Who Are Canada's Tech Workers?

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AUTHORS

VIET VU
Economist

Viet is an Economist at the Brookfield Institute for Innovation + Entrepreneurship. Viet is interested in how governments and companies can intentionally design policies and markets to drive human behaviour. He is also fascinated by how the world adapts to the emergence of new types of markets as legal frameworks often lag behind. Viet holds a Master of Science in Economics from the London School of Economics & Political Science and a Bachelor of Arts in Economics with Honours from the University of British Columbia.

viet.vu@ryerson.ca | @vviet93

ASHER ZAFAR
Fellow, Data Science

Asher's passion for civic innovation has led him through a career spanning technology, strategy consulting, and government. Now a Data Scientist on the Facebook News team, Asher spent the previous year as a consultant working on production machine learning models and advising on public sector digital strategy and data science projects. Previously, he built and managed a quantitative policy analysis team with the Ontario government, and was a public sector strategy consultant with Deloitte. Asher holds degrees in Economics from the University of Texas at Austin (B.A.) and York University (M.A.).

asherzafar.github.io | @asherzafar

CREIG LAMB
Senior Policy Analyst

Creig is a Senior Policy Analyst at the Brookfield Institute where he leads the Skills for an Innovation-Driven Economy workstream. Creig's research is focussed on examining how technology is reshaping skills demands and preparing Canadian firms and workers for the future. Creig holds a Master of Public Policy from the University of Toronto and a Bachelor of Communications from the University of Ottawa.

creig.lamb@ryerson.ca | @creiglamb

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@BrookfieldIIE

The Brookfield Institute for Innovation + Entrepreneurship

20 Dundas St. W, Suite 921
Toronto, ON M5G 2C2

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CONTRIBUTORS

Sarah Doyle, Director of Policy + Research

Andrew Do, Policy Analyst

Nisa Malli, Senior Policy Analyst

Melissa Pogue, Manager, Program Research and Operations, Talent Development, MaRS Discovery District

REVIEWERS

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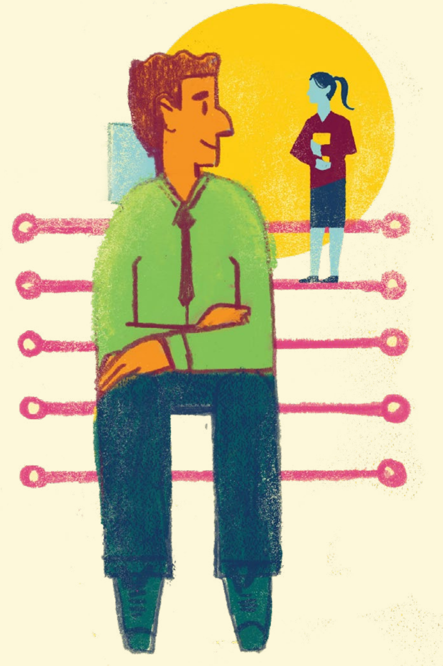


In recent years, Canadian governments at all levels have been placing some big bets on technology to propel our economy forward. We are investing billions of dollars into groundbreaking research in fields such as quantum computing and artificial intelligence, and supporting the creation of superclusters across the country. We are producing world-class tech companies and attracting the attention of large international firms such as Amazon and Google. Perhaps most importantly, we are also investing heavily in tech's most valuable resource: people.

As the lines between tech and the rest of the economy continue to blur, tech workers are becoming critical to the success of most industries.[1] From aerospace engineers to video game designers, to metallurgical engineers, tech workers are employed in firms of all shapes and sizes and they encompass a wide array of skills and outputs. However, many Canadians lack obvious pathways into tech jobs, and for those working in tech, pay and opportunities for progression are uneven.

This report sheds light on who Canada's tech workers are, and on diversity and equity within tech occupations. It recognizes the importance of the people working in tech occupations across Canada, while drawing attention to those who are underrepresented.

