in the industry where it originates, which they refer to as the direct effect.[1] However, progress in one industry can have broader labour market effects through several indirect channels, including input-output linkages, aggregate demand and cross-sector reallocations. Once they incorporate these indirect channels, Autor and Salomons (2018) conclude that during 1970–2007, for their international panel of countries, automation increased aggregate employment growth but resulted in a decline in the labour share of value added.[2]

Technological change in the early 20th century had a positive aggregate impact on several labour market outcomes. Alexopoulos and Cohen (2016) study the effects of technological change during this era using two measures of innovation. The first is based on the titles of new technologies curated from the machine-readable cataloguing records of the US Library of Congress. The second measure uses monthly historical records from *Publishers Weekly* on technical publications related to various technologies organized according to the Dewey Decimal Classification system. They find that technical innovations raised employment, labour turnover, vacancies and productivity and reduced unemployment and business failures. They relate their findings to the macroeconomic debate about whether technology shocks result in lower or higher short-run employment, which is an important distinction between the predictions of New-Keynesian and neoclassical macroeconomic models. Their results indicate that the effects of any frictions, imperfections or price and wage rigidities in the economy during this era were more than offset by the positive impact of technological change on employment in the short and medium run.

1.2 Job polarization during the first wave of information and communications technology

The effects of digitalization on labour markets since the late 20th century are often studied with a focus on computerization, automation and the introduction of the internet. The seminal work of Autor, Levy, and Murnane (2003) documented that **during the era of computerization, codifiable jobs involving routine tasks were the most vulnerable to automation.** Their contribution led to a large literature on "job polarization," a term coined by Goos and Manning (2007). Job polarization refers to the decline in routine jobs in the middle of the skills distribution and simultaneous growth of high-wage and low-wage employment at opposite ends of the skills distribution. Workers in the lower tail of the skills distribution often complete non-routine manual tasks that are difficult to automate because they involve personal interaction or a high degree of physical dexterity (e.g., personal support workers). Tasks performed by high-skilled workers are also difficult to automate because of the highly abstract and analytical nature of these jobs.

Green and Sand (2015) document evidence of employment polarization in Canada, but they argue that factors other than technological change, such as labour supply growth and the resource boom, are likely

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[1] The labour share of income measures workers' share of total income in the economy.

[2] Mann and Püttmann (2023) also find a positive effect of automation on employment in US local labour markets. They develop an automation measure from patent data between 1976 and 2014 and highlight service sector job growth as an important factor in explaining the positive effect of automation on employment.

more important in explaining this trend. Beaudry, Green and Sand (2016) show that since the turn of the 21st century, the demand for cognitive tasks has declined. They relate this finding to the elevated demand for cognitive tasks during the capital investment phase of the life cycle of IT. They argue that around 2000, there was a transition from a period of IT investment to a period of maintenance. They note that during this latter period, demand for cognitive skills remained higher than before the arrival of the technology but lower than it was during the period of peak investment. They show that this reversal in the demand for cognitive skills resulted in high-skilled workers moving down the occupational ladder—a de-skilling process that pushed low-skilled workers further down the occupational ladder and, to some extent, out of the labour force completely.

While job polarization characterized employment growth during the era of information and communications technology (ICT), the jobs at risk of automation in the future may differ from those of the past. New work by Kogan et al. (2022) highlights that the jobs most affected by the arrival of new technologies have changed over time. They create a granular occupation-specific measure of technology exposure using textual analysis of patent data dating back to 1850 and show that for 150 years, workers in occupations involving manual physical labour were the most exposed to technological innovations. However, since the 1980s, occupations involving cognitive tasks have become increasingly exposed, a trend they attribute to innovations related to computers and electronics. While the nature of each technology determines the occupations that are most affected, Kogan et al. (2022) find that occupations involving interpersonal skills persistently have lower exposure over time. This is consistent with the results of Deming (2017), whose research highlights the importance of social skills in labour markets. He relates this finding to social skills being difficult to automate and complementary to new technologies in the workplace. However, Brynjolfsson and Mitchell (2017) note that machine-learning algorithms are increasingly capable of performing certain tasks requiring emotional intelligence, noting examples such as the growing role of chatbots in answering simple queries and making sales.

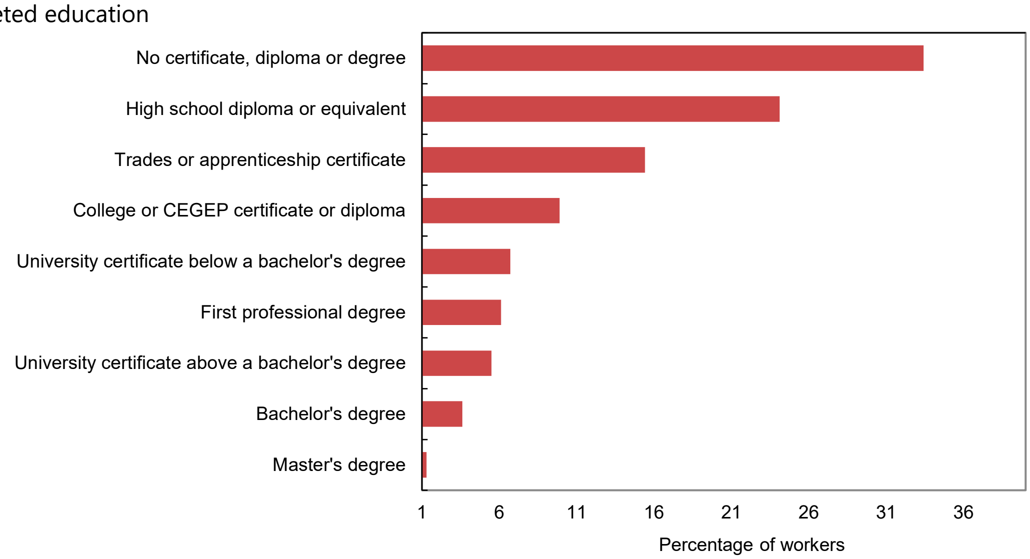
Frenette and Frank (2020) estimate that **10.6% of Canadian workers face a high risk of job transformation related to automation.**[3] **Chart 1** presents results from their analysis and shows that services sector jobs involving more routine tasks and those held by workers with lower levels of education are at greatest risk of automation. Frenette and Frank's (2020) estimates are much lower than those in the widely cited article by Frey and Osborne (2017), who estimated that 47% of total US employment is at risk of automation. Frenette and Frank's (2020) lower numbers reflect an evolution in the methodology to an approach that focuses on quantifying automatable tasks. This change was motivated by authors such as Acemoglu and Autor (2011), who argued that new technologies rarely replace entire occupations but instead involve automating certain tasks in the production process. Following this logic, Arntz, Gregory and Zierahn (2017) developed a measure of job automation risk that considers the tasks vulnerable to automation within each occupation. According to their results, only 9% of US jobs are at risk of automation, which casts doubt on the more dire predictions of Frey and Osborne (2017).

[3] Frenette and Frank (2020) define a worker as being at high risk if they face a model-predicted probability of 70% or higher of automation-related job transformation. Their probit fractional response model incorporates the automation risk estimates from Frey and Osborne (2017) and 25 different occupational tasks from the Canadian Longitudinal and International Study of Adults.

Chart 1: Occupations in the service sector and jobs held by workers with lower levels of education are at greatest risk of automation

a. Predicted share of workers at high risk of automation-related job transformation, by occupation

b. Predicted share of workers at high risk of automation-related job transformation, by highest level of completed education



Note: Occupations listed in panel a. include only those with the predicted share of workers at high risk of automation-related job transformation being 5% or greater.

Source: Frenette and Frank (2020)

In the late 20th century, ICT was transformed by the introduction of the internet; and in the decades since, researchers have endeavoured to quantify its impact on workers and labour markets. This research has found that **the diffusion of the internet has varied effects on labour market outcomes, with the greatest benefits going to high-skilled workers.** Hjort and Poulsen (2019) use data on the arrival of the internet in 12 countries in Africa and find robust positive effects on employment rates. They document increased employment for both low- and high-skilled workers, although employment increases more for high-skilled occupations. Using data from Norway, Akerman, Gaarder and Mogstad (2015) find evidence that broadband internet improves the productivity and labour market outcomes of high-skilled workers but worsens the outcomes for low-skilled workers. Research by Ivus and Boland (2016) on broadband deployment in Canada finds that broadband increased wage growth in the services sector (but not the goods sector) and employment growth in rural regions.

