Institut C.D. HOWE Institute

COMMENTARY
NO. 585

The Next Wave: Automation and Canada's Labour Market

An updated estimate shows about one in five Canadians are at high risk of job loss due to automation. But what role do factors such as job type, education, income, gender or ethnic group have to play? And what are the takeaways for policymakers?

Rosalie Wyonch

The C.D. Howe Institute's Commitment to Quality, Independence and Nonpartisanship

About The Author

Rosalie Wyonch
is a Policy Analyst at the C.D. Howe Institute.

The C.D. Howe Institute's reputation for quality, integrity and nonpartisanship is its chief asset.

Its books, Commentaries and E-Briefs undergo a rigorous two-stage review by internal staff, and by outside academics and independent experts. The Institute publishes only studies that meet its standards for analytical soundness, factual accuracy and policy relevance. It subjects its review and publication process to an annual audit by external experts.

As a registered Canadian charity, the C.D. Howe Institute accepts donations to further its mission from individuals, private and public organizations, and charitable foundations. It accepts no donation that stipulates a predetermined result or otherwise inhibits the independence of its staff and authors. The Institute requires that its authors disclose any actual or potential conflicts of interest of which they are aware. Institute staff members are subject to a strict conflict of interest policy.

C.D. Howe Institute staff and authors provide policy research and commentary on a non-exclusive basis. No Institute publication or statement will endorse any political party, elected official or candidate for elected office. The views expressed are those of the author(s). The Institute does not take corporate positions on policy matters.

Commentary No. 585
November 2020

Daniel Schwanen
Vice President, Research

$12.00
ISBN 978-1-989483-35-0
ISSN 0824-8001 (print);
ISSN 1703-0765 (online)

The Study In Brief

Technological change is a driving force behind economic growth. It can improve productivity for existing goods and services, meaning the same output can be achieved with fewer inputs, or more can be produced with the same amount of human labour. Technologies also enable the development of new products and services that can create new occupations and consumer demand where none existed before. The process of technological change is, however, disruptive, rendering particular occupations obsolete or changing entire industries relatively quickly. At the same time, new business models and occupations grow to replace them.

This *Commentary* assesses the likely impact of technological automation on Canada's labour market and compares these results to past predictions. In fact, they show a lower proportion of employment at high risk of automation (about 22 percent) than most previous estimates.

There are some occupations that are obviously highly automatable, and many are being automated already – gas station attendants, bank tellers and store cashiers, for example. There are others that are quite obviously not automatable due to a particular human element or specialized set of skills – neurosurgeons or detectives, for example. Most occupations are not fully automatable but they are not completely immune from automation either. The occupations that are more likely to be automated generally contain more well-defined tasks and repetition, such as those in manufacturing.

About one in five Canadian workers are employed in a job that could theoretically be automated. By 2028, projections indicate that employment in these occupations will decline by only about 90,000 jobs. Meanwhile, jobs that are only somewhat susceptible to automation (medium risk) make up about 40 percent of current employment. This proportion is projected to decline slightly to about 37 percent by 2028. These projections indicate that the labour market has been adapting to technological change over time and is likely to continue along a similar trajectory.

The analysis of automation susceptibility by individual characteristics indicates that Black and Indigenous Canadians are employed in occupations that are highly susceptible to automation in higher proportions than the population average. It is likely that the relatively higher susceptibility to automation is related to the worse average employment outcomes of Black and Indigenous people relative to the Canadian average.

Men, women and immigrants, however, face a similar average risk from automation. Overall, the differences are not large enough to warrant targeted pre-emptive policies specifically to prevent technology-induced unemployment for particular groups. Instead, the inequality effects of automation could be indirectly addressed through education and labour-market policies that target inequality more broadly. However, with growth in non-standard employment, traditional job-support policies may not be available to all workers impacted by automation. Following the current COVID-19 crisis, the government should analyze the effects of its emergency income support programs and use the insights to modernize employment insurance and address income- and employment-support gaps.

Policy Areas: Education, Skills and Labour Market.
Related Topics: Efficiency and Productivity; Employment and Employment Policies.
To cite this document: Wyonch, Rosalie. 2020. *The Next Wave: Automation and Canada's Labour Market.* Commentary 585. Toronto: C.D. Howe Institute.

C.D. Howe Institute Commentary© is a periodic analysis of, and commentary on, current public policy issues. Michael Benedict and James Fleming edited the manuscript; Yang Zhao prepared it for publication. As with all Institute publications, the views expressed here are those of the author and do not necessarily reflect the opinions of the Institute's members or Board of Directors. Quotation with appropriate credit is permissible.

To order this publication please contact: the C.D. Howe Institute, 67 Yonge St., Suite 300, Toronto, Ontario M5E 1J8. The full text of this publication is also available on the Institute's website at www.cdhowe.org.

Technology has transformed human life in previously unimaginable ways. Innovation liberated society from darkness with electric light and from deadly diseases with water treatment and plumbing, germ theory and vaccinations.

Innovations in telecommunications technologies have connected the world to information, news, entertainment and myriad consumer and business services via the Internet. More recent improvements in quantum computing, robotics and artificial intelligence have led some to speculate that software and machines will soon be able to replace human workers in many occupations.

Technological change is a driving force behind economic growth. It can improve productivity for existing goods and services, meaning the same output can be achieved with fewer inputs, or more can be produced with the same amount of human labour. Technologies also enable the development of new products and services that can create new occupations and consumer demand where none existed before. The process of technological change is, however, disruptive, rendering particular occupations obsolete or changing entire industries relatively quickly. At the same time, new business models and occupations grow to replace them.

The fear that machines and, more recently, software might replace people in performing many tasks is not new.[1] Recent developments in artificial intelligence, machine-to-machine communication and increased digitalization of various services

The author thanks Parisa Mahboubi, David Gray, Louis Morel, Matthias Oschinski, members of the Human Capital Policy Council of the C.D. Howe Institute, and anonymous reviewers for comments on an earlier draft. The author retains responsibility for any errors and the views expressed.

This project is funded by the Government of Canada's Future Skills Centre. The C.D. Howe Institute is solely responsible for the paper's contents.

This paper is produced in cooperation with Ryerson University's Diversity Institute, which conducts and coordinates multi-disciplinary, multi-stakeholder research to address the needs of diverse Canadians, the changing nature of skills and competencies, and the policies, processes and tools that advance economic inclusion and success. Our action-oriented, evidence-based approach is advancing knowledge of the complex barriers faced by underrepresented groups, leading practices to effect change, and producing concrete results. The Diversity Institute advances the research strategy for the Future Skills Centre.

The Future Skills Centre is a forward-thinking centre for research and collaboration dedicated to preparing Canadians for employment success. We believe Canadians should feel confident about the skills they have to succeed in a changing workforce. As a pan-Canadian community, we are collaborating to rigorously identify, test, measure and share innovative approaches to assessing and developing the skills Canadians need to thrive in the days and years ahead.

1 The earliest written example of the idea that technology might destroy jobs faster than new ones are created, to my knowledge, is Aristotle's speculations about slaves becoming redundant due to the invention of brooms (Campa 2014). There is, however, some evidence that the debate may have begun some 3,000 years earlier with the invention of the wheel (Woirol 1996).

have led to speculation that jobs will be automated faster than new ones are created to replace them. Furthermore, there are a number of unsettling predictions that large portions of the population face unemployment in the near future (Brynjolfsson and McAfee 2014, Frey and Osborne 2013, Lamb 2016). In contrast to these dire predictions, others show technology increasing employment (Bessen 2018) or proceeding similarly to past eras of technological change (Oschinski and Wyonch 2017). There is significant uncertainty about the proportion of employment at risk of being automated, with estimates for the US labour market ranging from 9 percent to 47 percent (Arntz, Gregory and Zierahn 2016, Frey and Osborne 2013). For Canada, estimates suggest that 9 percent to 42 percent of the labour market is at high risk of unemployment due to technology change (Arntz, Gregory and Zierahn 2016, Lamb 2016, Oschinski and Wyonch 2017).

This *Commentary* assesses the likely impact of technological automation on Canada's labour market and compares these results to past predictions. It also reviews recent literature on the implications of technological change: when it leads to employment growth, when it doesn't, and how these insights apply to Canada. Results from this analysis show no evidence of accelerating technological unemployment.[2] In fact, they show a lower proportion of employment at high risk of automation (about 22 percent) than most previous estimates. The risk of automation also has no direct relation to wages, suggesting that technological change is likely to affect income inequality through compositional changes to employment.[3]

Meanwhile, individual worker characteristics such as race, immigration status or ethnicity are not significantly related to a likelihood of being automated. However, some significant differences arise in particular types of occupations for some groups. Indigenous people, for example, are at a significantly higher average risk of automation in most occupations except for those in natural resources and agriculture. Women are more likely than men to be employed in occupations that are either low or high risk, as opposed to medium risk; but average risk is similar between genders.[4] The differences in risk arise from the underlying mix of jobs and who occupies them within each broad occupation type. The risk of automation also changes with age: young workers, 15 to 24 years of age, are more likely to be employed in occupations at a high risk of automation, while those aged 55 to 64 are the most likely to be employed in occupations with a low risk of automation.

Overall, this *Commentary* finds that Canada's labour market has been adapting quite well to technological change and that the risk of significant technology-induced unemployment remains low for the near future. This suggests that government should be moderating technological change's negative effects for those that are affected in the short term. Existing policies that provide job training and income support for unemployed

2 Technological unemployment refers to job losses caused by changes in technology. The concept encompasses both incremental process improvements that result in reduced demand for labour and significant technological change that disrupts established industries and business practices.

3 Previous research has implicated technology as a significant factor in US income inequality (Cheremukhin 2014). Employment changes in Canada, however, do not show significant income polarization related to potential for automation (Oschinski and Wyonch 2017).

4 Women are at higher average risk of losing their jobs to automation when working in business, finance, administration, manufacturing and utilities occupations. Men in education, law, social, community and government services occupations are at a slightly higher average risk of automation.

and low-income people provide a buffer against economic hardship (technology-induced or otherwise).[5] However, with growth in non-standard employment, traditional income- and employment-support policies may not be available to all workers affected by automation. The Canadian Emergency Support Benefit (CERB), an emergency income support program for individuals affected by the COVID-19 pandemic, was in part created to address coverage gaps in Employment Insurance. Following the current crisis, the government should analyze the effects of CERB, and use insights from the natural experiment to modernize Employment Insurance and address the income and employment support gaps revealed by COVID-19.[6]

The risk of automation is similar across different population groups, but some are at a disadvantage in particular types of occupations. It varies significantly with education level, which explains some of the variation related to individual characteristics. These results suggest that education is a critical factor in addressing the relative risk of being automated for more vulnerable population groups.

The Economics of Technological Change

Technological change has contributed massively to improvements in living standards and well-being. However, the process of technological change is one of "creative destruction" that renders some products, jobs, business practices or even entire occupations and industries obsolete as they are replaced by superior alternatives. At the same time, technology contributes to the growth of new industries, products, services and occupations. In the early 20th century, it would have been difficult, if not impossible, to envision occupations like data systems administrator or artificial intelligence researcher, but both existed by the beginning of the 21st century. Similarly, those living today cannot accurately predict what new technologies may be developed or the effects they might have on society in the distant future.

Over the long term, technology adoption contributes to economic growth, improves productivity and raises living standards. In the short term, however, it can be quite disruptive as some businesses fail to adapt to the changes and some people lose their jobs. In some cases, it has taken decades for the economy and society to fully adapt to significant technological change and for its benefits to be fully diffused.[7] New occupations created by technological change might require different skills than those that are automated, while some existing jobs change dramatically. Technology development and adoption don't affect all sectors simultaneously, but rather in growth bursts in certain sectors and declines in others. Meanwhile, rapidly growing economies show high levels of both job creation and destruction (Howitt 2015).

The prevailing view of technological change is that it is desirable. Technology improvements allow more to be produced with the same or less human labour than was required before. Consequently, labour is freed up and directed toward other tasks. Improved productivity contributes to economic growth, which in turn contributes to higher wages.