UNDERSTANDING TECH WORKERS

For this report, we define tech workers as individuals that either produce or make extensive use of technology, regardless of industry. We have taken a bottom-up, skills-based approach to identify tech occupations, which allows these definitions to evolve as technology, skills, occupations and industries evolve. We examine who tech workers are, where they work, and what they earn, as well as which demographic groups are underrepresented in tech occupations.

The main takeaway is that Canada is home to a large, growing and diverse tech workforce; ensuring its continued growth is vital for Canada's economy. However, there are gaps in terms of pay and participation along gender, race, and ethnic lines. Canada has a significant opportunity to more fully engage it's diverse labour market to contribute to an already vibrant tech workforce.

In addition to this report, we have also released open data sets and an interactive data visualization to allow readers to explore our data and findings in more detail, and to build upon them with their own analysis.

DEFINING TECH WORKERS

To analyze tech workers, we must first define them. Our definition aims to capture the pervasiveness of tech talent across industries and occupations.

Many groups around the world have attempted to define tech occupations in the past, including the Brookings Institution, the US Bureau of Labor Statistics and Economic Analysis, and academic researchers at Carnegie Mellon University and elsewhere. We scanned these definitions to inform and contextualize our approach (see Appendix A).

Our approach is founded on an assessment of the tech intensity of the work involved in an occupation. This allows us to explore tech occupations across the economy.

TECH SKILLS AND OCCUPATIONS[2]

To reach our tech occupations definition, we analyzed the skills involved in different occupations. To do this, we linked the US Bureau of Labour Statistics' (BLS) O*NET database[3] to Canada's National Occupational Classification (NOC) and selected six skills used by O*NET that clearly relate to the production or use of technology: Interacting with Computers, Computers and Electronics, Engineering Design, Engineering and Technology, Programming, and Telecommunications.

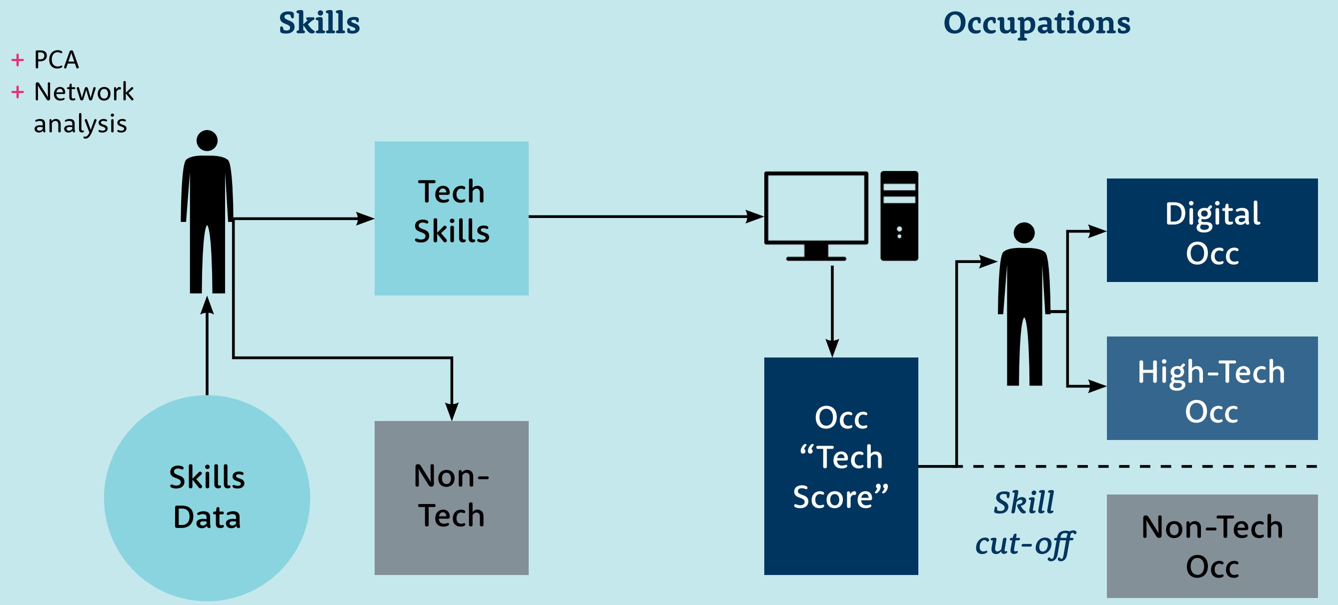
We ranked each occupation based on how important each of these six skills is in performing the work of the occupation, as well as the mastery one is expected to have of these skills within the occupation. We used this information to generate a "tech ranking" for each occupation. We then defined tech occupations as those with a composite ranking in the top 5 percent (this cut-off was chosen to focus on the most tech-intensive jobs). Sensitivity tests were performed when we relaxed this constraint, and relatively small employment impacts were observed.