2. Labour demand, new technologies and the distribution of economic activity

2.1 Reallocation of labour across firms, sectors and occupations

An important impact of digitalization is the potential **reallocation of labour in response to the arrival of new technologies**. We begin this section by delving deeper into the reallocation process associated with the adoption of industrial robots and artificial intelligence (AI), and then discuss the shifts in the distribution of economic activity and organizational practices that occurred alongside digitalization.

The adoption of robots results in labour reallocation across sectors and occupations. For example, Dauth et al. (2021) find that in Germany, industrial robot adoption results in employment losses in manufacturing but that these losses are fully offset by new jobs created in the services sector at the local labour market level. They also find interesting results on the effects of robots on workers of different ages, and these findings are relevant for countries with an aging population, such as Canada. Younger workers suffer larger earnings losses and transition to services employment. Older workers are more likely to be retained by automating plants and move into higher paying jobs that require higher skill levels and that involve more abstract tasks. However, other studies suggest that the effects of digitalization are less favourable for older workers. Bessen et al. (2019) find that automation in Dutch firms resulted in large wage losses for older workers and also raised the likelihood that these workers would retire early.

Evidence on robot adoption at the firm level suggests a positive direct effect on employment in adopting firms (Aghion et al. 2022). Larger, more productive firms are more likely to adopt robots. Koch, Manuylov and Smolka (2021) find that robot adoption by manufacturing plants in Spain increased output and resulted in net job creation. Research by Dixon, Hong and Wu (2021) on the adoption of robots by Canadian firms also suggests that adopters increase total employment.

In addition, **firms that adopt robots also change the composition of their workforce**. Bonfiglioli et al. (2020) use French data over 1994–2013 and find that firms that import robots experience productivity gains and increase their share of high-skilled workers. Humlum (2021) uses administrative data from Denmark and finds that firms adopting robots subsequently expand output, hire more tech workers and lay off production workers.

While robots tend to increase employment within adopting firms, employment may decline in competing non-adopting firms. Acemoglu, Lelarge and Restrepo (2020) find evidence of this offsetting effect in their research on French firms, and in fact they find that the net effect is an aggregate decline in employment.[4] This raises an important question about the effects of robot adoption on aggregate employment more generally.

Empirical findings are mixed, but **the balance of evidence suggests that the increased use of robots decreases aggregate employment.** Acemoglu and Restrepo (2020) use data from the International Federation of Robotics (IFR) and find that an additional robot per thousand workers reduces local wages in US local labour markets by 0.42% and the employment-to-population ratio by 0.2 percentage points.[5] The authors argue that while robots increase demand for labour by increasing productivity, the net effect on employment is negative owing to the direct displacement of workers by robots. Other research finding a negative effect of robots on aggregate employment includes Aghion, Antonin and Bunel's (2019) study of France and Chiacchio, Petropoulos and Pichler's (2018) study of six European countries. Relative to other studies using the IFR data, Graetz and Michaels (2018) paint a more favourable depiction of the aggregate effects of robots. Using an international panel of countries over 1993–2007, they find that an increase in the number of robots increases productivity, lowers output prices and has no significant effect on employment.

Research on the labour market effects of AI is in its infancy, and to date no consensus exists on their magnitude. The diffusion of AI has expanded rapidly in recent years and this technology has the potential to transform labour markets. Compared with robots, AI is a more intangible form of capital, and this raises challenges with respect to measuring it and identifying its effects. Recent work by Acemoglu et al. (2022) attempts to address these issues using comprehensive data on US online job vacancies from 2010 to 2018. They find that firms posting AI-related positions reduce postings of non-AI positions and modify the skill requirements for other positions. This suggests that AI adoption leads to within-firm shifts in the demand for skilled labour. However, they also find that in terms of wages and aggregate employment, the effects of AI are as of yet too small to be detectable. Babina et al. (2022), in a related paper, develop a measure of AI investment at the firm level. They identify AI-related skills using job postings microdata and then use this information to classify AI workers according to the job history information found in their résumés. They then construct firm-level AI-investment measures by aggregating the résumé and job postings data. They find that AI investment leads to higher sales, employment and market valuation, with growth being driven by increased product innovation resulting from the investment.

[4] Acemoglu, Lelarge, and Restrepo (2020) also find that robot adoption is associated with higher value added and productivity as well as declines in labour shares and the share of production workers at adopting firms.

[5] The IFR data are discussed in greater detail in section 2.2 of Faucher and Houle (forthcoming).

2.2 Effects of digitalization on the geographic distribution of economic activity

The stock of human capital in cities interacts with the diffusion of technologies to shape the labour market trajectories of different regions. Personal computers were adopted more intensively in US cities that had a greater share of college-educated workers in the late 20th century; these cities also experienced the largest increases in returns to college education (Beaudry, Doms and Lewis 2010).[6] In related research, Berger and Frey (2016) find that computer adoption in the late 20th century explains much of the variation in employment growth across US cities and argue that the pattern of adoption is linked to the city-level endowment of abstract skills (e.g., software engineering and computer programming) in the workforce.

Tech clusters like Silicon Valley foster innovation that pushes digitalization forward. Kerr and Robert-Nicoud (2020, 51) define a tech cluster as "locations where new products (be they goods or services) and production processes are created that affect multiple parts of the economy." They argue that knowledge spillovers are at the heart of tech clusters, with the diffusion of ideas being the essential mechanism that advances innovation. However, tech clusters are not easily created; top-down attempts to engineer them often fail. Instead, the formation of clusters is a dynamic process that results from the scaling of emerging industries.

The recent emergence of platforms and online labour markets (the so-called gig economy) has also transformed the nature of work. Some of the services that use platforms involve local and tangible goods that require in-person interaction (e.g., Uber, SkipTheDishes, Instacart, TaskRabbit). Other services are completely remote and can be done from anywhere in the world (e.g., Amazon Mechanical Turk, Clickworker, CrowdFlower). Research by Cantarella and Strozzi (2021) shows that workers engaged in online employment are paid less, which may be partly the result of monopsony power in online labour markets, as documented in Dube et al. (2020). However, these labour markets may have also resulted in the emergence of new forms of work leading to net job creation (Bearson, Kennedy and Zysman 2020). Furthermore, the flexibility inherent to the gig economy may help reduce the gender pay gap, as other types of flexible work arrangements have done in the past (Goldin 2014). Although estimates of the size of this sector vary considerably,[7] findings by Katz and Krueger (2018) for the United States suggest that most net employment growth between 2005 and 2015 was linked to the gig economy and similar types of alternative work arrangements.[8]

Digitalization and the shift to remote and hybrid work during the pandemic has reduced commuting and changed the distribution of population over urban space. Bloom and Ramani (2021) find an increased preference for living and locating business establishments in suburbia in the largest US cities—referred to as the "donut effect"—as real estate demand, households, individuals and business

[6] "Returns to college education" refers to the additional earnings an average individual with a college degree makes, net of the cost of acquiring such education level.

[7] See section 3.3 of Faucher and Houle (forthcoming).

[8] Estimates of the share of workers in the gig economy for the United States and Canada vary between 0.3% and 30% of total employment (Katz and Krueger 2018; Kostyshyna and Luu 2019; Federal Reserve Bank 2022).

establishments have migrated to less dense zip codes in those cities. They do not find evidence of migration of workers and businesses across cities and little evidence of a donut effect in smaller cities. This is likely because of the concentration of jobs suitable for remote work (which tend to be done by skilled workers) in the largest cities and the anticipated hybrid nature of remote and in-person work in the future (see Althoff et al. 2022 for this argument).