5 Further, the Canada Training Credit and the Employment Insurance Training Support Benefit, new programs announced in the 2019 federal budget, have not had time to take full effect and aim to address issues related to technological unemployment and the need to adapt to technological change throughout people's careers.

6 This emergency policy should not be made permanent, but was necessary due to existing gaps in employment and income support. Post-crisis, addressing those gaps should be a priority.

7 During the Industrial Revolution, real wages in England grew slowly from 1781 to 1819 but then grew quickly until 1851. In particular, blue-collar workers saw real wages double over the latter 32-year period (Lindert and Williamson 1983).

The fear of technological unemployment – that new technology will destroy jobs faster than new ones are created – has accompanied past eras of technological change. Yet, until now, the bogeyman of mass technological unemployment has failed to materialize. Still, recent developments in artificial intelligence and machine-to-machine communication have led to debate about whether this time it will be different.

In past eras of technological change, machines have predominantly replaced human labour in a physical sense. With the development and continued improvement in computing and communications technologies, machines are now starting to replace humans in performing cognitive labour in addition to physical. Some argue that digital technological development could replace human workers more quickly than new jobs are created (Krugman 2013, Levy and Murnane 2004, Sirkin, Zinser and Hohner 2011, Cowen 2013). Such a possibility means that large portions of the population would face technology-induced unemployment in the years to come (Brynjolfsson and McAfee 2014, Frey and Osborne 2013, Lamb 2016).

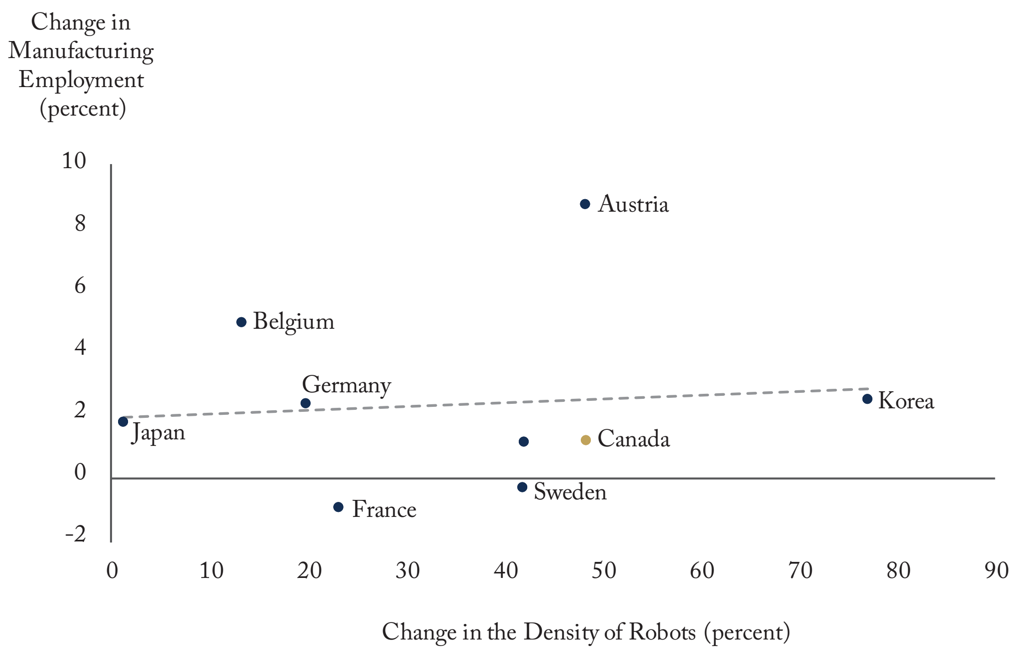
There are, however, counterbalancing factors such as the development of new occupations and complex tasks for humans to perform that moderate the negative effects of technological change. Demographic aging is associated with more rapid adoption of automating technologies as labour productivity improvements are required to maintain production levels as the proportion of population of working age shrinks (Acemoglu and Restrepo 2019). Still, if automation outpaces the creation of new jobs, it puts downward pressure on wages. When human labour is cheaper, the incentive to develop and adopt labour-saving technologies diminishes. As a result, investment in research and development is more likely to be directed toward the creation of new complex tasks than to labour-saving (automating) technologies (Acemoglu and Restrepo 2016, 2018). In addition, where automation has occurred, productivity is improved, which leads to lower prices and a higher quantity of demand (Acemoglu and Restrepo 2016, 2018, Autor and Salomons 2018, Bughin, Manyika and Woetzel 2017). Meanwhile, Bessen (2018) notes that both productivity-enhancing technologies and employment in manufacturing grew for a century or more before productivity gains brought declining employment. As a result, he postulates that until a market is saturated, technology can have positive employment effects.

Other research links demographic change to automation – countries experiencing more rapid population aging are also those with the most rapid development of automation technologies (Acemoglu and Restrepo 2019). This research also finds that almost half of the cross-country variation in the adoption of automating technologies can be explained by demographic factors.

Overall, the economic effects of current technological change are far from settled. There is research indicating little chance of significant technology-induced unemployment while others suggest that up to four in 10 workers could find themselves without work in the near future (Oschinski and Wyonch 2017, Lamb 2016). The fear that technology will replace humans faster than new occupations are created has accompanied past eras of technological change. The history of technological change, and the analysis that follows, suggests that this time is no different and that mass technological unemployment in the near future is highly unlikely.

However, as with past eras of technology growth, some people will likely face significant hardship in the short term. Government policy should be used to moderate the negative effects on the one hand, while encouraging the adoption and development of new technology on the other. Adopting technologies contributes to maintaining or improving the global competitiveness of Canadian industries and improves productivity, which lessens

Figure 1: Industrial Robot Use and Manufacturing Employment (2014-2018)



Sources: OECD 2020, International Federation of Robotics, author's calculations.

the fiscal strain of an aging population. For the economy's long-term health, technology should be celebrated rather than feared.[8]

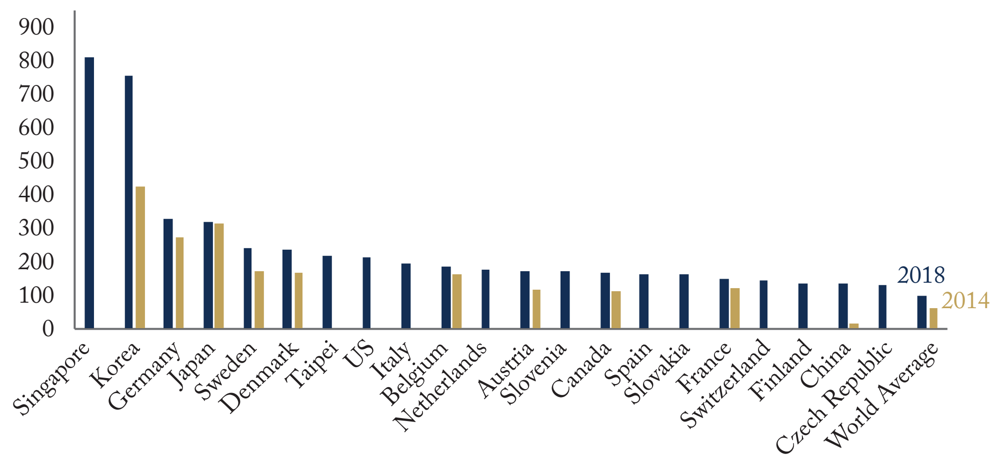
Robots at Work

One area where automation has been ongoing for quite some time, and is likely to continue, is manufacturing. The adoption of industrial robots and their relation to manufacturing employment provide some basis for predicting future employment effects, as well as a measure of technology adoption that can be compared across countries. After years of annual growth, installations of industrial robots in Europe and the Americas declined in 2019, which indicates that automation is not increasing in pace, at least for industrial robot applications (International Federation of Robotics 2019).

Canada was the 13th largest market for industrial robots in 2018. Automotive and electronics manufacturing account for the largest number of installations, but the largest area of growth in sales has been in "unspecified" industries (44 percent increase in 2018), even though "collaborative" industrial robots remain a niche representing just

8 For an extensive analysis of the interactions between technology diffusion, business practices and government policy see Andres Criscuolo and Gal (2015).

Figure 2: Density (robots per 10,000 employees)



Source: International Federation of Robotics.

3 percent of global sales in 2018 (International Federation of Robotics 2019).

In Canada, the number of industrial robots per manufacturing worker has increased significantly in recent years. From 2014 to 2018, the density of industrial robots in manufacturing (the number of robots per 10,000 employees) increased 48 percent. With such a dramatic jump, one might expect a decline in manufacturing employment, but manufacturing jobs increased by 1.2 percent over the same period (OECD 2020). In fact, across countries, there is no relationship between robot density and manufacturing employment (Figure 1).[9] Graetz and Michaels (2015) found that increased robot density is associated with a slight growth in manufacturing employment when using a longer time period and larger sample of countries, but the correlation is statistically weak. Meanwhile, increased automation does not necessarily lead to a decline in employment (Autor and Salomons 2018, Bughin, Manyika and Woetzel 2017, Acemoglu and Restrepo 2016, 2018).

Despite the significant increase in the number of industrial robots performing various manufacturing and industrial activities, there remains significant potential for further adoption in Canada. There are many countries with a higher density of robotics in industrial applications than Canada (Figure 2). Indeed, Singapore and South Korea, the countries with the highest density of industrial robots, have

9 Graetz and Michaels (2015) found a similar result for the 1993-2007 period using a larger sample of countries and defining manufacturing hours worked as the measure of employment.

Table 1: Attributes that are Difficult or Currently Impossible to Automate

Social Perception	Being aware of others' reactions and understanding why they react as they do.
Originality	Ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
Assisting and Helping Others	Providing personal assistance, medical attention, emotional support or other personal care to others such as coworkers, customers or patients.
Philosophy	Knowledge of different philosophical systems and religions. This includes their basic principles, values, ethics, ways of thinking, customs, practices and their impact on human culture.
Initiative	Willingness to take on responsibilities and challenges.
Leadership	Willingness to lead, take charge, and offer opinions and direction.
Innovation	Creativity and alternative thinking to develop new ideas for and answers to work-related problems.
Adaptability and Flexibility	Being open to change (positive or negative) and to consider variety in the workplace.
Independence	Developing one's own way of doing things, guiding oneself with little or no supervision and depending on oneself to get things done.

Note: See Appendix to learn how these attributes are measured.
Source: O*NET Database.

more than 4.5 times as many robots per worker than in Canada. Similarly, Canada's adoption of industrial robots in manufacturing lags behind that of Germany, Japan, Sweden, Denmark, the US and other nations. This international comparison signals that the potential for further robotic automation in Canadian manufacturing and other industrial applications remains quite high. But, since the density of industrial robots is not related to manufacturing employment, it is unclear what effects further technology adoption could have on employment.

Estimating the Likelihood of Automation

To estimate the effect of automation on the labour market, I follow methods similar to Frey and Osborne (2013) and Oschinski and Wyonch (2017). Data on skills, work activities and interpersonal interactions were sourced from the O*NET database, a US initiative containing hundreds of standardized and job-specific descriptors on almost 1,000 occupations.[10] The skills, knowledge and activities selected are those that are difficult or impossible for a computer or robot to perform and

10 The implicit assumption underlying use of this data is that occupations in Canada require similar skills, knowledge and activities to equivalent occupations in the US.

likely will be for the foreseeable future (Table 1).[11] Different occupations require different levels and intensities of these attributes. In principle, occupations for which these attributes are very important or where a high level of performance is required are more difficult to automate. Some portion of these occupations may be computerized but while technology would improve labour productivity, it would be unable to replace people completely.

Conversely, occupations for which the selected attributes are unimportant are more likely to be automated. Automation is, therefore, more likely to replace labour in performing most of the tasks required by those occupations.