Furthermore, we distinguish between two groups among tech occupations: digital occupations and high-tech occupations:

+ Digital occupations are those which typically contribute to the development of computer hardware or software solutions (i.e., software developers or technology architects).

+ High-tech occupations, on the other hand, require advanced technical skills in which computers are used as a means to other ends (i.e., engineers or scientists).

DEFINING TECH



Based on PCA and the network analysis of O*Net skills knowledge, and work activities, six items are selected as core tech capabilities.

Science and math skills correlate with these, but are no included. These are averaged into a "tech score" for each occupation (4-digit NOC).

Occupations with a tech score below the aforementioned cut-off were excluded. Those above a tech score are sorted into two categories:

+ **Digital Occupations:** Primarily contributes to the output of hardware or software.
+ **High-Tech Occupations:** Not primarily a digital output, but makes advanced, intrinsic use of digital technology.

CONCEPTS CALCULATED AND EXAMINED

Participation in tech: Share of a demographic group that works in a tech occupation. E.g. if there were 100 male workers in the Canadian economy and 8 of those workers worked in a tech occupation, the participation rate for male workers would be 8 percent.

Share of tech workers: Share of tech workers that belong to a specific demographic. E.g. if there were 100 tech workers in Canada and 20 of them were women, we would say women workers made up a 20 percent share of tech workers.

Pay in tech: Weighted average of pay in tech occupations for the considered demographic groups, where the weight placed on each occupation is the number of people employed in that occupation.

Pay in non-tech: Weighted average of pay in non-tech occupations for the considered demographic group, where the weight placed on each occupation is the number of people employed in that occupation.

GLOSSARY OF STATISTICS CANADA'S DEMOGRAPHIC CONCEPTS FOR THIS REPORT

This report relies on a series of statistical definitions from [StatCan's 2016 Census Dictionary].

Working Individuals: Under Statistics Canada's 2016 Census Dictionary definition, those considered working individuals were people who worked for any amount of time during the reference year (2015), even if only for a few hours.

Sex: Statistics Canada recently updated their sex and gender variables. Under the new definitions, "sex" refers to "sex assigned at birth" which is typically "based on a person's reproductive system and other physical characteristics." Gender, on the other hand, refers to "the gender that a person internally feels ('gender identity' along the gender spectrum) and/or the gender a person publicly expresses ('gender expression')."

We recognize that there are important differences in meaning between the terms "sex" and "gender," as well as "female/male" and "woman/man"; however, in this report we use these terms interchangeably given that this distinction was not made in Statistics Canada's last Census, which is the primary data source for this report.

Age: Under Statistics Canada's definition, age refers to the age of a person at their last birthday (or relative to a specified, well-defined reference date)

Visible Minority: Under the Statistics Canada's definition, visible minority refers to "whether a person belongs to a visible minority group as defined by the Employment Equity Act and, if so, the visible minority group to which the person belongs. The Employment Equity Act defines visible minorities as 'persons, other than Aboriginal peoples, who are non-Caucasian in race or non-White in colour.' Categories in the visible minority variable include South Asian, Chinese, Black, Filipino, Latin American, Arab, Southeast Asian, West Asian, Korean, Japanese, Visible Minority, n.i.e. ('n.i.e.' means 'not included elsewhere'), Multiple Visible Minorities and Not a Visible Minority."