2.3 Managerial and organizational responses to new technologies

The effects of digitalization on the management and design of organizations may lead to a shift in the relative demand for different skills. Dixon, Hong and Wu (2021) find that robot adoption in Canadian firms results in an increase in total employment but a decrease in the number of managers. They provide evidence that firms invest in robots primarily to increase product and service quality, and they argue that robots' ability to improve quality control reduces the need for managers to serve in this role. The distinction between product and process innovation is also addressed in recent work by Hirvonen, Stenhammar and Tuhkur (2022). Using granular data from Finland tracking investment in specific technologies, they find that adopting advanced technologies increases firm-level employment but has no effect on the skill composition of the firm. They show that firms use new technologies mainly for producing new products rather than for improving the production process. They interpret their findings as evidence that technological adoption does not always lead to skill reallocation, particularly when firms direct the new technologies at improving product quality. In this respect, their conclusions contradict the findings of Dixon, Hong and Wu (2021), highlighting the need for more research to better understand how digitalization affects product and process innovation as well as skill reallocation within and across firms.

Firms enjoy greater gains from ICT investment when it complements business and human resource practices. Aral, Brynjolfsson and Wu (2012) find that firms adopting human capital management software[9] experience greater productivity benefits when it is implemented with performance pay and human resources analytics practices. Brynjolfsson, Hitt and Yang (2002) find that the financial market rewards to firms from ICT investment are greater when they make complementary investments in organizational capital. Furthermore, Bresnahan, Brynjolfsson and Hitt (2002) show that firms tend to use more skilled labour when they invest in ICT in combination with reorganizing the workplace and introducing new products and services. Finally, Bloom, Sadun and Van Reenen (2012) argue that US firms' approach of combining ICT investment with management practices helps explain the stronger productivity growth in the United States relative to Europe in the late 20th and early 21st centuries.

3. Labour supply: Demographics, skills and education

Taking full advantage of digitalization requires a skilled labour force and entrepreneurs and innovators that advance the frontier of technological progress. **The profile of the Canadian labour force stands in good**

[9] Human capital management software is designed to equip executives, human resources (HR) professionals, and line managers with information needed for workforce support and HR analytics, including accurate planning on performance pay, employee performance feedback, talent management and the ability to continuously monitor work performance" (Aral, Brynjolfsson and Wu 2012, 914).

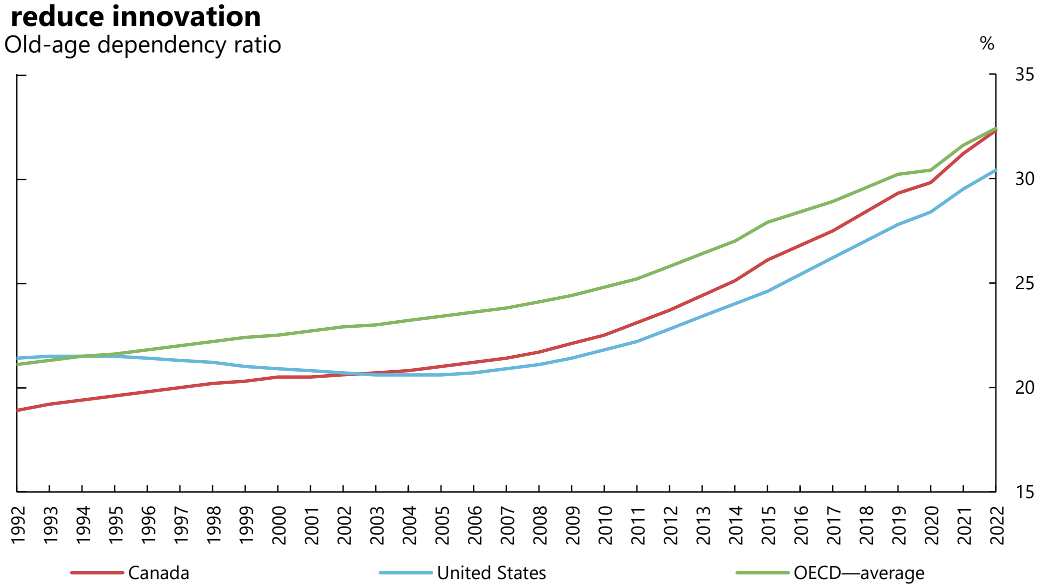
stead to leverage the benefits of digitalization. In this section, we focus on how the demographic, skill and education profile of the labour force affects digitalization.[10]

3.1 An aging labour force: More automation, less innovation

The aging of Canada's labour force has important implications for future innovation and automation (**Chart 2**). As a population ages, the scarcity of middle-aged workers can result in the automation of the manual production tasks these workers specialize in. Acemoglu and Restrepo (2022) provide empirical evidence of this theory by showing higher automation in response to aging in industries that are more dependent on middle-aged workers. While Gordon (2016) argues that aging and other demographic changes may slow future economic growth, Acemoglu and Restrepo (2017) find no evidence of a negative relationship between aging and growth of gross domestic product (GDP) per capita over 1990–2015. They argue that the adoption of labour-saving technologies may have mitigated the potential drag on growth stemming from labour scarcity. Furthermore, Fougère et al. (2009) argue that in recent decades, population aging in Canada has spurred young adults to acquire higher levels of education, and this pool of skilled labour may reduce the economic costs of an aging population.

Chart 2: The aging of populations of advanced economies may induce automation and reduce innovation

Old-age dependency ratio



Note: The old-age to working-age dependency ratio is the number of individuals aged 65 and over per 100 people of working age (aged 20–64). Values for 2021 and 2022 are projected by the Organisation for Economic Co-operation and Development (OECD).

Source: OECD

Last observation: 2022

Population aging in a society may also affect the pace of innovation. Jones (2010) finds that great inventors and Nobel Prize recipients most often make breakthrough discoveries in their 30s and 40s, although he also finds that the mean age of achievement has increased by five or six years over the past

[10] Parts of this section were co-authored with Gaelan MacKenzie.

century. In their analysis of 21 countries of the Organisation for Economic Cooperation and Development (OECD), Aksoy et al. (2019) find that aging reduces innovation. In sum, the empirical literature suggests that **aging induces automation but reduces innovation**.

What is the end result for growth? As a population ages, how do the associated impacts on automation and innovation affect societal welfare? Basso and Jimeno (2021) provide a framework for answering these questions using a life-cycle model that features a trade-off between innovation and automation, specifically robot adoption. In their model, aging affects innovation and automation through multiple channels: by altering labour supply, which alters the relative prices of the economic inputs to production and hence the profitability of innovation and automation; by changing the savings available for investment and hence the interest rate; and by directly affecting the arrival rate of new ideas as the proportion of the working population engaged in research and development decreases with age. Their analysis predicts that while lower fertility and higher mortality rates increase automation, **aging of the population leads in the long run to a decline in GDP per capita growth and the labour income share**. While this result does not bode well for an aging Canadian labour force, recent trends in immigration and educational attainment that encourage innovation and growth may counteract it.

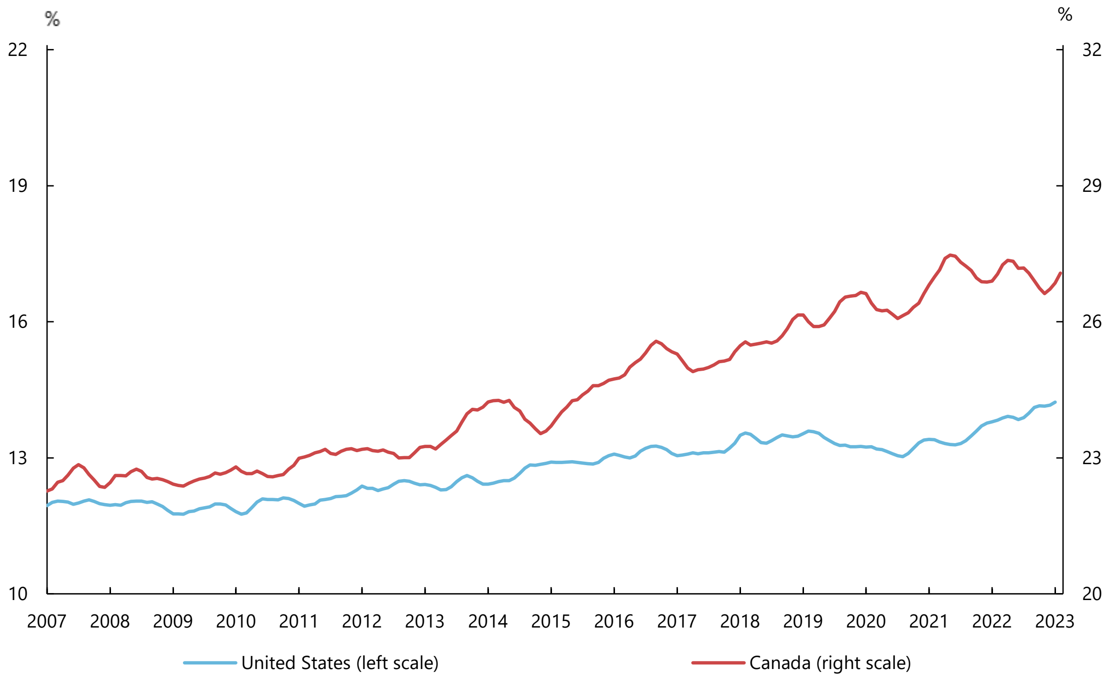
3.2 Immigration and education: Sources of innovation