There are some occupations that are obviously highly automatable, due to examples of them being automated already – gas station attendants, bank tellers and store cashiers, for example. There are others that are quite obviously not automatable due to a particular human element or specialized set of skills – neurosurgeons or detectives, for example. Most occupations are not fully automatable but they are not completely immune from automation either. To construct a classification of occupations as "automatable," "not automatable" and "somewhat automatable," I use the classifications and outputs from four different labour-market automation studies: Autor and Dorn (2013), Josten and Lordan(2019), Frey and Osborne (2013) and Oschinski and Wyonch (2017). With the exception of Autor and Dorn (2013), which used binary classification, automatable or not, these studies classified occupations into three categories – high, medium and low risk of automation.[12] Across the four classification outputs, there were many occupations that were given a similar classification. Those cases form the vector to "train" the algorithm.

The statistical analysis estimates the likelihood an occupation could be automated based on the selected attributes and the classifications in the training vector. The method used is Gaussian Process regression, a basic machine-learning, non-parametric classification and probability-estimation technique.[13] The regression was implemented with the "kernlab" R statistical package (Karatzoglou, Smola and Hornik 2019). The resulting output provides an estimate of the probability that an occupation could be automated. This output, using US occupational codes, is then linked to Canadian labour market data,[14] using the concordance from Frenette and Frank (2017, 2018).

Automation in Canada's Labour Market

The results show that in 2019 about 22 percent of Canadian employment was in jobs highly susceptible to automation, while about 39 percent have low susceptibility.[15] Occupations in health, law, education and community, and government services are the job types least likely to be automated

11 These attributes are the same selected in Oschinski and Wyonch (2016). To validate the selection of non-automatable attributes and test the sensitivity of estimates to that selection, various other sets of attributes – selected in other research using various methods – were used to estimate the likelihood of automation (Autor and Dorn 2013, Josten and Lorden 2019, Frey and Osborne 2013). Attribute selection has marginal effects on the classification of individual occupations but does not significantly affect aggregate results.

12 Lorden and Jorden (2019) classify occupations as "automatable," "not automatable" and "polarized automatable" but use less granular occupational definitions.

13 See Appendix for detailed explanation of methods used in this analysis.

14 See Census (2016) and Canadian Occupational Projection System (COPS) employment estimates (2019).

15 Probability thresholds for categorization are: [0, 0.36) = low susceptibility; [0.36, 0.72) = medium susceptibility; [0.72, 1] = high susceptibility.

Box 1: Comparing Results: Why do Predictions Differ so Much?

Estimates of the potential for automation in Canada's labour market suggest that 9 percent to 42 percent of workers could be at risk of losing their job due to technological change (Arntz, Gregory and Zierahn 2016, Lamb 2016). The results of this analysis estimate 22 percent of employment at high risk of automation, 13 percent lower than previously estimated with a similar method but a different approach to classification of occupations (Oschinski and Wyonch 2017). With estimates varying so widely, some of the technical differences and their effects on the resulting analyses at least somewhat reconcile the differences. There is more agreement among the various results than is immediately apparent.

Each estimate of the proportion of employment at risk of unemployment due to technological change in the Canadian labour market has made adjustments and improvements to the methods used. Lamb (2016) applied the results of Frey and Osborne (2013) to Canadian data and was the first calculation of a "risk of automation" applied to the Canadian context. Oschinski and Wyonch (2017) used a similar method to previous studies, but a modified set of skill variables and set of occupations classified as "automatable" or "not automatable." In addition, Oschinski and Wyonch (2017) were the first to link the "risk of automation" with analysis of changes to the composition of employment over time.

The lowest estimate (of which I am aware) of the potential for technology-induced unemployment in Canada is 9 percent (Arntz, Gregory and Zeirahn 2016). This research uses a method quite distinct from that used in the other studies and this analysis (task-based approach including worker skill heterogeneity). A more recent Canadian study using similar methods finds that about 10 percent of the Canadian labour force is at high risk of automation (Frenette and Frank 2020).

The analysis in this study made further adaptations to the methods of calculating the risk of automation for individual occupations. In particular, using the combined results of research yielding different classifications of occupations as "automatable" or not and added a third category of "partially automatable." The addition of the third category and inclusion of classifications from research using a task-based approach to determine classification resulted in less polarized probability estimates than previous studies using similar methods. In addition, this analysis utilizes an improved concordance between occupational codes (Frenette and Frank 2017, 2018).

The different results from each successive estimate of the effect technology could have on employment should be interpreted as a progressive adaptation of methods and incorporation of new research results. Initial studies produced completely different distributions of estimated probability of automation (Frey and Osborne 2013, Arntz et al. 2016). Each successive study has resulted in estimates that generally fall between the two extremes (Lamb 2016, Oschinski and Wyonch 2017, Frenette and Frank 2020). The analysis in this paper incorporates results from task-based framework analyses (Josten and Lorden 2019 and Autor and Dorn 2013) in addition to those using the occupation-based approach (Frey and Osborne 2013, Oschinski and Wyonch 2017) and incorporates an additional category for analysis. These methodological changes also result in the distribution that falls between the extremes of earlier analyses. With each successive study, the estimated distribution of risk appears to be converging (Figure B1.1).

Box 1: Continued

The differences in estimates of the potential for automation in the Canadian labour market appear to be caused by methodological differences. As more research is conducted, the estimates appear to be converging over time. The earliest estimates ranged from 9 to 42 percent (Lamb 2016, Artnz, Gregory and Zeirahn 2016), but the most recent ones suggest a lower proportion – 10 to 22 percent – of employment in Canada is highly susceptible to automation (Frenette and Frank 2020, Gresch 2020, results of this analysis). Regardless of the estimation method or proportion of employment estimated to be at high risk of automation, there are many factors that affect the rate of adoption of new technologies such as the prevailing competitive environment, competitiveness of the labour market, resources available for new capital investments. Being employed in an occupation that could be theoretically automated does not necessarily translate to those jobs being automated in the near future due to the complexity of adapting automating technologies to new applications and real-world cultural and economic factors.

(Table 2 and Figure 3). Those in agriculture, natural resources, utilities and manufacturing are more susceptible to automation.

Notably, the estimated proportion of high-risk employment is lower than found in previous studies using similar methods: Lamb (2016) and Oschinski and Wyonch (2017) estimated the proportion of employment at high risk of being automated as 42 percent and 35 percent, respectively (see Box 1 for further discussion of comparative results.). Furthermore, this analysis's estimated results for 2019 are more favourable than was projected by Oschinski and Wyonch (2017) (Figure 4).

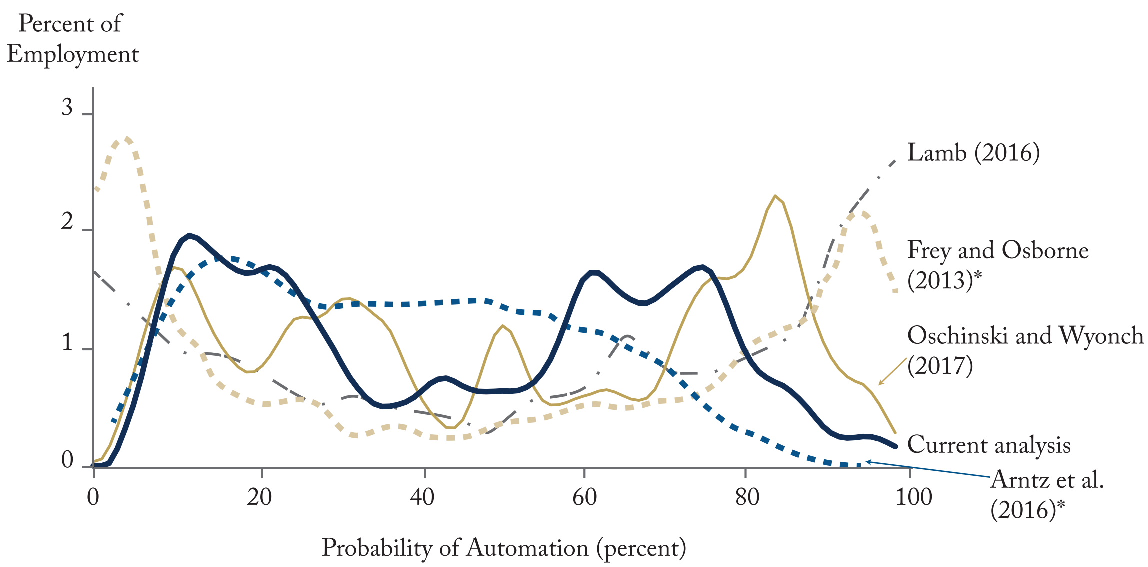
Meanwhile, the proportion of employment at low risk of automation, 40 percent, is slightly higher than previous studies. The proportion of employment at high risk of automation is significantly lower than previous analyses using similar methods, but there were no significant increases in Canadian unemployment during the period between studies. The difference between the results could be explained by a number of different factors. For example, automation could be progressing faster than previously thought, since the proportion at high risk is declining more quickly than previously projected. In that case, the lack of significant unemployment growth during the 2015 to 2019 period signals that employment in Canada has been adapting to the potential for automation over time.[16]

To project the effects of technological change and automation on Canada's labour market in the years to come, I use data from the Canadian Occupational Projection System for employment

16 It is also worth noting that results calculated for this analysis combine the classifications of multiple research papers on automation. The resulting estimates are less polarized than those from Oschinski and Wyonch (2017), meaning that a larger proportion of occupations were classified here as "medium risk." This difference had a larger effect on "high-risk" than "low-risk" employment due to the composition of Canada's labour market. The estimated probability that an occupation could be automated was calculated using the classifications individually and in combination. Results from the combined classification fall between extremes for all occupations.

Box 1: Continued

Figure B1.1: Comparing Estimated Distributions of Risk of Automation and Employment



*Estimate for US labour market.
Sources: Author's calculations, Oschinski and Wyonch (2017), Arntz, Gregory and Zeirahn (2016), Lamb (2016) and Frey and Osborne (2013).

forecasts.[17] To model the effects of automation on employment growth, I assume a 2.1 percent annual adoption rate, equivalent to the projected average growth rate in productive capital stock across OECD countries (OECD 2019).[18] These projections represent employment effects from 2020 technology levels and do not include changes to, or projections for, future technology levels. They are based solely on the ongoing adoption of current technologies. If fundamental breakthroughs are made related to the attributes identified as difficult or impossible to automate, it would alter the

17 The COPS projections include current employment data and projections of future trends in job openings and job seekers by occupation at the national level. The latest projections cover the 2019-2028 period. Employment data for past years is sourced from the Forum for Labour Market Ministers Labour Market Information Toolkit (2016).

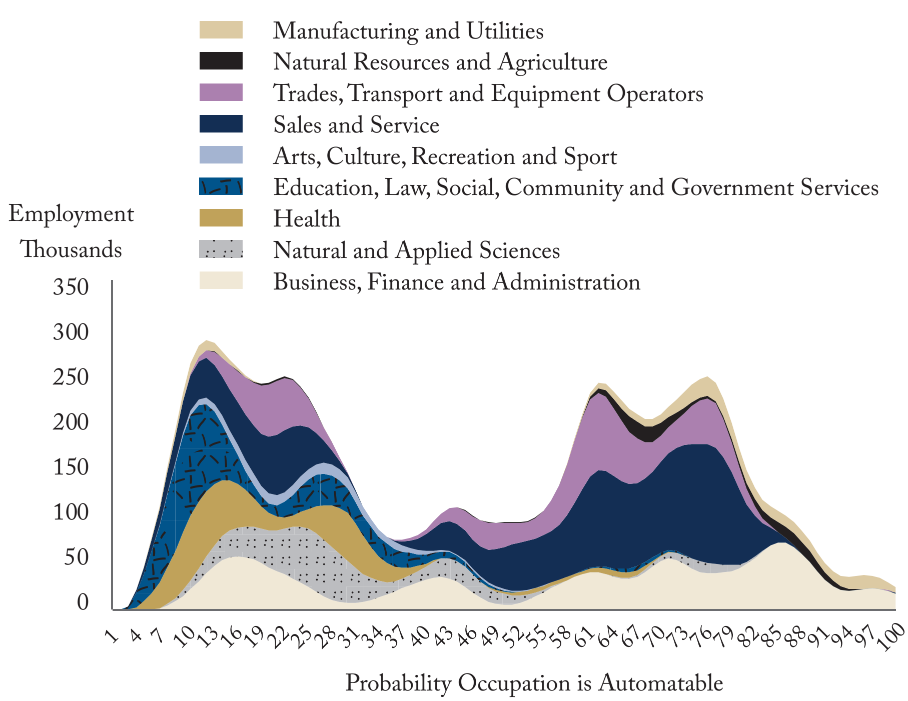
18 $emp_{2020} = (emp_{2019} \times growth_{2019}) - (risk \times adoptionrate \times emp_{2019})$ calculated for each occupation, then aggregated to project total employment composition by risk category. To test the sensitivity of the projections to the assumption of a 2.1 percent technology adoption rate, I also projected adoption rates of 1.7 percent and 4.3 percent, representing 2019 growth in Canadian productive capital stock and highest growth in productive capital stock among OECD countries. Projection results using different adoption rates can be found in the Appendix (Table A4).