Immigrant Status: Under Statistics Canada's definition, immigrant status refers to whether the person is a non-immigrant, an immigrant or a non-permanent resident. Immigrants are those who have been granted the right to live in Canada permanently, including naturalized citizens.

Aboriginal Identity: Under Statistics Canada's definition, "Aboriginal identity refers to whether the person reported identifying with the Aboriginal peoples of Canada. This includes those who reported being an Aboriginal person, that is, First Nations (North American Indian), Métis or Inuit and/or those who reported Registered or Treaty Indian status, that is registered under the Indian Act of Canada, and/or those who reported membership in a First Nation or Indian band." While Statistics Canada used the term "Aboriginal" in the last Census, for this report we instead use the term "Indigenous" to better represent all of the Indigenous Peoples in Canada.

Unfortunately, due to data limitations, we were unable to examine other critical intersections, such as LGBTQ+ or disabled tech workers.

PART 1: TECH WORKERS AT A GLANCE

In this first section, we provide an overview of Canada's tech workers, including: how many there are, what they earn, what level of education they have, what age they are, as well as what cities and industries they work in.

SIZE AND BREAKDOWN

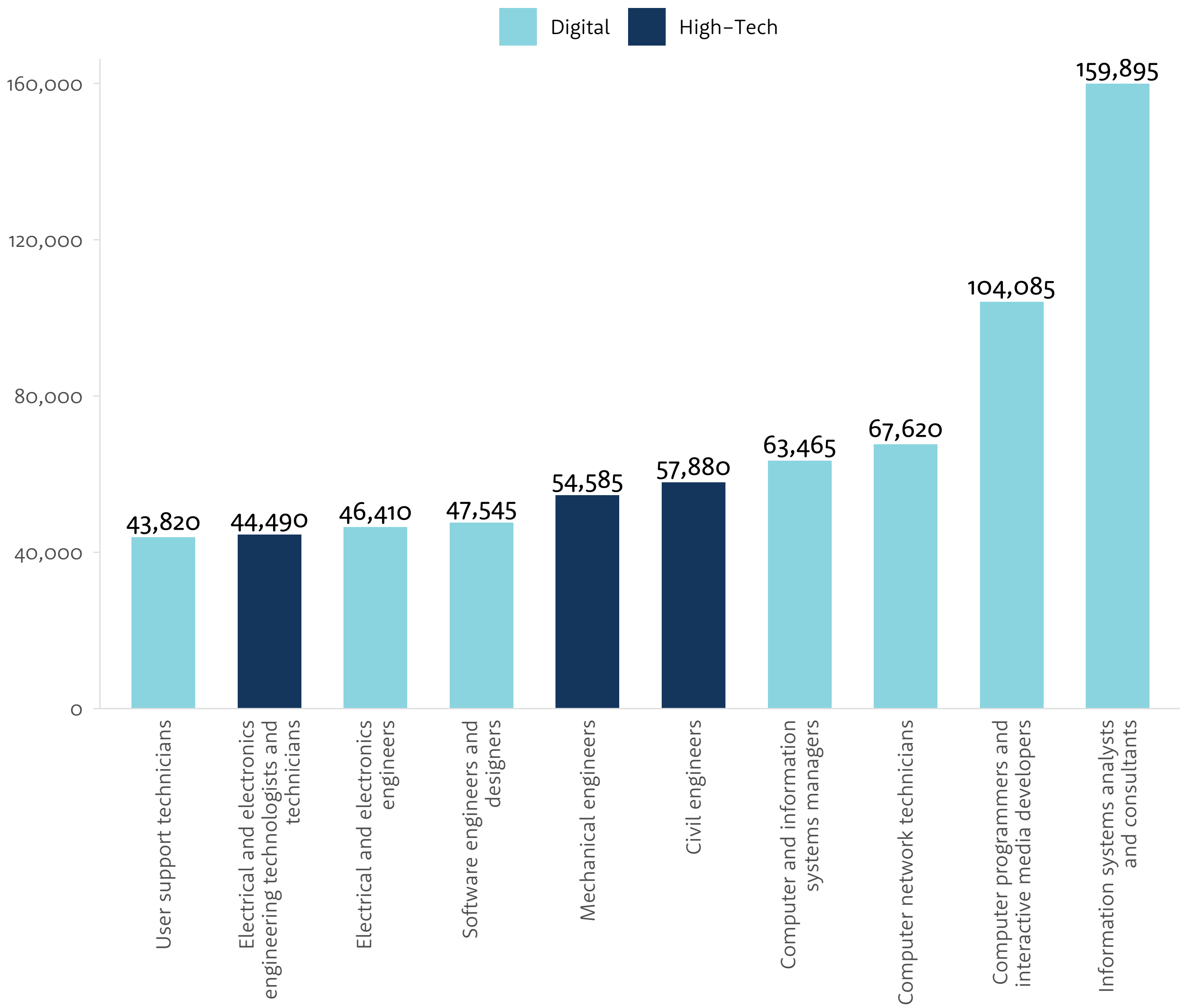
In 2016, around 935,000 Canadians were working in tech occupations, representing 5.1 percent of the Canadian labour force. Of these, 681,000 were in digital occupations while 254,000 were in high-tech occupations.