While the aging of the Canadian population has the potential to slow innovation, immigration may help mitigate this trend. Research shows that immigrants have been an important source of innovation. For example, Akcigit, Grigsby and Nicholas (2017) show that growth in patenting was markedly faster in technologies where the immigrant population was more active. One reason for this may be linked to their role in facilitating knowledge diffusion. Bernstein et al. (2022) find that immigrants support cross-border knowledge flows because they are relatively more likely to collaborate with foreign inventors, rely on foreign technologies and be cited in foreign markets. They argue that developing inventor teams from different knowledge pools is important to the success of innovation. A more general takeaway from Bernstein et al. (2022) is that a deficiency in local innovative activity can be overcome by engaging in global innovation through international collaboration.

The Canadian immigration system favours university-educated immigrants, and the mobility of the Canadian immigrant population is highly responsive to shifts in demand in the local labour market. Albouy et al. (2019) find that a 10% increase in local employment demand results in a 15% increase in the foreign-born population in Canadian cities. In recent years, immigration growth has been more rapid in Canada than in the United States (**Chart 3**). The high rate of mobility in the Canadian foreign-born population is complementary to digital innovation and labour market dynamics in response to automation in the Canadian economy. Immigration also gives Canada flexibility to adjust to the needs of the economy. Addressing skills gaps exclusively through the use of the domestic labour force requires educational investment and a considerable time lag, whereas a skills-based immigration program can target prospective candidates to fill vacancies more quickly. However, a recent report by Employment and Social Development Canada (2020) on the Foreign Credential Recognition Program acknowledges that this process could be improved, as multiple barriers prevent Canadian immigrants from working in occupations that match their qualifications.

Chart 3: Immigration growth in Canada has outpaced that in the United States in recent years

Landed immigrants as a percentage of total population, three-month moving average



Sources: Statistics Canada and Federal Reserve Economic Data Last observations: United States, March 2023; Canada, April 2023

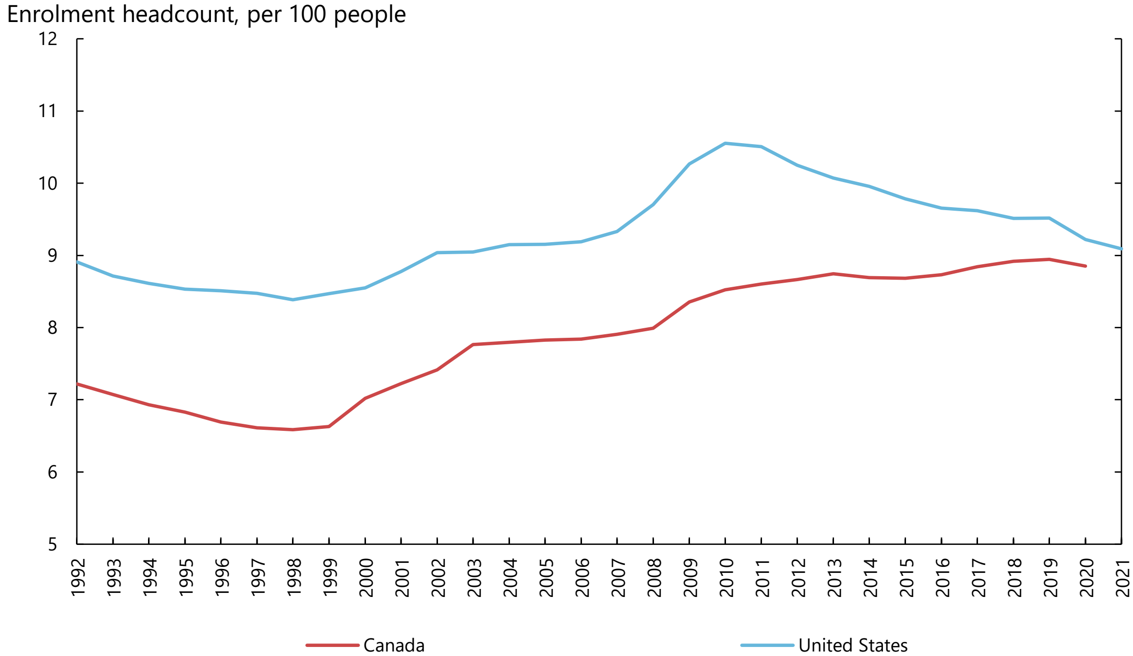
Innovation and growth will also be supported by the high level of post-secondary educational attainment in Canada. In 2021, 61% of Canadian adults aged 25–64 had a college or university degree, compared with 50% of adults in the United States (OECD 2022c). **Chart 4** shows that growth in the enrolment rate in post-secondary institutions in Canada has been strong since the late 1990s, whereas it levelled off and started to decline in the United States after the global financial crisis (2008–09). Despite the narrowing of the Canada–United States enrolment gap in recent years, for decades the enrolment rate in Canada has been lower than in the United States. This is somewhat counterintuitive, given that the OECD's statistics reported above indicate that a higher share of Canadian adults have a post-secondary degree. Several factors likely explain this puzzle. One issue, noted by the OECD (2022a, Annex 3), is that that tertiary educational attainment in Canada is somewhat inflated by the data and methodology used to classify these degrees in Canada.[11] In addition, while enrolment rates are lower, graduation rates from post-secondary

[11] Usher (2021) notes that after adjusting to the extent possible for methodological differences, Canada's tertiary educational attainment might not be substantially different from the comparable number in the United States.

education are higher in Canada than in the United States.[12] Also, Canada's immigration program uses economic criteria and favours university-educated immigrants. This boosts the educational attainment level in the Canadian adult population relative to that of the United States, where most immigrants enter the country under the family reunification policy (Albouy et al. 2019). Finally, generational differences in educational attainment rates may cause levels of enrolment and educational attainment to diverge in each country.

The skills learned in science, technology, engineering and math (STEM) programs are highly complementary to digitalization. In Canada, the share of total graduates who are STEM degree recipients is higher than in the United States but lags global leaders such as Germany, demonstrating that Canada has both strength and room to improve in this regard (**Chart 5**).

Chart 4: The Canada–US gap in enrolment per capita has narrowed since the 2008–09 global financial crisis



Note: The data include total fall enrolment in degree-granting post-secondary institutions, full time and part time, undergraduate and graduate. For both United States and Canada, per capita calculations, per 100 people, use the civilian population (military excluded), aged 15–64, as denominator.