Table 2: Employment Susceptibility to Automation by Occupation Type (2019)

	Average Risk of Automation (percent)	Share of Total Employment (percent)
Natural Resources and Agriculture	74	2.9
Manufacturing and Utilities	70	5.1
Business, Finance and Administration	57	17.5
Sales and Service	54	27.2
Trades, Transport and Equipment Operators	52	15.9
Natural and Applied Sciences	32	8.6
Arts, Culture, Recreation and Sport	26	3.1
Health	22	7.8
Education, Law, Social, Community and Government Services	19	11.9

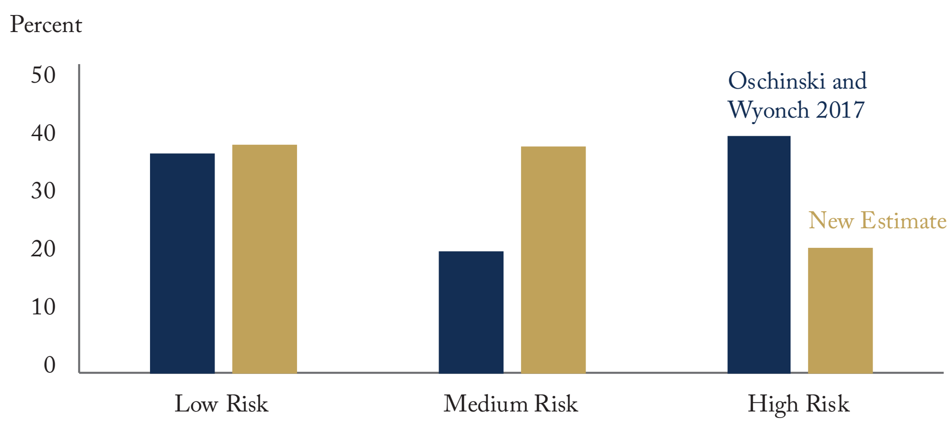
Sources: Canadian Occupational Projection System (COPS) 2019, author's calculations.

Figure 3: Employment Automation Risk, by Occupation Type (2019)



Source: Author's calculations.

Figure 4: Comparing Estimates of 2019 Employment Risk



Sources: Oschinski and Wyonch 2017, author's calculations.

susceptibility to automation of many occupations and would, therefore, also alter projected employment.

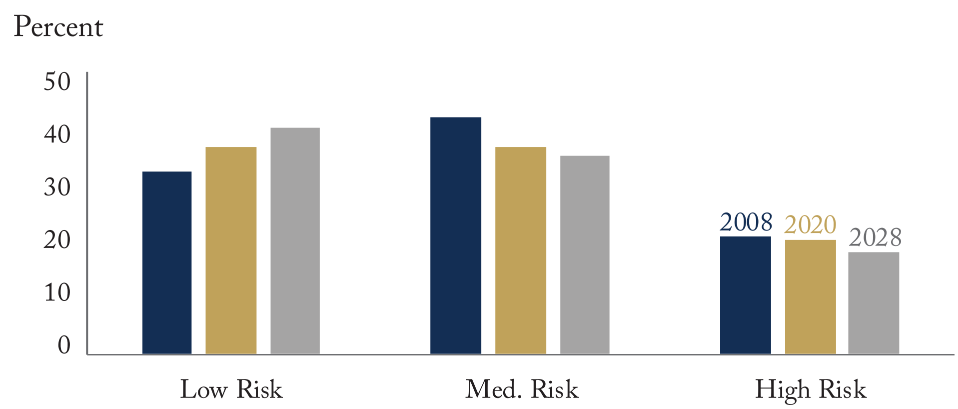
Furthermore, these projections show compositional change in employment in the coming years. In 2020, about 40 percent of employment is in jobs that are unlikely to be fully automated (Figure 5). By 2028, this proportion is projected to increase to 43 percent of the labour market, with about 490,000 new jobs created.

Employment in occupations categorized as at medium or high risk of automation is projected to decline collectively by about 580,000. Depending on the rate of adoption of new technology, the estimated change in jobs as a result of technological change ranges from a net gain of 90,000 to a net loss of 1.38 million, with a 2.1 percent annual adoption rate corresponding to a net decline of 90,000 jobs. One important limitation of these projections is that they don't account for job growth due to the development of new innovative technologies or the creation of new occupations related to current technologies.

Further, since projected growth is sourced from COPS, it is worth noting that previous projections have tended to undershoot actual job creation.[19] These projections should be interpreted only as the decline in employment due to technological change, not growth in employment due to the creation of new jobs or further technological developments. Even so, these estimates suggest that only about 4 percent of current employees are at risk of losing their jobs due to automation over the next eight years. This is significantly less dire than previous

19 For example, 2015 projections for employment estimated total employment of 18.72 million in 2020,2017 projections estimated 2020 employment at 18.8 million and 2019 projections predicted total 2020 employment at 19.1 million.

Figure 5: Change in Employment Composition Over Time



Sources: Author's calculations, Labour Market Monitoring Toolkit (2016), COPS (2019).

predictions that about four in 10 workers could lose their jobs within a similar time frame.[20]

Overall, there is a relatively low risk of unmanageable disruption in the labour market due to automation in the near future. However, since the provinces have different economic and labour market compositions, some may be more susceptible to automation than others. In 2019, employment data by province showed a similar risk profile across the country (Figure 6). A slightly larger proportion of employment is in occupations at a high risk of being automated in PEI and Saskatchewan, while Ontario had the highest proportion of employment at low risk[21] (see Box 2 for further discussion of provincial results).

Automation and Equality: Income, Age and Individual Characteristics

Aside from concerns of future mass technological unemployment, it is possible that automation could have different effects for different population groups. The occupations that are more likely to be automated generally contain more well-defined tasks and repetition, such as those in manufacturing. Historically, employees in those occupations account for a significant portion of middle-income jobs for those without advanced degrees and a university education. South of the border, middle-income jobs declined relative to both low- and high-wage jobs since the 1990s[22] (Cheremukhin

20 Lamb (2016) stated that 42 percent of all Canadian jobs were highly susceptible to automation within a decade.

21 These differences are not statistically significant.

22 In particular, following economic downturns in 1990-1991, 2001, 2008-2009 middle-income jobs did not recover during the expansions that followed, unlike earlier downturns (Cheremukhin 2014).

2014), and technology change has been identified as one of the factors driving the hollowing out of middle-income employment (Autor, Levy and Murnane 2003, Autor and Dorn 2013). In Canada, however, growth of low-income jobs has been outpaced by growth in both middle- and high-income jobs (Green and Sand 2015). That means Canada has not experienced wage polarization similar to the US, at least until recently.

To determine if automation and technological change is likely to increase wage polarization in Canada, I use employment income data from the 2016 Census and match median income levels for each occupation to their estimated likelihood of automation (Figure 7). There is little relationship between income and susceptibility to automation in Canada, which suggests that wage differences are not the mechanism by which technology affects inequality.

However, technological change could affect inequality via compositional changes to the labour market over time. Research indicates that compositional changes to the labour market explain a larger portion of the changes in inequality related to technological advancements than changes to wages. As Kaltenberg and Foster-McGregor (2020) explain:

> Workers are moving away from low-paying, high- and medium-automation risk jobs towards higher-paying low-automation risk jobs, but this shift is increasing inequality. Jobs that are at high risk of being automated tend to have relatively similar wage levels, while jobs that are less likely to be automated have a much higher dispersion of wages. Thus, as workers move into jobs that are less likely to be automated, inequality rises.

It is likely that compositional changes in employment due to technological change could have income-equality effects in Canada. Across education levels, a lower level is related to higher risk of automation and lower wages. The dispersion of wages is higher in jobs at low risk of automation than for jobs at high risk (Table 3). Furthermore, the dispersion of wages across risk categories increases with level of education. Together, these results suggest that technological change contributes to income inequality predominantly through compositional changes to the labour market, as opposed to changes in wages.

Technological change can have inequality implications aside from wages (Kaltenberg and Foster-McGregor 2020). While technology itself doesn't discriminate based on age, younger workers have more of an incentive to adapt than older workers, who may choose to retire instead of investing in new skills and training. Older and younger workers are also employed in different jobs, meaning the risk profile of automation differs across age groups (Figure 8). Only about 14 percent of workers aged 15-24 years are employed in occupations with a low risk of automation, compared to about 43 percent of workers aged 55-64. Conversely, only about 16 percent of workers aged 55-64 are employed in occupations are high risk of automation, while nearly half (46 percent) of young workers are highly susceptible to automation.

This result makes intuitive sense: since older workers have significantly more experience than those who have recently entered the labour market, they are more likely to have progressed to positions requiring higher skill levels and more likely to manage nuanced decisions related to resource and people management. They are, therefore, less likely to be in occupations subject to automation. Workers aged 15 to 24 are more likely to be employed part-time and are likely actively acquiring new knowledge and skills through education. With the exception of arts, culture, recreation and sports-related occupations, younger workers are employed in occupations more likely to be automated (Table 4). Older workers, those 55-to-64 years of age, are less likely to be automated if they are employed in business, finance, administration, sales and customer service occupations.

To further investigate the relationship between automation and equity in the labour market, I calculate the proportion of employment in each risk category for different individual characteristics:

Box 2: Comparing Differences in the Rate of Automation across Provinces

Comparing the provincial results calculated in this study with those from similar but more comprehensive analysis in Wyonch (2018) shows a decline in the average risk of automation (See Box 1 for discussion of technical differences and the affects on results between studies). Similar changes to the risk of increasing unemployment related to technology adoption results in only marginal relative differences in risk profiles of provincial labour markets between the two studies. Wyonch (2018) also found that PEI and Saskatchewan are the provinces most likely to experience labour market disruption due to technological change.

One notable observation from comparing the results of the two analyses is that the provinces that had the highest average-risk and highest proportion of employment in "high-risk" occupations in 2016 showed slightly larger declines in average-risk (Figure B2.1) but not in the proportion of employment at high risk when comparing the results of the current analysis to the former (Figure B2.2). Without deeper analysis, it is difficult to determine the cause of these differences and how best to interpret them. It is likely that employment in "high risk" occupations in the provinces more at risk of labour market disruption is more concentrated in occupations that have a higher likelihood of automation within the "high risk" category, relative to other provinces.

This analysis should be interpreted as a comparative risk assessment. When compared to the results of previous analysis, the relative risk between provinces remains largely unchanged. This result suggests that technological adoption has resulted in similar changes to provincial labour markets with respect to the risk of disruption. The effects of automation are likely to differ between provinces, even if similar proportions of the labour market could potentially be automated. As previously mentioned, an aging population is a driver of the adoption of automating technologies (Acemoglu and Restrepo 2019). Immigration can have ambiguous effects on the adoption of automating technologies. High-skill immigration can contribute to the adoption of automating technologies, but also decreasing wage inequality (Jaimovich and Siu 2017). Low-skilled immigration conversely contributes to slower adoption of automating technologies (Lewis 2011). The progression of technology adoption is affected by demographics, employment and labour market policy, industrial regulation, market dynamics and technical barriers.