Occupational Group	Number of workers	Share of workforce
Digital	681,000	3.7%
High-Tech	254,000	1.4%
Non-Tech	18,300,000	94.9%

Of the top 10 technology occupations in Canada in 2016, the top 4 occupations that employed the most Canadians were primarily digital ones. This included 160,000 people working as information systems analysts and consultants, forming the largest occupational group in tech; this was followed by 104,000 people working as computer programmers and interactive media developers. The high-tech occupation with the highest employment was civil engineers, with nearly 58,000 workers.

Figure 1:

Top 10 Tech Occupations by Employment in Canada



Source: 2016 Canadian Census

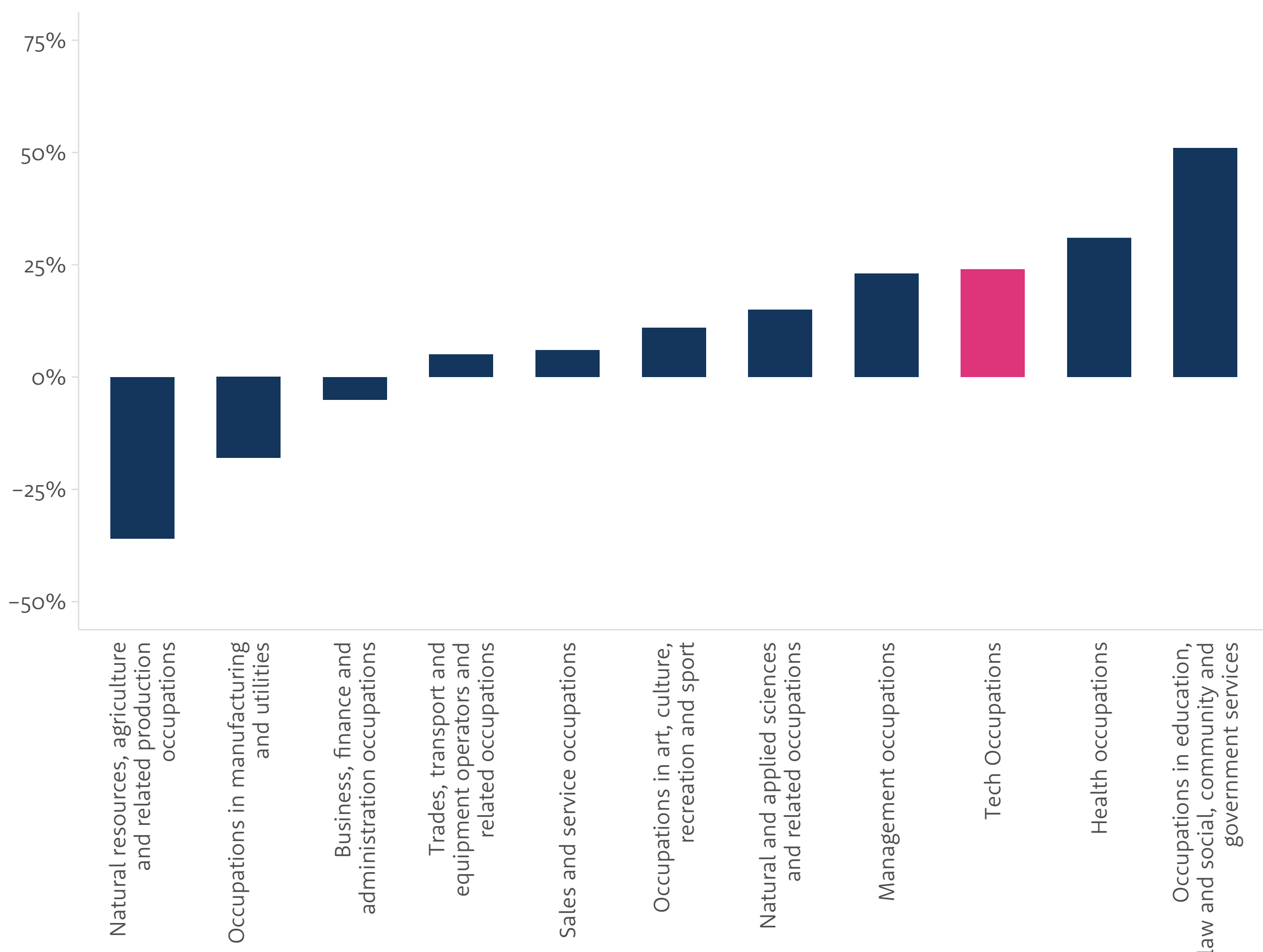
GROWTH

Tech occupations grew relatively faster than the rest of the workforce. Between 2006 and 2016, there were 183,000 more people in the tech workforce.

The share of tech workers in the workforce over this period grew by 0.66 percentage points to 5.1 percent. In addition, employment in tech occupations grew by 24 percent, which was faster than most other occupational categories. Tech occupations, as defined in this report, exist across Statistics Canada's occupational categories (2 digit NOCs); these categories are therefore not mutually exclusive. Even so, the fact that only two occupational categories experienced a higher percentage change in employment compared to tech occupations suggests that the relative importance of tech workers in Canada's economy is growing.[4]

Figure 2:

Percent Change in Employment between 2006 and 2016 for 2 digits NOCs compared to tech occupations