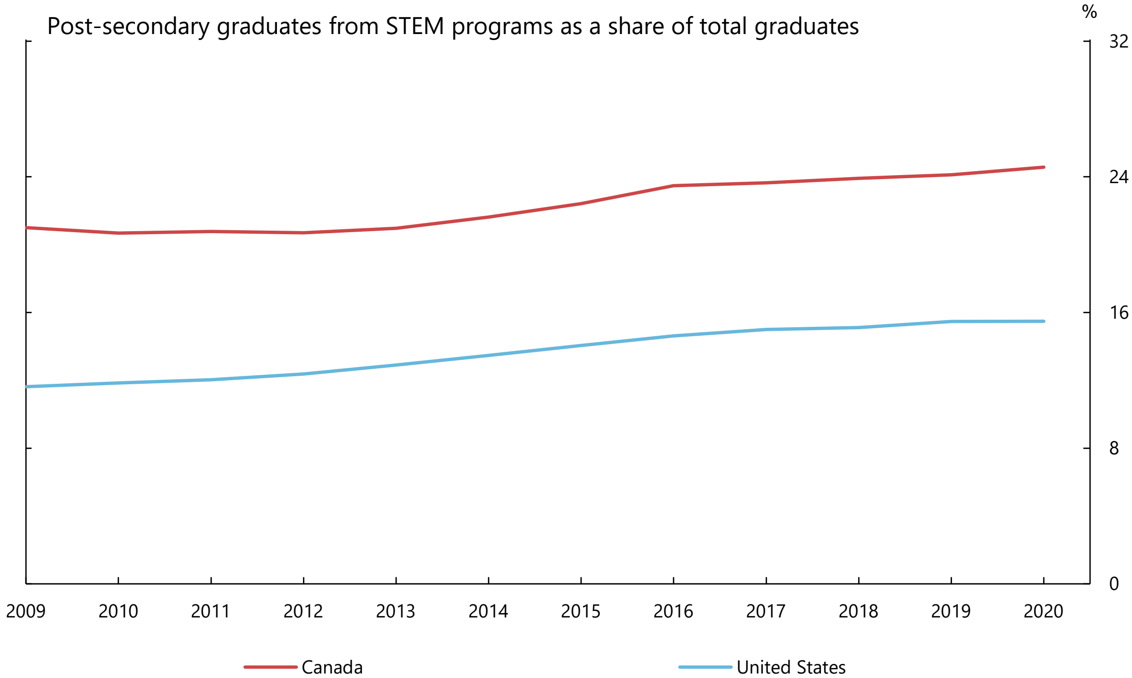
Sources: Statistics Canada, National Center for Education Statistics and Federal Reserve Bank of St. Louis

Last observations: Unted States, 2021; Canada, 2020

[12] In Canada, 74% of the students who started undergraduate studies in 2010 completed their degree in six years (Statistics Canada 2019). In the United States, 62% of the 2010 entry cohort in four-year institutions graduated within six years (National Center for Education Statistics 2021).

Chart 5: Number of graduates from STEM programs continues to rise in Canada and the United States

Post-secondary graduates from STEM programs as a share of total graduates



Note: US data are for post-secondary institutions participating in Title IV federal financial aid programs. STEM stands for science, technology, engineering and math. US STEM fields include biological and biomedical sciences, computer and information sciences, engineering and engineering technologies, mathematics and statistics, and physical sciences and science technologies. Degree counts are limited to degree-granting institutions; certificate counts include both degree- and non-degree-granting institutions. Canadian STEM fields include physical and life sciences and technologies, mathematics, computer and information sciences, and architecture, engineering and related technologies. A list of programs and credential types used can be found in Statistic Canada's Table: 37-10-0012-01. For Canada, "total graduates" is the total number of post-secondary graduates for all fields of study, while for the United States, "total graduates" is the total number of degrees/certificates awarded at post-secondary institutions and is based on 5,832 institutions.

Sources: Statistics Canada and National Center for Education Statistics

Last observation: 2020

3.3 The post-pandemic digital skills gap

Demand for digital skills often outstrips the supply of these skills in the labour force, and the gap has become more apparent with the accelerated pace of digitalization during the COVID-19 pandemic. In a multi-country study covering Australia, Canada, New Zealand, Singapore and the United States, the Asia-Pacific Economic Cooperation (APEC 2020) finds that 69% of 2019 job postings required digital skills. At the same time, evidence from the Bank's Business Outlook Survey shows increased investment intentions in digital technologies during the first two years since the onset of the pandemic (see e.g., Bank of Canada 2020; 2021; 2022). These trends suggest a possible uptick in the use of digital technologies. Quantifying job displacement and other effects of the pandemic on labour markets are important topics for future research. The shift to remote work and e-commerce, supply chain disruptions and other factors accelerated digitalization and increased the demand for digital skills in the workplace. In a survey run by McKinsey (2020), respondents reported that many of shifts introduced during the pandemic would be permanent, notably those related to remote work, migration of assets to the cloud and customer preferences for remote interaction.

Pandemic-related disruptions in immigration may have short-term implications for the supply of workers with digital skills. However, the Canadian immigration rate has quickly recovered to above pre-pandemic levels. Landing fewer immigrants during the pandemic may have decreased the supply of workers with the necessary skills to support digitalization. For example, foreign-born workers accounted for 55% of the growth between 2000 and 2018 of hours worked in occupations likely to be involved in the production of AI (Hanson 2021). Relative to 2019, 2020 saw a 46% decline in the number of immigrants landed in Canada; however, by 2021, the number of immigrants landed was 19% higher than it was in 2019. This strong rebound continued in 2022, with the number of landed immigrants growing by 8% relative to 2021 (Statistics Canada 2023a).

Divergent trends in post-secondary enrolment during the pandemic in Canada and the United States will have implications for the supply of skilled labour in each country. Enrolment in Canadian post-secondary institutions held roughly constant between the 2019/20 and 2020/21 academic years, dropping by only 0.56% (Statistics Canada 2022a). This contrasts with the experience in the United States, where fall enrolment declined by 3.07% between 2019 and 2020 (National Center for Education Statistics, 2022). This is consistent with the divergent enrolment trends between Canada and the United States in **Chart 4**. In the United States, community colleges experienced a large drop in enrolment, and Schanzenbach and Turner (2022) find that one-quarter of this drop can be explained by disruptions to courses requiring capital and "hands-on" experiential learning. Much less is known about the variation in post-secondary enrolment rates across different programs of study in Canada during the pandemic. As data become available, work is needed to better understand how changes in program-specific trends during the pandemic relate to current and future skills gaps in the Canadian labour market.

School closures during the pandemic will likely also affect the supply of skills and the productivity of workers in the future. Worldwide, a peak of 1.6 billion children were affected by partial or full school closures during the pandemic (UNESCO 2021), and we already see the effects on student learning. In the United States, recent national test results show that the math and reading scores of nine-year-olds have dropped to the lower levels of achievement from two decades ago (Mervosh 2022). While assessing the far-reaching consequences of this trend is difficult, overcoming these setbacks in educational achievement will be critical to meeting the demands of a digitalized economy that relies on high-skilled workers. On a positive note, the OECD (2022b) reports that a majority of countries participating in a recent survey had plans to continue to provide digital tools and training for teachers and students after the pandemic.

4. Digitalization's impact on wages, labour share and inequality: Mixed results

Understanding the effects of digitalization on wages is central to determining the welfare implications of new technologies. However, it has proven difficult to determine the signs of these effects and even more challenging to quantify the magnitude of the wage effects of digitalization. Several factors pose a challenge to characterizing the nature of this relationship. For example, the wage effects of digitalization may vary by the type of worker and the technology being studied, and they may differ depending on whether wages are measured in adopting firms, in non-adopting firms or in the aggregate. In light of these nuanced considerations, it is perhaps not surprising that no consensus exists in either the theoretical or empirical literature on the effects of digitalization on wages.

At the country and local labour market level, the estimated wage effects of robot adoption are mixed. Research in this area relies on robot adoption data from the IFR, and the signs and significance of the estimated effects vary considerably in analyses. For example, Acemoglu and Restrepo (2020) find a negative effect of robots on wages in local labour markets in the United States, while Graetz and Michaels (2018) find that robot densification is linked to higher wages in 17 developed countries. Finally, Chiacchio, Petropoulos and Pichler (2018), in their analysis of six European countries, do not find a robust statistically significant effect.