Box 2: Continued

Figure B2.1: Comparing Estimates: Average Risk of Automation, by province

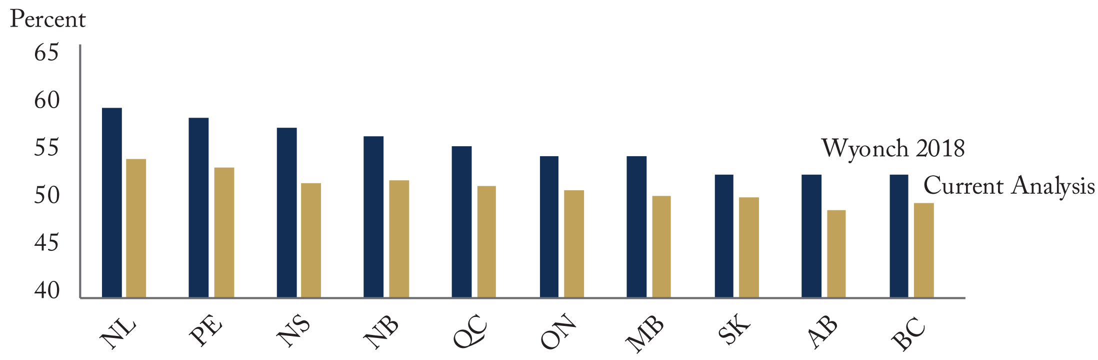
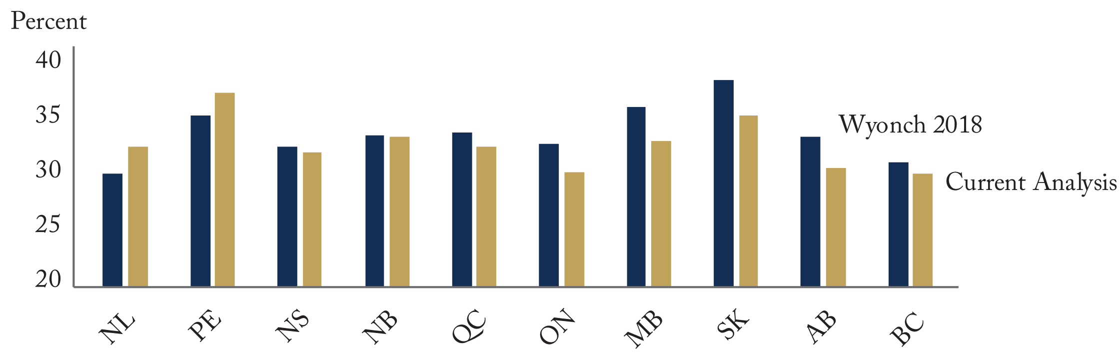
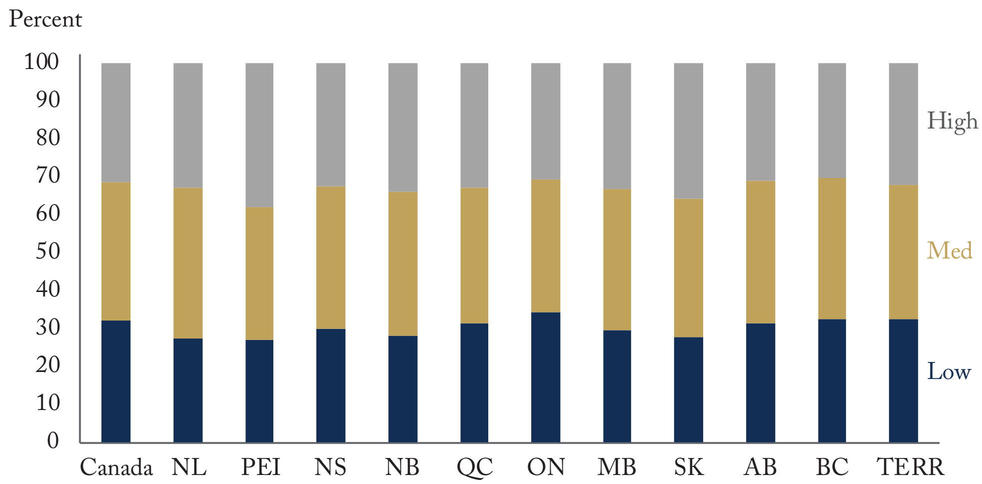


Figure B2.2: Comparing Estimates: Proportion of Employment at High Risk of Automation, by province



Source: Author's calculations.

Figure 6: Employment Automation Risk, by province



Sources: Author's calculations, COPS (2019).

gender, race and immigration status (Figure 9).[23] Results show some variation in the proportions of employment at high, medium and low risk of being automated, but generally provide a similar picture across groups. The proportion of employment at low risk of automation is lower than the Canadian average for both Black and Indigenous[24] individuals.

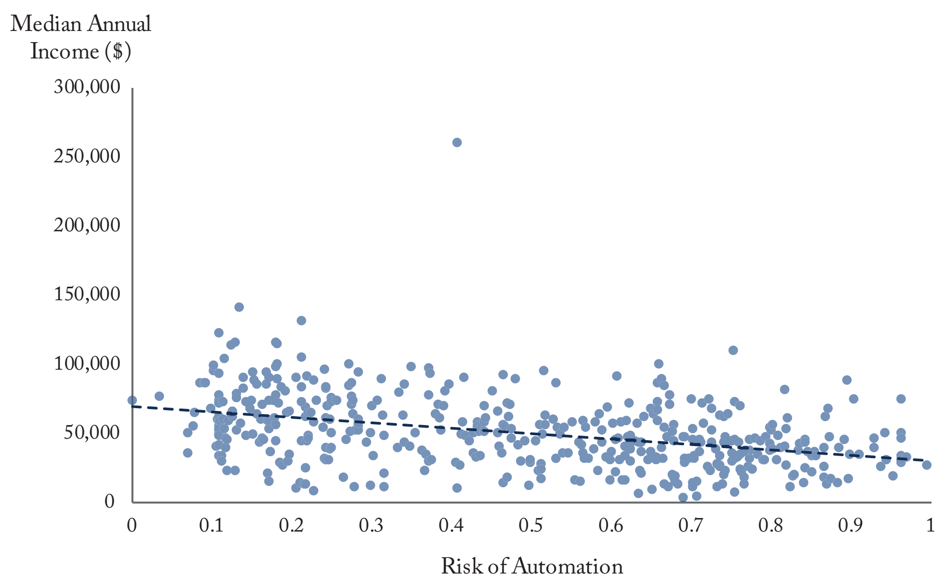
Indigenous workers in particular have higher average likelihood of being automatable with the exception of those in natural-resource extraction, agriculture, trades or transport occupations (Table 5). Workers who identify as visible minorities employed in education, community, government and legal services, and trades and transport occupations are more likely to be automated than average for those occupations.

Results from occupation-level analysis, using a different underlying method for calculating the likelihood of automation, show that visible minority, Indigenous, female and youth workers are over-represented in occupations that are at a high risk of being automated (Gresch 2020). Over-representation of these groups in such occupations is likely one of the main drivers of the different risk profiles between groups at the aggregate level shown here.

23 The data sources and language used throughout this discussion reflect categorizations that do not reflect distinctions between biological sex and gender identity, visible minorities and racialized persons, and utilizes a single category for Indigenous peoples and does not reflect heterogeneity within different groups. The author would like to acknowledge these distinctions and that the language used in this analysis reflects data definitions of Statistics Canada.

24 Indigenous refers to the statistical definition of "Aboriginal" and includes First Nations, Metis and Inuk peoples. These are the three groups defined as the Aboriginal peoples of Canada in the Constitution Act, 1982, Section 35 (2).

Figure 7: Automation Risk and Income



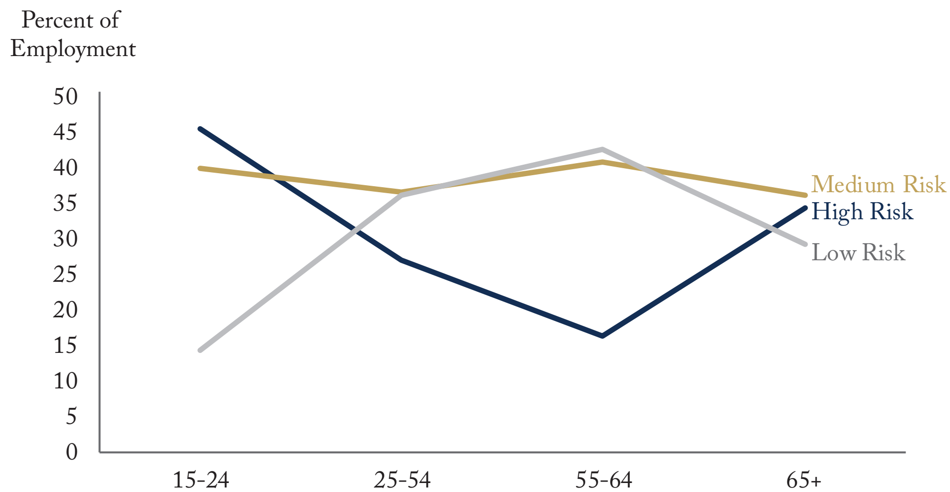
Sources: Author's calculations, COPS (2019).

Table 3: Automation Risk, by Education and Income

	Total	Below Secondary	Secondary Education	Apprentice-ship/Trade	College	University, below Bachelor's	Bachelor's and Graduate
Percent of employment by automation risk category							
Low Risk	36	13	21	20	36	43	64
Medium Risk	41	46	46	57	43	38	27
High Risk	23	41	33	23	21	19	10
Average Risk	50	**65**	**60**	**56**	50	**46**	**46**
Median Annual Income ($)							
Low Risk	71,000	52,000	59,000	59,000	65,000	68,000	75,000
Medium Risk	56,000	44,000	50,000	54,000	56,000	55,000	58,000
High Risk	47,000	41,000	47,000	48,000	49,000	50,000	49,000

Sources: Census (2016), author's calculations.

Figure 8: Automation Risk by Age



Sources: Census (2016), author's calculations.

The risk profile for immigrant employment is very similar to the Canadian average, though their employment profile gives a slight advantage in natural and applied science occupations and a slight disadvantage in education, law, community and government service occupations.

Men and women[25] face a similar average risk of automation, but female employment is more polarized – women are employed in both high- and low-risk occupations in larger proportions than men. Female workers in business, finance, administration, manufacturing and utilities occupations are, on average, more susceptible to automation. Meanwhile, male workers employed in business, finance and administration occupations are eight percent less likely to be automated than the average for those occupations.

Discussion and Policy Implications

About one in five Canadian workers (22 percent) are employed in a job that could theoretically be automated. By 2028, projections indicate that employment in these occupations will decline by only about 90,000 jobs. Meanwhile, jobs that are only somewhat susceptible to automation (medium risk) make up about 40 percent of current employment. This proportion is projected

25 Gender-specific language is used interchangeably with biological sex. While this use of language could be considered exclusionary of transsexual and non-binary individuals, the author is uncertain about proportion of survey respondents' who chose to identify their biological sex or their gender identity. Throughout this discussion, "men" refers to respondents reporting "male" as their sex.

Table 4: Automation Risk by Age and Occupation Type

	Average Risk (*percent*)	Difference from Average by Age				Total Employment (2019) (*percent*)
		15-to-24 years	25-to-54 years	55-to-64 years	65 + years	
Education, Law, Social, Community and Government Services	18.8	**5.2**	-0.3	-0.5	**-1.1**	11.9
Health	24.0	**5.8**	-0.2	0.1	**-3.2**	7.8
Arts, Culture, Recreation and Sport	29.2	**-2.6**	-0.3	-0.8	**5.5**	3.1
Natural and Applied Sciences	31.2	**5.2**	-0.7	-0.6	0.8	8.6
Trades, Transport and Equipment Operators	58.4	**3.7**	-0.8	**4.9**	1.5	15.9
Sales and Service	59.2	**7.1**	**-3.4**	**-4.2**	-0.3	27.2
Business, Finance and Administration	61.1	**7.9**	-2.1	**-9.3**	**3.8**	17.5
Manufacturing and Utilities	67.0	**8.8**	-1.4	1.0	**-1.7**	5.1
Natural Resources and Agriculture	77.5	-1.3	-2.6	4.4	**8.5**	2.9

Note: Bold text indicates statistically significant difference from the average (95 percent confidence).
Sources: Census (2016), COPS (2019), author's calculations.

to decline slightly to about 37 percent by 2028. These projections are within the range of estimates calculated in past research and indicate that the pace of technological change is unlikely to create significant technology-induced unemployment in the near future. Furthermore, they indicate that the labour market has been adapting to technological change over time and is likely to continue along a similar trajectory. The COVID-19 health crisis, however, has recently caused significant economic and labour market disruption due to the restrictions necessitated to combat the pandemic. This shock will also likely affect the dynamics of technology adoption and its associated labour market effects, at least in the short term (See Box 3).