Digital technologies are used for different purposes in the workplace, and the wage effects of digitalization depend on the degree of substitutability between digitalization and worker tasks. Models featuring technologies that can easily substitute for labour predict that digitalization decreases the labour demand of firms that adopt the technology (Acemoglu and Restrepo 2020). In contrast, models emphasizing the productivity gains from digitalization predict an increase in labour demand in automating firms (Aghion et al. 2020). Furthermore, changes in labour demand by automating firms interact with equilibrium effects, such as a decline in market share and labour demand by non-automating firms. Commonly employed models in the literature predict an ambiguous (Aghion et al. 2020) or negative (Acemoglu and Restrepo 2020) relationship between digitalization and wages, and this theoretical ambiguity mirrors an empirical literature that has found mixed results.

Drawing any definitive conclusions about the wage effects within firms that actively adopt robots and other digital technologies is also difficult. While firm-level data provides granular evidence on the pattern of adoption, the estimates of wage changes in adopting firms vary considerably from study to study. Koch, Manuylov and Smolka (2021) find no statistically significant effect on the average wages paid in Spanish firms that adopt robots. Bessen et al. (2019) find statistically significant, but economically small, daily wage losses in Dutch firms that automate. Acemoglu, Lelarge and Restrepo's (2020) unweighted estimates suggest a positive wage effect from firm-level robot adoption; however, their weighted estimates are not statistically significant. Finally, Barth et al. (2020) find that robot adoption in Norway over 1999–2016 had a positive effect on the average wage for manufacturing workers.

While determining the wage effects of digitalization is difficult, most researchers agree that automation has contributed to a decrease in the labour share of national income (Grossman and Oberfield 2022). The labour share was constant for much of the 20th century but has declined significantly in Canada and the United States since the turn of the century (Gutiérrez and Piton 2020). Various potential mechanisms link the declining labour share to digitalization: declines in the economy-wide price of capital initiated by advances in digital technologies (Karabarbounis and Neiman 2014); increases in the productivity of ICTs and the rise of market concentration (Autor et al. 2020); and labour becoming more substitutable with capital with new technologies (Acemoglu and Restrepo 2020).[13] Using an approach that incorporates both the direct and indirect effects, Autor and Salomons (2018) find that between 1970 and 2007, automation resulted in a 10% drop in the labour share relative to its mean value of 67% in 1970, as averaged across the 19 countries considered in their analysis.

The declining labour share is one of several potential links between automation and inequality. Recent waves of automation have led to larger gains for high-skilled workers, and this may also be the case for future technologies such as AI (Ing and Grossman 2022). Graetz and Michaels (2018) find that robot adoption reduced the employment share of low-skilled workers but had no statistically significant effect in reducing aggregate employment. Barth et al. (2020) find that robot-adopting firms in Norway increase the wages of high-skilled workers relative to low-skilled workers, with the largest gains going to managers. Furthermore, Moll, Rachel and Restrepo (2022) find that the gains from automation raise the incomes of high-skilled workers and the owners of capital, thereby contributing to increased inequality.

Although automation has supported employment growth in low- and high-skilled occupations, wage growth has been more concentrated in the upper tail of the skills distribution. Over 1979–2012 in the United States, labour demand increased for low-skilled occupations, yet the inherently elastic supply of low-skilled workers prevented robust wage growth (Autor 2015). Green and Sand (2015) find that for Canada between 1971 and 2005, wage growth is also characterized by rising income inequality, but likely for different reasons than in the United States. High-paid occupations enjoyed the strongest wage growth, followed by middle-paid occupations, in turn followed by low-paid occupations. Green and Sand (2015) do find limited evidence of wage polarization between 2005 and 2012, but they argue that this is less likely to be related to technological change than to the natural resource boom.

More discussion about the relationship between digitalization and inequality is provided in **Box 1**.

[13] Arguments linking the declining labour share to capital deepening rely on the assumption that capital and labour are substitutes in production. However, a recent paper by Glover and Short (2020) provides evidence that labour and capital are not gross substitutes. They estimate that the aggregate elasticity of substitution is below one and argue that this rules out capital deepening as the cause of the declining labour share in recent decades.

Box 1: Inclusion and inequities in the benefits and costs of digitalization

Digitalization creates new hurdles to achieving an inclusive work environment.

The digital divide

Digitalization benefits only those who have both physical access to digital technology and certain minimum skills. The "digital divide" refers to the barriers to access and use of digital technologies that exist for certain demographic groups. For example:

- Canadian seniors and people with lower levels of education are less likely to have the skills to use the internet and digital technologies (Wavrock, Schellenberg and Schimmele 2021).
- US households on federally recognized Indigenous reservations have worse access and pay higher prices for internet access than neighbouring off-reservation areas (Bauer, Feir and Gregg 2022).
- The higher costs of digital access in remote areas result in disparities between rural and urban internet users (Feijao et al. 2021).
- Lower female enrolment and higher rates of attrition in STEM fields of study contribute to significantly fewer women than men being employed in occupations related to cloud computing, engineering, data science and AI (Feijao et al. 2021).

Access to digital technologies provides learning opportunities and fosters the development of skills that are essential for success in the labour market. Uneven access to digital technologies today may increase the digital divide in the future. This issue became acute during the COVID-19 pandemic, when unequal access to technology presented a major barrier to online learning for students from low-income communities (UNICEF 2020).

Labour market inequities perpetuate the digital divide. Lamb, Vu and Zafar (2019) find that:

- tech workers tend to be better educated and earn higher salaries than the average worker in the Canadian economy
- women, Indigenous and Black Canadians are much less likely to work in tech jobs, and when they do, they are paid significantly lower salaries

Bias

The indiscriminate use of digital tools can perpetuate existing biases or even introduce new ones.

Incorporating digitalization into business and management practices may reinforce systemic discrimination in the workplace. Some worry that the use of AI-streamlined decision making might perpetuate the biases present in the data used as input. Many of these models are built by learning from historical decisions, which means that unrepresented groups may be missing from or assigned the wrong outcome in the data. For example, Amazon recently had to discontinue using its recruitment AI tool after finding it had a large bias against hiring women for tech jobs. This illustrates the need to be vigilant in applying these digital tools.

Box 1 (continued)

Even if variables identifying under-represented groups are not explicitly present in the data, hidden correlations between these groups and socio-economic variables might put them at a disadvantage. The fact that many AI systems are not explainable or interpretable exacerbates this. AI models use input data to output a result, but we cannot observe how the data features are combined to make predictions.

Notably, Caliskan Bryson, and Narayanan (2017) show how semantic biases result from the simple use of machine learning on text data. They examine the widely used GloVe word embedding natural language repository (Pennington, Socher and Manning 2014), which measures how words are related to one another based on their co-occurrence in a wide body of literature. They find that:

- significant bias occurs in the joint distribution of gender with respect to careers or first names
- many science, technology, engineering and math careers occurred more frequently with male than female names

Other papers report similar problems in various areas, such as:

- criminal justice (Mayson 2019; Barocas and Selbst 2016; Bushway and Smith 2007; Starr 2014)
- firm hiring decisions (Peña et al. 2020; Raghavan et al. 2019; Tilmes 2022)
- facial recognition (Acien et al. 2018; Drozdowski et al. 2020)
- credit lending decisions (Brotcke 2022; Costello, Down and Mehta 2020; Knight 2019)
- health care (Evans and Mathews 2019; Gianfrancesco et al. 2018)

The hope is that models can be trained to counter human bias in decision making and that AI prediction can actually reduce this bias. Some statistical techniques show promising results in terms of correcting for biases in training AI models (e.g., Kamishima et al. 2012; Raghavan et al. 2019; Houser 2019; Roselli, Matthews and Talagala 2019; Zafar et al. 2017). This highlights the crucial need to carefully consider the potential biases present in the data used to make predictions and to correct for them.