The analysis of automation susceptibility by individual characteristics indicates that Black and Indigenous Canadians are employed in occupations that are highly susceptible to automation in higher proportions than the population average. Other research has found that Indigenous and visible minority individuals[26] make lower wages than

26 Visible minority classification does not include Indigenous persons nor those who are not members of a visible minority group. Visible minority groups are: South Asian, Chinese, Black, Filipino, Latin American, Arab, Southeast Asian, West Asian, Korean, Japanese, multiple visible minorities and visible minorities not included elsewhere – for example "Tibetan", "Guyanese", "Polynesian", etc.

Box 3: COVID-19 and Automation

The COVID-19 pandemic resulted in unprecedented restrictions on economic activity and increased the risks and costs associated with physical interaction. The long-term effects of the pandemic on labour market conditions and technology adoption are not yet known. But the necessity of physical distancing has already resulted in significant changes to business practices.

COVID-19 and the associated economic restrictions have disproportionally affected more vulnerable populations: people with informal or precarious employment, hourly-wage essential workers and elderly people living in institutional settings in particular. The ability to work from home and maintain employment income while in isolation is predominantly a privilege of higher-income professionals. The pandemic and associated shock are both likely to contribute directly to increasing income inequality. In addition, many businesses are actively transitioning their operations to a more digital model: expanding online shopping or installing automating technologies to minimize the need for physical contact between staff, for example. As a result, it is likely that some of the job losses resulting from the pandemic will not return. The continuing threat of COVID-19 and ongoing investments in automating or digitizing operations also mean some businesses are not likely to return to their pre-pandemic practices following the crisis.

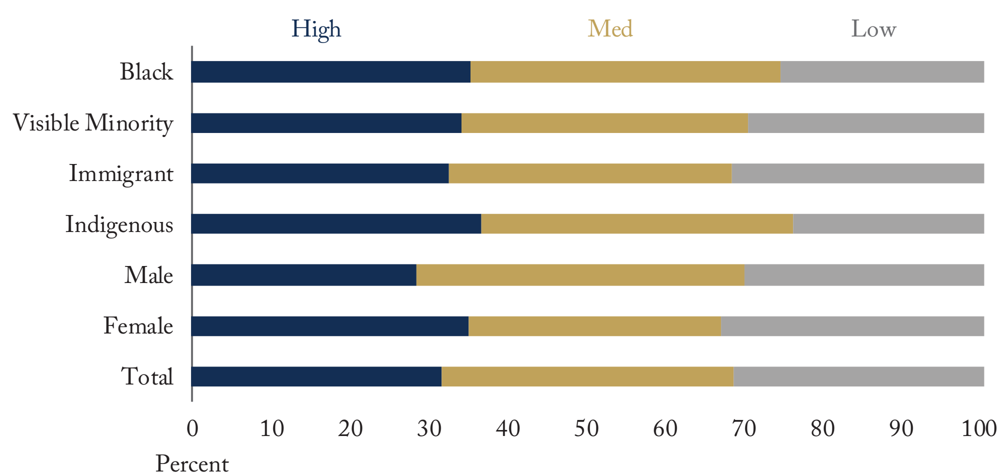
The pandemic will also affect population demographics. The elderly population has experienced much higher infection and mortality rates. The emergency measures implemented to control the spread of infection resulted in significant disruption to the flow of labour and goods across international borders. These factors could increase or decrease the rate of technology adoption and income inequality, given the interrelated effects of demographics and immigration on technology adoption and automation.

The economic disruption caused by the pandemic, combined with the short-term necessity of adapting operations to emergency measures, suggests that there has been significant investment in automating technologies that will likely continue in the short term. Following the initial crisis period, however, it is likely that the pace of automation will slow due to the combined factors of an excess supply of labour and limited resources for further capital investments.

white male Canadians (Schirle and Sogaolu 2020). Indigenous individuals are already at a disadvantage as measured by skills and educational attainment, compared to non-Indigenous Canadians (Mahboubi 2019). It is likely that the relatively higher susceptibility to automation is related to the worse average employment outcomes of Black and Indigenous people relative to the Canadian average.

Men, women and immigrants, however, face a similar average risk from automation. Overall, the differences are not large enough to warrant targeted pre-emptive policies specifically to prevent technological unemployment for particular groups. Instead, the inequality effects of automation could be indirectly addressed through education and labour-market policies that target inequality more broadly. The higher risk of automation for Black and Indigenous Canadians is more likely related to prevailing labour market gaps than to automating technologies specifically. The results do, however, suggest that technological change is likely to affect Indigenous and Black employment, particularly

Figure 9: Automation Risk, Individual Characteristics



Sources: Census (2016), author's calculations.

Table 5: Automation Risk and Individual Characteristics, by Occupation Type

	Total (*percent*)	Female	Male	Indig-enous	Immi-grant	Minority	Black	Employ-ment (*percent*)
		(Difference from Average)						
Education, Law, Social, Community and Government Services	18.8	-0.5	**0.9**	**1.8**	**1.3**	**2.6**	**2.8**	11.9
Health	24.0	0.2	-0.6	1.4	0.7	1.0	-0.3	7.8
Arts, Culture, Recreation and Sport	29.2	-0.1	0.1	**1.9**	1.2	-0.5	-0.8	3.1
Natural and Applied Sciences	31.2	-0.7	0.2	**5.6**	**-2.6**	**-2.6**	0.0	8.6
Trades, Transport and Equipment Operators	58.4	-2.3	0.2	1.4	1.7	**3.5**	**4.8**	15.9
Sales and Service	59.2	2.1	**-2.6**	**3.9**	-0.1	1.1	**4.2**	27.2
Business, Finance and Administration	61.1	**3.7**	**-8.2**	**5.1**	-0.7	-0.7	0.4	17.5
Manufacturing and Utilities	67.0	**3.7**	-1.5	**3.3**	2.4	**4.2**	5.7	5.1
Natural Resources and Agriculture	77.5	4.6	**-1.2**	**-4.9**	0.5	-1.3	-4.9	2.9

Note: Bold text indicates statistically significant difference from the average (95 percent confidence).
Sources: Census (2016), COPS (2019), author's calculations.

those in sales, customer service, law, education, social, community and government service occupations.

Previous research has indicated that technology may be a driving factor in growing wage inequality. However, the risk of automation is not related to median wages in Canada. Still, there is some evidence that technological change could increase inequality through compositional changes to the labour market. These results suggest that education is a critical factor in addressing relative risk of being automated out of a job for more vulnerable population groups.

Overall, these findings indicate that Canada's labour market is adapting to technological change over time and is likely to continue to do so in the future. It has been a few years since we heard predictions of mass technological unemployment within a decade. This analysis yields no evidence of accelerating technological change negatively affecting the labour market. Furthermore, the likelihood of mass technological unemployment in the near future remains low.

As a result, this analysis suggests that the appropriate role for government is moderating the negative effects of technological change for those that are affected in the short term. Existing policies that provide job training and income support for unemployed and low-income people provide a buffer against economic hardship (technology-induced or otherwise). However, with growth in non-standard employment, traditional job-support policies may not be available to all workers impacted by automation. The Canadian Emergency Support Benefit (CERB), an emergency income-support program for individuals affected by the COVID-19 pandemic was in part created to address coverage gaps in Employment Insurance. Following the current crisis, the government should analyze the effects of CERB and use insights from the unfortunately necessary natural experiment to modernize employment insurance and address income and employment-support gaps.

Appendix:

Analysis Method: Bayesian Gaussian Process Regression

This *Commentary*'s aim is to estimate the likelihood that a given occupation can be automated, based on its skill content. The O*Net database used contains detailed information for 954 occupations, including the level of each skill required and importance of that skill to the job, as well as the level of various activities required.

The conceptual basis for the model is that there are some skills or tasks where humans still dominate robots. Jobs that require high levels of these skills cannot be fully automated, as humans are still better than machines at completing the job tasks. Conversely, jobs that do not require these skills, or where the skill is not important to the job, are more likely to be automatable.

The skill variables described in Table 1 fully specify an explanatory variable set or a *feature vector* for each occupation. The dependent variable (whether or not a job is automatable) is incomplete and, for the most part, unknown. I only know which jobs are fully automatable and, with some certainty, the jobs that are currently impossible to automate. For those jobs that are partially automatable, the level is unknown.

To handle this difficulty with the data, I employ a Bayesian Gaussian process regression, which is a powerful kernel-based classification method. It is a method that uses "training data" – the information about which I am certain – to probabilistically determine the remaining unknown values. This method also does not limit the relationship between skills and the potential for automation to constant relationships (ie. how much a certain skill effects the chances of being automated is not constant over all automation levels).

There are some important limitations to this method of analysis. The results should be interpreted as the probability that an occupation could be automated in theory, or the approximate percentage of a given occupation that could be automated. It does not account for growth in demand as a result of labour-productivity improvements nor the creation of new occupations as a result of technological change. Despite these limitations, analyses of automation in the Canadian labour market have used some variant of a similar regression analysis, allowing for the current analysis to be compared to previous results.

A Gaussian process is defined as a collection of random variables, any finite number of random variables that have a joint Gaussian distribution (Rasmussen and Williams 2006).[27] Gaussian processes have been extensively used for many different variants of nonparametric estimation (Seeger 2002). In addition, this method has been applied to estimate occupations' susceptibility to automation in previous studies (Frey and Osborne 2013, Oschinski and Wyonch 2017).

A classification of some occupations as fully automatable ($y_i = 1$), not automatable ($y_i = 0$) or partially automatable ($y_i = 0.5$) is required to "train" the model. To develop a classification, I use the output classification results of previous studies on occupational automation: Autor and Dorn (2013), Josten and Lorden (2019), Frey and Osborne (2013) and Oschinski and Wyonch (2017). With the exception of Autor and Dorn (2013), which used binary classification, these studies classified occupations into three categories. Across the classification outputs, there were many occupations that were given a similar classification. Those were

27 For an extensive discussion of the applications and theory of Gaussian processes for machine learning and statistical analysis, see Rasmussen & Williams (2006).

classified equivalent to previous research. Occupations that were classified as "medium risk" in the studies using trinary classification were classified similarly for the training set, ignoring the binary classification from Autor and Dorn (2013) in these cases. Where previous research did not agree on a particular classification, no class was designated in the training data. This effectively combines the information about occupational automation that has been consistent across different methods of analysis.

The training data set is defined by $\mathcal{D} = (X, \boldsymbol{y})$, where X is the matrix of feature vectors and $\boldsymbol{y}$ gives the associated class label. Each element $x_{i,j}$ of X represents the level of each skill (j) required, weighted by the importance of that skill to the specified occupation (i). I assume $\mathcal{D} = (X, \boldsymbol{y})$, $\boldsymbol{x}_i \in \mathrm{R}^9$, $y_i \in \{0,1\}$ is a noisy independent, identically distributed sample from latent function $f : \boldsymbol{x} \rightarrow R$ where $\boldsymbol{w} = P(y \mid f)$ where denotes the noise distribution.

Given dataset of observations, $\mathcal{D} = \{(\boldsymbol{x}_i, y_i) \mid i = 1,2, \ldots, n\}$, we wish to make predictions ($\boldsymbol{y}_*$) for new input features X_* that are not in the training set $\mathcal{D}$. To estimate $\boldsymbol{y}_*$, I employ a zero-mean Gaussian process prior ($\boldsymbol{w} \sim N(0,\Sigma)$) and a generative Bayesian method. The process gives a prior probability weight to every possible function that describes the relationship specified by $\mathcal{D}$, where higher probabilities are assigned to functions I consider more likely. The likelihood of a function is determined by its relative proximity to training data points and the prior specification that fixes the properties of functions to be considered for inference.