5. COVID-19: Accelerating automation and the changing nature of work

The COVID-19 pandemic altered the trajectory of digitalization and its interaction with labour markets. We begin this section with a general discussion of how recent recessions affected the pace of automation and then look at trends in automation and digitalization specific to the pandemic.[14]

5.1 Digitalization during recent recessions and the pandemic

Automation intensified during the recessions of the late 20th and early 21st centuries. For example, around the Global Financial Crisis, US firms in locations that were harder hit persistently increased skill requirements in job postings' descriptions and investments in capital (Hershbein and Kahn 2018). Jaimovich and Siu (2020) find that US employment losses in routine occupations have been concentrated in recessions, and that employment in those occupations has not rebounded when the economy recovered.[15] Similar trends are seen in Canada, where nearly all losses in routine employment have occurred during the recessions of the late 20th and early 21st centuries (Blit 2020). The pandemic recession and recovery will likely lead to further losses of routine employment, driven in part by health-related incentives to automate.

As employers invest in technology to safeguard against COVID-19 and future pandemics, some occupations are more exposed than others. Chernoff and Warman (2023) find that occupations in the United States held by women with wage and education levels in the mid- to low range were at greatest risk of being pushed to automate during the pandemic. Using comparable data for 25 other countries, they also find that women in this demographic faced a similarly elevated level of risk of automation internationally. Leduc and Liu (2020) note that the uncertainty during a pandemic may lower aggregate demand and curb investment; yet, even after taking this into account, their analysis finds that that a pandemic may still encourage automation because firms have an incentive to replace workers with technologies that are not susceptible to disease.

The pandemic has affected the pace of technological change and the skills demanded in the workplace. Lemieux et al. (2020) show that between February and April 2020, aggregate weekly work hours declined by 32% and employment declined by 15% for workers aged 20 to 64. Alexopoulos and Lyons (2021) note that the diffusion of AI, robots and data science technologies slowed down in Canada during these early months of the pandemic. The authors attribute this slowdown to disruptions from lockdowns and the recession. However, according to Bank staff analysis of Indeed job postings (Bellatin and Galassi 2022), online vacancies in sectors linked to the production of digital infrastructure—that is, software, hardware and information technology support—outpaced vacancies in other sectors in 2021 and 2022. Recently, the demand for jobs in digital production has slowed down, as indicated by the drop in job

[14] Parts of this section were co-authored with Gaelan MacKenzie and Tatjana Dahlhaus.

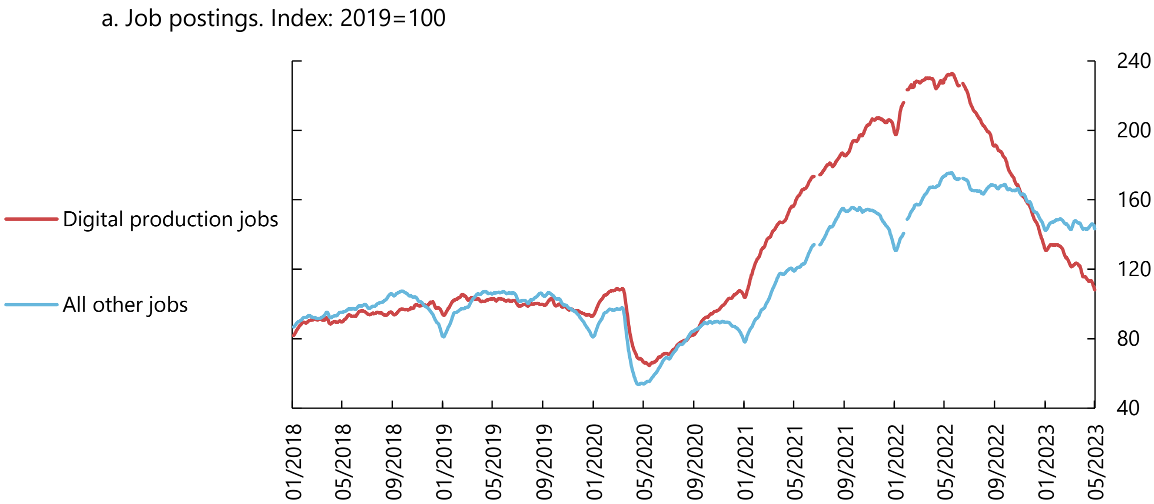
[15] Demographically, Cortes, Jaimovich and Siu (2017) find that the decline in routine manual employment in the past 35 years is due largely to the changes experienced by young and prime-aged men. Compositional changes (i.e., aging and higher educational attainment) along with a drop in the propensity for routine employment in this demographic group explains the decline in routine manual employment. In contrast, the employment decline in routine cognitive work is attributed mainly to a lower propensity for employment in these occupations among young and prime-aged women with mid-level educational attainment.

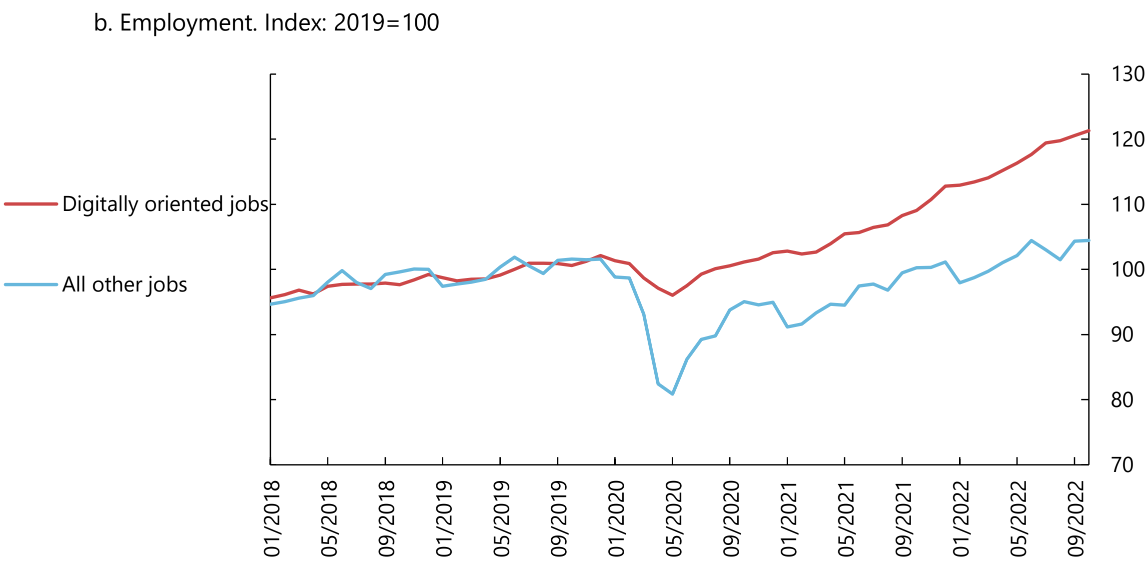
postings for these jobs since the spring of 2022 (**Chart 6,** panel a). But employment in these occupations has increased at a steady pace, seen in the employment growth from the Survey of Employment, Payrolls and Hours (SEPH) (**Chart 6**, panel b). Thus, while demand has slowed from where it was at the peak of the pandemic, employment in these occupations is much higher than it was pre-pandemic. This reflects the increased demand for digital skills since the onset of the pandemic.

Digitally intensive sectors have been more resilient to the effects of the pandemic relative to other sectors. Digitally intensive sectors also fared better in terms of productivity growth during the pandemic.[16] According to Statistics Canada (2021; 2023b), the ICT sector, which represented 89% of the estimated GDP of the digital economy in 2019, grew by 1.9% in 2020, in contrast to the more than 5% fall in total GDP. Using a composite index of digital intensity in industry, Statistics Canada researchers find that, at the beginning of the pandemic, digitally intensive sectors suffered a smaller initial decline in employment and GDP than non-digitally intensive sectors (Liu and McDonald-Guimond 2021; Liu 2021). By September 2020, total employment across digitally intensive sectors had returned to its September 2019 level while their total GDP was only slightly lower.

[16] See Box 3 in Mollins and Taskin (2023).

Chart 6: While employment in digital production jobs has grown since the beginning of the pandemic, job postings have recently moderated





Note: Daily data for panel a have been converted to a seven-day moving average. Data for both charts have been normalized to the 2019 average. Digitally oriented jobs are those linked to production of digital technologies. In the Indeed data, they include jobs in sectors such as software development, electrical engineering and information technology operations. In data from the Survery of Employment, Payrolls and Hours (SEPH), they include jobs in industries such as computer and electronic product manufacturing, software publishers, telecommunications, and data processing, hosting and related services.