The model is then computed by:

(1) Introduce $\phi(\boldsymbol{x})$ which maps input vector $\boldsymbol{x}$ into an N-dimensional feature space. Further, let $\Phi(X)$ be the aggregation of the columns $\phi(\boldsymbol{x})$. The model is defined by:

$$f(\boldsymbol{x}) = \phi(\boldsymbol{x})^{\mathrm{T}} \boldsymbol{w}$$

(2) Conditioning the prior distribution on the data $\mathcal{D}$, resulting in a posterior distribution:

$$posterior = \frac{likelihood \times prior}{marginal\ likelihood}, \qquad p(w|\boldsymbol{y}, \Phi(X)) = \frac{p(\boldsymbol{y}|\Phi(X), \boldsymbol{w})p(w)}{p(y|\Phi(X))}$$

$$p(\boldsymbol{w}|\boldsymbol{y}, \Phi(X)) \sim N\left(\bar{w} = \frac{1}{\sigma_n^2} A^{-1}\Phi(X)\boldsymbol{y}, A^{-1}\right)$$

Where $A = \sigma n^{-2}\, \Phi(X)\Phi(X)^{\mathrm{T}} + \Sigma^{-1}$

(3) The marginal posterior is the predictive distribution.

$$f_* | \boldsymbol{x}_*, \mathcal{D} = \int p(f_* | \phi_*, w) p(w|\Phi, \boldsymbol{y}) dw \ \sim N\left(\frac{1}{\sigma_n^2} \phi_*{}^T A^{-1} \Phi \boldsymbol{y}, \phi_*{}^T A^{-1} \phi_*\right)$$

Where $\Phi = \Phi(X)$ and $\phi^* = \phi(\boldsymbol{x}_*)$

An alternative formulation is given by:

$$f_*|\boldsymbol{x}_*, \mathcal{D} \sim N(\phi_*^T \Sigma \Phi (K + \sigma_n^2 I)^{-1} \boldsymbol{y},\ \ \phi_*^T \Sigma \phi_* - \phi_*^T \Sigma \Phi (K + \sigma_n^2 I)^{-1} \Phi^T \Sigma \phi_*) \tag{5}$$

Where $K = \Phi^T \Sigma \Phi$

Notice that in equation (5) the feature space always enters in a form that dictates entries in the matrices are of the form $\phi(\boldsymbol{x})^T \Sigma \phi(\boldsymbol{x}')$ where $\boldsymbol{x}$ and $\boldsymbol{x}'$ are in either the training set or the test set.

Let $k(x,x') = \phi(x)^T \Sigma \phi(x')$ be the kernel or covariance function. The specification of a covariance function implies a distribution over functions. A Gaussian process is completely specified by its mean function and covariance function.

$$f(\boldsymbol{x}) \sim GP\ (m(\boldsymbol{x}), \mathrm{k}(\boldsymbol{x}, \boldsymbol{x}')) \tag{6}$$

$$\boldsymbol{y} = f(\boldsymbol{x}) + \varepsilon \tag{7}$$

For our model $f(\boldsymbol{x}) = \phi(\boldsymbol{x})^T \boldsymbol{w}$ with prior $\boldsymbol{w} \sim N(\mathbf{0}, \Sigma)$ I have mean and covariance

$$E[f(\boldsymbol{x})] = 0 \tag{8}$$

$$E[f(\boldsymbol{x}) f(\boldsymbol{x}')] = (\boldsymbol{x})^T \Sigma \phi(\boldsymbol{x}') = k(\boldsymbol{x}, \boldsymbol{x}') \tag{9}$$

Notice, the covariance between outputs is a function of inputs. I define the kernel as the squared exponential covariance function:

$$k(\boldsymbol{x}, \boldsymbol{x}') = \exp\left(-\frac{1}{2} |\boldsymbol{x} - \boldsymbol{x}'|^2\right) \tag{10}$$

Assuming additive, identically distributed Gaussian noise with variance , the prior on noisy observations becomes:

$$cov(\boldsymbol{y}) = K(X, X) + \sigma_n^2 I. \tag{11}$$

The free parameter σ_n^2 is referred to as a hyperparameter to emphasize that it refers to a parameter of a non-parametric model. The parameters (weights) of the underlying parametric model have been integrated out.

To compute the model, I employ the "kernlab" R package (Karatzoglou, Smola and Hornik 2019). Specifically, I use the "gausspr" function, an exponentiated quadratic covariance (radial basis function kernel = "rbfdot") and an optimized hyperparameter selection. The accuracy of the model is estimated by a 10-fold cross validation error, which yields an error estimate of 0.09 on predicted probabilities.

Attribute Selection and Sensitivity Analysis

The attributes selected as barriers to automation in the main analysis are detailed in Table 1. There are, however, additional factors that could affect the likelihood that an occupation could be automated (Table A1). Similarly, results will be affected by the classification given for occupations in the training set.

Table A1: Attributes that Pose Barriers to Automation

Social Perception	Being aware of others' reactions and understanding why they react as they do.
Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
Assisting and Helping Others	Providing personal assistance, medical attention, emotional support or other personal care to others such as coworkers, customers, or patients.
Philosophy	Knowledge of different philosophical systems and religions. This includes their basic principles, values, ethics, ways of thinking, customs, practices and their impact on human culture.
Initiative	Willingness to take on responsibilities and challenges.
Leadership	Willingness to lead, take charge, and offer opinions and direction.
Innovation	Creativity and alternative thinking to develop new ideas for and answers to work-related problems.
Adaptability and Flexibility	Being open to change (positive or negative) and to consider variety in the workplace.
Independence	Developing one's own way of doing things, guiding oneself with little or no supervision and depending on oneself to get things done.
Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
Resolving Conflict and Negotiating with Others	Handling complaints, settling disputes and resolving grievances and conflicts, or otherwise negotiating with others.
Repairing or Maintaining Electronic or Mechanical Equipment	Servicing, repairing, calibrating, regulating, fine-tuning or testing machines, devices, equipment, and moving parts.
Public Speaking or Interpreting the Meaning of Information for Others	Frequency of public speaking, translating or explaining what information means and how it can be used.
Developing Objective Strategies	Establishing long-range objectives and specifying the strategies and actions to achieve them.

Source: O*NET Database.

Table A2: Models Specifying Different Attributes Posing Barriers to Automation

	Main analysis	Expanded attribute selection	Work activities only
Attributes	Social perception, originality, assisting and helping others, knowledge of philosophy, initiative, leadership, innovation, independence, adaptability and flexibility	Social perception, originality, assisting and helping others, initiative, leadership, innovation, independence, adaptability and flexibility, complex problem solving, resolving conflict and negotiating with others, repairing and maintaining equipment, public speaking and developing objective strategies	Assisting and helping others, complex problem solving, resolving conflict and negotiating with others, repairing and maintaining equipment, and developing objective strategies
Mean Automation Risk Across Occupations (unweighted %)	48.4	45.7	46.1
Correlation of Estimated Probability of Automation (Model output)			
Main Analysis	1	0.954	0.889
Expanded Attribute Selection	0.954	1	0.921
Work Activities only	0.889	0.921	1

Source: Author's calculations.

Table A3: Models Specifying Different Input Classifications – Correlation and Average Risk of Automation

	Oschinski and Wyonch	Frey and Osborne	Meta	Autor and Dorn	Josten and Lorden
Oschinski and Wyonch	1	0.93659	0.943999	0.636234	0.822301
Frey and Osborne		1	0.93865	0.642068	0.803695
meta			1	0.828096	0.941843
Autor and Dorn				1	0.861623
Josten and Lorden					1
Unweighted average automation risk	0.56	0.54	0.48	0.40	0.41

Source: Author's calculations.

Table A4: Change in Employment by Risk Category (2020 to 2028)				
Technology Adoption Rate (%, annual)	2.1	1.7	4.3	7.5
Number of Employees				
Low Risk	490,000	522,000	254,000	-58,000
Med Risk	-262,000	-176,000	-878,000	-1,611,000
High Risk	-322,000	-260,000	-753,000	-1,236,000
Net Employment	-93,000	87,000	-1,377,000	-2,906,000
Percent Change				
Low Risk	3.3	3.4	1.8	-0.1
Medium Risk	-1.4	-0.9	-5.2	-9.7
High Risk	-1.9	-1.5	-4.5	-7.5

Source: Author's calculations.

The attributes listed as barriers to automation are those identified by similar research studies included in the analysis. A selection of these attributes is included in the main analysis. Alternative analysis using an expanded selection and one that includes work activities only (similar to Autor and Dorn 2013) shows that addition or removal of individual attributes has little effect on aggregate results (Table A2). It does, however, have marginal effects on the classification of particular occupations as low, medium or high risk of automation.

Skills or attributes that enable humans to work with technology but could also be performed by computers or machines, such as data analysis and pattern recognition, are ambiguous in their impact on automation. For attributes or skills to pose a barrier to automation, by definition, machines/computers cannot outperform humans at them. Analytical skills or digital competencies are likely to be growing aspects of many, if not all occupations as technology continues to be developed and adopted. A recent report from the UN Industrial Development Organization summarizes the relationship between human skills and automating technologies (p. 75):

> "Technological change tends to favour skills that are complementary to the new technology (Acemoglu 2002, Rodrik 2018). Even if debate on the set of skills that will be required to perform with ADP technologies is still open, the needed skills are expected to be biased towards three broad categories: analytical, technology-related and soft skills (Kupfer et al. 2019)."

For analytical and technology-related skills, humans might compliment machines, but they might also compete with them – so while they are complimentary to technology, having advanced analytical skills does not necessarily mean that the analysis couldn't be automated. Those who have strong technology-related and analysis skills might be better able to adapt to changing business practices but many analysis-based tasks can be significantly automated. Improving these skills throughout the population regardless of age, income or occupation would likely reduce the negative employment effects of technology adoption and growth. In addition, a highly skilled workforce enables businesses to more readily adopt productivity improving technologies that increase output without changing the demand for labour.

This analysis focusses on the risk of an occupation being automated, and not on what efficiency improvements technology adoption might lead to or how it will be complimented by human labour. The method used to calculate the likelihood of automation requires that the skills and attributes included in the model be exclusively human, or at least areas where humans are likely to outperform machines for quite some time.

To determine whether the training input classification significantly affects the results of the analysis, I also estimated the probability that an occupation is automatable using classifications from Autor and Dorn (2013), Lorden and Jorden (2019), Frey and Osborne (2013) and Oschinski and Wyonch (2017) independently. Similarly, to determine whether the attribute selection significantly affects the results, I estimated the model with different combinations of attributes and a similar classification input.

Collectively, the results are quite consistent across differing input classifications and explanatory attribute selections. Varying the selection of attributes that pose barriers to automation yields average likelihoods of automation of about 46 percent to 48 percent (Table A2). In addition, the estimated likelihood of automation is highly correlated across the variant selections tested here. Similarly, probability estimates calculated using differing input classifications resulted in broadly similar results (Table A3). There is, however, significant variability in the estimates for individual occupations. Across the seven model selections specified in Tables A2 and A3, the average gap in estimated probability of automation for individual occupations is 30 percent (maximum gap is 0.82, minimum gap is 0.06).

The estimates associated with the combined classification (labelled "meta" in Table A3) are highly correlated with those calculated from each classification individually. The average likelihood of automation falls in the middle of the estimates. Similarly, the probability of automation estimates for individual occupations all fall between the extremes. Due to remaining uncertainty about which classification most reflects real-world potential for automation and the rather convenient result that the combined classification yields estimates that fall between the extremes estimated in other models, the "meta" classification is used for the main analysis of the potential effects of automation on Canada's labour market.