Sources: SEPH and Bank of Canada calculations

Last observations: SEPH, August 2022; Indeed, October 25, 2022

Pre-pandemic IT investments partially shielded labour markets from the worst effects of the pandemic. In Italy, industries that made greater use of robots before the pandemic faced lower risk from COVID-19 contagion in the workplace (Caselli, Francasso and Traverso 2021). In the United States, ICT investment made at the local labour market level before the pandemic helped mitigate the increase in unemployment during the pandemic recession (Oikonomou, Pierri and Timmer 2023).

5.2 New ways of working

Workplaces changed dramatically during the pandemic when remote and hybrid work became commonplace. The hybrid work model, with employees working a mix of days at home and at work each week or month, has gained popularity. While the proportion of employed Canadians who work exclusively from home declined from about 24% in January 2022 to about 16% as of December 2022, **the proportion of Canadian workers with a hybrid work arrangement increased over 2022** to about 10% in December 2022 from 3.6% in January 2022, when Statistics Canada first started tracking the statistic (Statistics Canada 2022b and 2023c).[17]

Digitalization is changing the workplace of the future. The pandemic led to an explosion worldwide in the use of applications such as Skype, Zoom and Microsoft Teams (UNCTAD 2021). For example, the number of Zoom users went from 10 million in December 2019 to 300 million by April 2020 globally. However, because employers are still deciding on future work arrangements, it remains unclear how many of them will return to in-office work, apply hybrid work models or allow for remote work entirely. A recent international study by Aksoy et al. (2022) finds that employers plan to offer employees 0.7 days working from home per week, whereas workers would like 1.7 days. In the United States, employer plans for working from home had been increasing throughout 2021 and stabilized between 2.3 and 2.4 days per weeks (for persons able to work from home) as of August 2022 (Barrero, Bloom and Davis 2021).[18]

As flexible work arrangements become embedded, productivity gains from them may materialize. Using US survey data on employer plans and the relative productivity of working from home, Barrero, Bloom and Davis (2021) find that re-optimized working arrangements in the world coming out of the pandemic could result in a 5% productivity boost. Only one-fifth of this gain would show up in conventional productivity measures because they do not capture the time savings from less commuting. A study by Bloom, Han and Liang (2022) relies on a randomized control trial of 1,612 engineers and marketing and finance employees of a large technology company. The study compares a hybrid work model (working from home two days a week) with a full-time in-office model and finds that employees' self-assessed productivity was 2% higher in the hybrid work model. Using a supplement to the Canadian Labour Force Survey of February 2021, Mehdi and Morissette (2021) find that 58% of all those who recently started working from

[17] The Canadian Labour Force Survey measured hybrid work in January 2022 to December 2022, while employers implemented arrangements to resume in-office work. According to Deng, Morissette and Messacar (2020), about 39% of Canadians are in jobs that could be completed from home, while Bank staff estimate that 53% of Indeed's job postings during 2019–21 could be performed remotely (Bellatin and Galassi 2022). For the United States, Dingel and Neiman (2020) find that 37% of jobs could be performed entirely at home.

[18] The work by Barrero, Bloom and Davis (2021) is based on the Survey of Working Arrangements and Attitudes. Regular updates of their analysis can be found at WFH Research.

home reported accomplishing about the same amount of work per hour as when working in the office, while 32% reported accomplishing more work per hour. However, a reduction in face-to-face interactions is also costly: employees who did less work per hour reported that lack of interaction with co-workers was a main barrier to productivity. A caveat to studies using self-reported productivity estimates is that employees may not accurately report their productivity for a variety of reasons. For example, Aksoy et al. (2022) find that employees want to work from home more than employers plan to offer it, and that this may motivate employees to overstate their remote work productivity. Given the increased prevalence of working from home, further research is needed to determine its effect on productivity.

Pandemic-induced innovations in technologies that support working from home will likely increase the productivity of remote work. Text analysis of new patent applications filed in the United States suggests that the share of innovations targeted at technologies supporting working from home increased markedly since the beginning of the pandemic (Bloom, Davis and Zhestkova 2021). Further, as remote work becomes more pertinent in the future (in both hybrid and fully remote work models), the incentives to enhance those technologies increase. The rapid expansion of the market for a new technology can affect the pace and direction of future innovations (see, e.g., Schmookler 1966; Acemoglu 2002).

Two important side effects of working from home are the massive drop in time spent commuting. Barrero, Bloom and Davis (2020), using the mid-2020 waves of their survey of American workers, estimate that American workers saved 60 million hours per day in aggregate. Both men and women allocated this freed-up time in part to working longer hours but also to household chores and child care. Morissette, Deng and Messacar (2021) find that a full transition to working from home would reduce average commuting time by about one hour per day. Workers living in Toronto could save an average of 72 minutes per day, while those living in Montréal and Vancouver could save 64 and 60 minutes, respectively.

Hybrid and remote work could decrease greenhouse gas emissions. Morissette, Deng and Messacar (2021) find that if workers who can work from home did so to the greatest extent possible, Canadian annual greenhouse gas emissions could be reduced by an amount equivalent to approximately 6% of the direct greenhouse gas emissions from households in 2015.

6. Open questions and important future trends

In this section we discuss emerging issues related to digitalization and labour markets that have yet to be fully investigated in the literature. The following questions identify trends and topics that are important for future research.

Will the labour market effects of digitalization differ from those associated with other periods of rapid technological change? As discussed throughout this paper, automation disrupted labour markets, resulting in reallocation of labour across occupations and sectors, and also affected distributional outcomes. However, the labour market effects of future technologies may differ from those associated with the recent waves of automation. For example, in recent work, Webb (2020) uses granular data from the text of job task descriptions and the text of patents to construct a new measure of exposure to automation. In comparing AI with earlier technologies (software and robots), he finds that AI targets the upper tail of the skills distribution and he predicts that AI will reduce inequality. However, as a recent book by Agrawal, Gans and Goldfarb (2019) makes clear, economists hold differing views about the future effects of AI on labour markets. Santor (2020) suggests that while most economists generally hold positive views of the potential of AI to improve welfare, others warn that AI has the potential to worsen inequality. AI, cloud computing and other cutting-edge technologies are spreading fast throughout the economy.

How will demographic trends affect the future trajectory of digitalization in Canada, and what will the associated impacts on labour markets be? As noted in section 3, an aging population is associated with more automation but less innovation. However, the potential benefits of higher levels of educational attainment and an immigration policy that favours high-skilled immigrants may partially offset the potential drag on innovation from Canada's aging population.

How will the transition to renewable energies (to address climate change) interact with digitalization, and what will the associated impacts on labour markets be? This is a relevant question given the historical importance of natural resources to the Canadian economy. To the best of our knowledge, no research has been done on how the potential overlap of efforts to decarbonize and automate industries will affect labour markets. Many renewable technologies are digitally intensive in both their production and consumption.

How will trends in digitalization and international trade affect labour markets? The interaction of trends in digitalization and international trade could affect labour market outcomes. For example, the rise of cloud computing could shift firms' investments in computing infrastructure to multi-national cloud-service providers and reduce the market share and employment of domestic service providers. Another example, explored in new work by Baldwin and Dingel (2022), is the relationship between remote work and offshoring. They analyze the migration of jobs overseas due to COVID-19 and enabled by remote work technologies. Using estimates of jobs that can be done offshore and foreign workers with relevant skills, they provide simulations of the extent of telemigration—that is, people from one county working for an office in another country—when the trade costs of services change.

Several gaps in the Canadian literature on labour markets and digitalization call for further study. Examples of meaningful work that could be done with readily available data include the following:

- Researchers could use the robotics data from Dixon, Hong and Wu (2021) to study the local labour market effects of robots in Canada, drawing on the methodology of Acemoglu and Restrepo (2020).
- Researchers could quantify the potential push to automate jobs in the Canadian economy during the COVID-19 pandemic.
- Researchers could update estimates of the fraction of jobs at risk of automation in the Canadian economy, particularly given the rapid pace of technological change and recent advances in AI and machine learning.

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