Mapping O*NET data to Canadian Labour Market Data

The statistical analysis estimates the likelihood an occupation can be automated based on the selected attributes and the classifications in the training vector. The skills and attribute information for each occupation is sourced from the O*NET database, sponsored by the US Department of Labor. O*NET data are based on ratings from employers, workers and occupational analysts. The O*NET data are coded to the 2010 Standard Occupational Classification (SOC2010). To apply the O*NET information to Canadian occupational data, I utilize a concordance developed by Statistics Canada and follow the method used in Frenette and Frank (2017):

"A concordance between the six-digit SOC2010 codes (provided in the O*NET database) and the four-digit 2011 National Occupational Classification (NOC2011) codes was developed. This concordance was determined based on the similarity of the occupational descriptions.

In some instances, a six-digit SOC2010 code had "breakout" (i.e., new or emerging) sub-occupations. Since there were no estimates of population size for these sub-occupations, it was assumed that they were of equal size within a six-digit SOC2010 code. After the breakout occupations were aggregated, 1,058 SOC2010–NOC2011 matched pairs remained. This number included 495 unique four-digit NOC2011 codes.

Of these 495 unique NOC2011 codes, 336 were matched with a six-digit SOC2010 code. For the remaining 159 NOC2011 codes, higher-level SOC2010 codes had to be used, because more than one six-digit SOC2010 code mapped to them (i.e., the ACS data were used at this stage). Among these 159 NOC2011 codes, 119 were matched with five-digit SOC2010 codes, 38 were matched with four-digit SOC2010 codes and the remaining two were matched with three-digit SOC2010 codes.

At this stage, the 495 unique NOC2011 codes contained the information on occupational skill requirements from O*NET. The data on occupational skill requirements were then linked to the NOC2011 codes.”

REFERENCES

Acemoglu, Daron, and Pascual Restrepo. 2016. "The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares, and Employment." NBER Working Paper 22252. Cambridge, MA: National Bureau of Economic Research. May.

________. 2018. "Artificial Intelligence, Automation and Work." NBER Working Paper 24196. Cambridge, MA: National Bureau of Economic Research. January.

________. 2019. "Demographics and Automation." NBER Working Paper 24421. Cambridge, MA: National Bureau of Economic Research. March.

Andrews, Dan, Chiara Criscuolo, and Peter N. Gal. 2015. "Frontier firms, technology diffusion and public policy: micro evidence from OECD countries." The Future of Productivity: Main Background Papers. OECD.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2016. "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." OECD Social, Employment and Migration Working Papers No. 189. OECD: June.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labour Market." *American Economic Review*. Vol. 103, No. 5, August, pp. 1553-97.

Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill-Content of Recent Technological Change: An Empirical Investigation." *Quarterly Journal of Economics*. 118:1279-1333.

Autor, David, and Anna Salomons. 2018. "Is Automation Labor-Share Displacing: Productivity Growth, Employment, and the Labor Share." Brookings Papers on Economic Activity. Spring: 1-63.

Bessen, James. 2018. "Automation and Jobs: When Technology Boosts Employment." Law and Economics Paper No. 17-09. Boston University School of Law: March.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work Progress and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton.

Bughin, Jacques, James Manyika, and Jonathan Woetzel. 2017. "Jobs lost, jobs gained: Workforce transitions in a time of automation." McKinsey & Co. December. Available at: https://www.mckinsey.com/~/media/mckinsey/featured%20insights/Future%20of%20Organizations/What%20the%20future%20of%20work%20will%20mean%20for%20jobs%20skills%20and%20wages/MGI-Jobs-Lost-Jobs-Gained-Report-December-6-2017.ashx.

Campa, Riccardo. 2014. "Technological Growth and Unemployment: A Global Scenario Analysis." *Journal of Evolution and Technology* 24 (1): 86–103

Cheremukhin, Anton. 2014. "Middle-Skill Jobs Lost in U.S. Labor Market Polarization." *Dallas Fed Economic Letter* 9 (5): 1–4.

Cowen, Tyler. 2013. "Who will prosper in the new world?" *New York Times*. August 31.

Frenette, Marc, and Kristyn Frank. 2017. "Do Postsecondary Graduates Land High-skilled Jobs?" Analytical Studies Branch Research Paper Series, no. 388. Ottawa: Statistics Canada.

________. 2018. "Are Canadian Jobs More or Less Skilled than American Jobs?" Analytical Studies Branch Research Paper Series, No. 406. Ottawa: Statistics Canada.

________. 2020. "The Demographics of Automation in Canada: Who's at Risk?". No. 77. IRPP: June.

Frey, Carl Benedikt, and Michael A. Osborne. 2013. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" Oxford: Oxford University, Oxford Martin School. Programme on the Impacts of Future Technology. September.

Graetz, George, and Guy Michaels. 2015. "Robots at Work." CEP Discussion Paper 1335 London: Centre for Economic Performance.

Green, David, and Benjamin Sand. 2015. "Has the Canadian Labour Market Polarized?" *Canadian Journal of Economics*. 48 (2): 612–46

Gresch, Darren (2020). Responding to Automation: How adaptable is Canada's labour market? Issue Briefings, May 2020. The Conference Board of Canada.

Howitt, Peter. 2015. *Mushrooms and Yeast: The Implications of Technological Progress for Canada's Economic Growth*. Commentary 433. Toronto: C.D. Howe Institute. September.

International Federation of Robotics. 2019. IFR Press Conference. Shanghai. September.

Jaimovich, Nir, and Henry Siu. 2017. "High-Skilled Immigration, STEM Employment, and Non-Routine-Biased Technical Change." https://faculty.arts.ubc.ca/hsiu/pubs/immigration20170427.pdf.

Josten, Cecily, and Grace Lorden. 2019. "Robots at Work: Automatable and Non Automatable Jobs." IZQ DP 12520. Bonn: IZA – Institute of Labor Economics. July.

Kaltenberg, Mary, and Neil Foster-McGregor. 2020. "The impact of automation on inequality across Europe." (No. 009). UN University. Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT).

Karatzoglou, Alexandros, Alex Smola, and Kurt Hornik. 2019. "Kernel-Based Machine Learning Lab. Version 0.9-29." Comprehensive R Archive Network. Available at https://cran.r-project.org/package=kernlab.

Krugman, Paul. 2013. "Sympathy for the Luddites." *New York Times*. June 14

Lamb, Creig. 2016. *The Talented Mr. Robot: The Impact of Automation on Canada's Workforce*. Toronto: Brookfield Institute for Innovation + Entrepreneurship. June.

Levy, Frank, and Richard Murnane. 2004. *The New Division of Labor: How Computers are Creating the Next Job Market*. Princeton, NJ: Princeton University Press.

Lewis, Ethan. 2011. "Immigration, Skill Mix, and Capital Skill Complementarity." The Quarterly Journal of Economics 126(2): 1029–1069.

Lindert, Peter, and Jeffrey Williamson. *The Economic History Review New Series*. Vol. 36, No. 1. February 1983. pp. 1-25. Available at: https://www.jstor.org/stable/2598895?seq=1.

Mahboubi, Parisa. 2019. *Bad Fits: The Causes, Extent and Costs of Job Skills Mismatch in Canada*. Commentary 552. Toronto: C.D. Howe Institute. September.

Mahboubi, Parisa, and Colin Busby. 2017. "Closing the Divide: Progress and Challenges in Adult Skills Development among Indigenous Peoples." E-Brief. Toronto: C.D. Howe Institute. September.

OECD. 2019. "Productive Capital Stock, volume, annual, average growth." *Economic Outlook Number 106*. Edition 2019(2). Available at: https://www.oecd-ilibrary.org/economics/data/oecd-economic-outlook-statistics-and-projections/oecd-economic-outlook-no-106-edition-2019-2_8aa5bebb-en?parentId=http%3A%2F%2Finstance.metastore.ingenta.com%2Fcontent%2Fcollection%2Feo-data-en.

OECD. 2020. Employment by activity (indicator). doi: 10.1787/a258bb52-en

Oschinski, Matthias, and Rosalie Wyonch. 2017. *Future Shock? The Impact of Automation on Canada's Labour Market.* Commentary 472. Toronto: C.D. Howe Institute. March.

Rasmussen, Carl, and Christopher Williams. 2006. *Gaussian Processes for Machine Learning*. Cambridge, MA: MIT Press.

Schirle, Tammy, and Sogaolu Moyosoreoluwa. 2020. *A Work in Progress: Measuring Wage Gaps for Women and Minorities in the Canadian Labour Market*. Commentary 561. Toronto: C.D. Howe Institute. January.

Seeger, Matthias. 2004. "Gaussian Processes for Machine Learning." *International Journal of Neural Systems*. 14 (2): 69-106.

Sirkin, Harold, Michael Zinser, and Douglas Hohner. 2011. "Made in America, Again: Why Manufacturing Will Return to the U.S." Boston Consulting Group. August.

United Nations Industrial Development Organization. 2019. Industrial Development Report 2020: Industrializing in the digital age. UNIDO: Vienna.

Woirol, Gregory R. 1996. *The Technological Unemployment and Structural Unemployment Debates*. Westport, CT: Greenwood Press.

Notes:

Recent C.D. Howe Institute Publications

October 2020	Bishop, Grant, Mariam Ragab, and Blake Shaffer. *The Price of Power: Comparative Electricity Costs across Provinces.* C.D. Howe Institute Commentary 582.
October 2020	Drummond, Don. "Canada's Foggy Economic and Fiscal Future." C.D. Howe Institute E-Brief.
October 2020	Drummond, Don, and Duncan Sinclair. "COVID-19: A Catalyst for Change in Health and Healthcare?" C.D. Howe Institute Verbatim.
October 2020	Ambler, Steve, and Jeremy M. Kronick. "Canadian Monetary Policy in the Time of COVID-19." C.D. Howe Institute E-Brief.
October 2020	Robson, William B.P., and Farah Omran. *Busted Budgets: Canada's Senior Governments Can't Stick to Their Fiscal Plans.* C.D. Howe Institute Commentary 581.
September 2020	Tombe, Trevor, and Daniel Schwanen. *Alberta's Opportunity: The Ins, Outs and Benefits of Greater Job Mobility.* C.D. Howe Institute Commentary 580.
September 2020	Koeppl, Thorsten V., and Jeremy Kronick. *Open Banking in Canada – The Path to Implementation.* C.D. Howe Institute Commentary 579.
September 2020	Klassen, Kenneth J., and Nick Pantaleo. "Assessing the Canada Revenue Agency: Evidence on Tax Auditors' Incentives and Assessments." C.D. Howe Institute E-Brief.
August 2020	Koeppl, Thorsten V., and Jeremy Kronick. *"Going Direct": Not a New Tool, But an Old Pitfall for the Bank of Canada.* C.D. Howe Institute Commentary 578.
August 2020	Robson, William B.P., and Farah Omran. *The ABCs of Fiscal Accountability: Grading Canada's Senior Governments, 2020.* C.D. Howe Institute Commentary 577.
July 2020	Richards, John. *Student Performance in PISA 2018: Nettlesome Questions for Canada.* C.D. Howe Institute Commentary 576.
July 2020	Mysicka, Robert, Lucas Cutler, and Tingting Zhang. *Licence to Capture: The Cost Consequences to Consumers of Occupational Regulation in Canada.* C.D. Howe Institute Commentary 575.
July 2020	Robson, William B.P. *Quirks and Fixes: Accounting for Broader Public-Sector Pension Plans in Canada.* C.D. Howe Institute Commentary 574.

Support the Institute

For more information on supporting the C.D. Howe Institute's vital policy work, through charitable giving or membership, please go to www.cdhowe.org or call 416-865-1904. Learn more about the Institute's activities and how to make a donation at the same time. You will receive a tax receipt for your gift.

A Reputation for Independent, Nonpartisan Research

The C.D. Howe Institute's reputation for independent, reasoned and relevant public policy research of the highest quality is its chief asset, and underpins the credibility and effectiveness of its work. Independence and nonpartisanship are core Institute values that inform its approach to research, guide the actions of its professional staff and limit the types of financial contributions that the Institute will accept.

For our full Independence and Nonpartisanship Policy go to www.cdhowe.org.

C.D. HOWE
INSTITUTE

67 Yonge Street, Suite 300,
Toronto, Ontario
M5E 1J8

Canadian Publication Mail Sales
Product Agreement #40008848