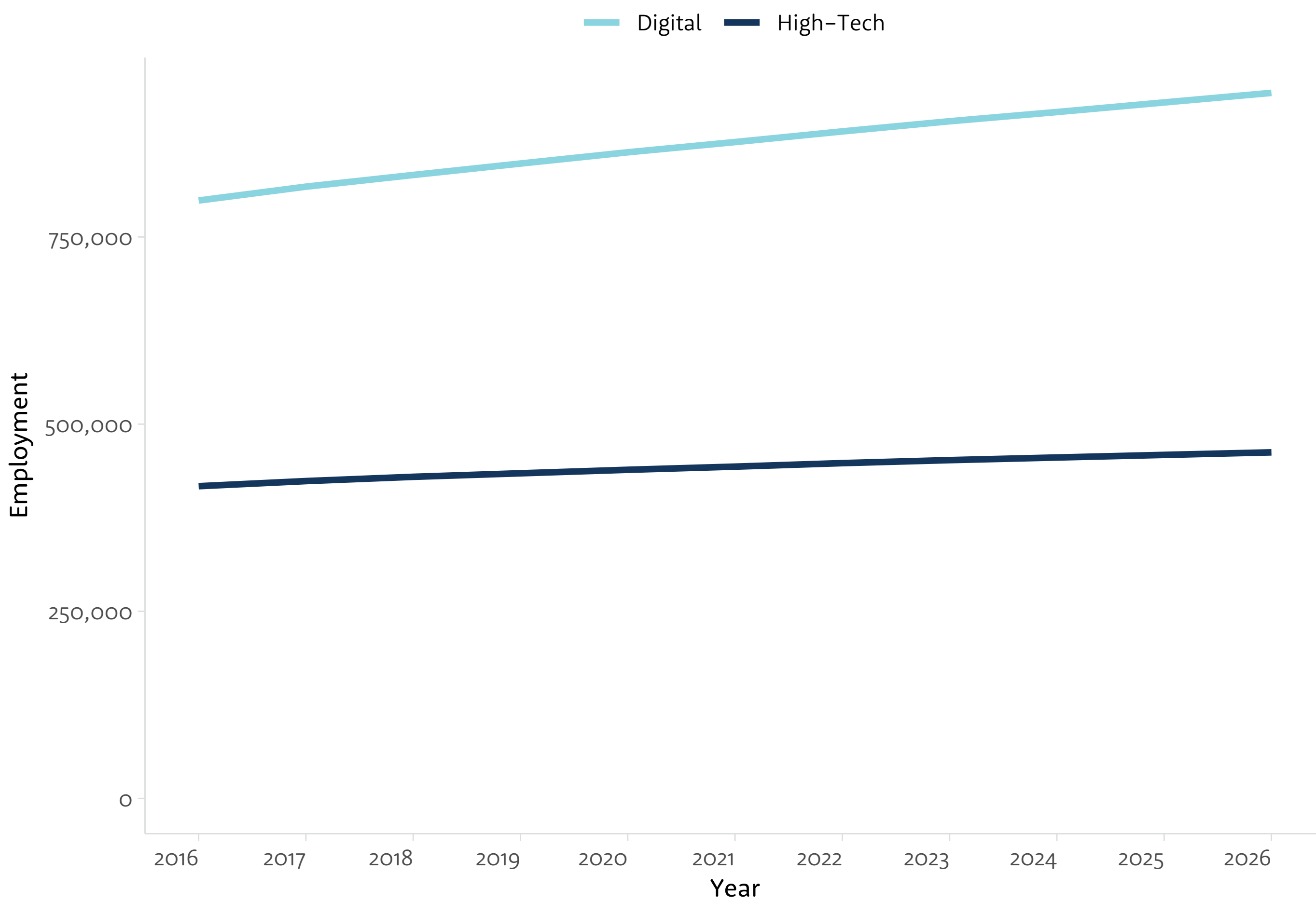
Source: 2006, 2016 Canadian Census, BII+E Analysis

Using Employment and Social Development Canada's (ESDC) Canadian Occupational Projection System (COPS)[5], we forecasted future digital and high-tech employment in Canada. Employment is projected to grow by eight percent (around 45,200 workers) in high-tech occupations from 2016 to 2026, and 18 percent (around 143,800 workers) in digital occupations, totalling 189,000 new workers in tech occupations. Employment in non-tech occupations is expected to increase by 8.6 percent.

The share of high-tech occupations in Canada's labour market is expected to remain mostly unchanged over this period, at 2.3 percent, while the share of employment in digital occupations is expected to increase to 4.8 percent—an 8 percent increase in its share of the total workforce. COPS, like other forecasts, relies on many assumptions about future economic conditions and the size and distribution of occupation demand. If the rate of tech growth increases, these figures may underestimate the potential growth in tech jobs.

Figure 3:

Projected Employment Growth for Tech Occupations: 2016-2026



Source: Canadian Occupational Projection System (COPS)

SALARY

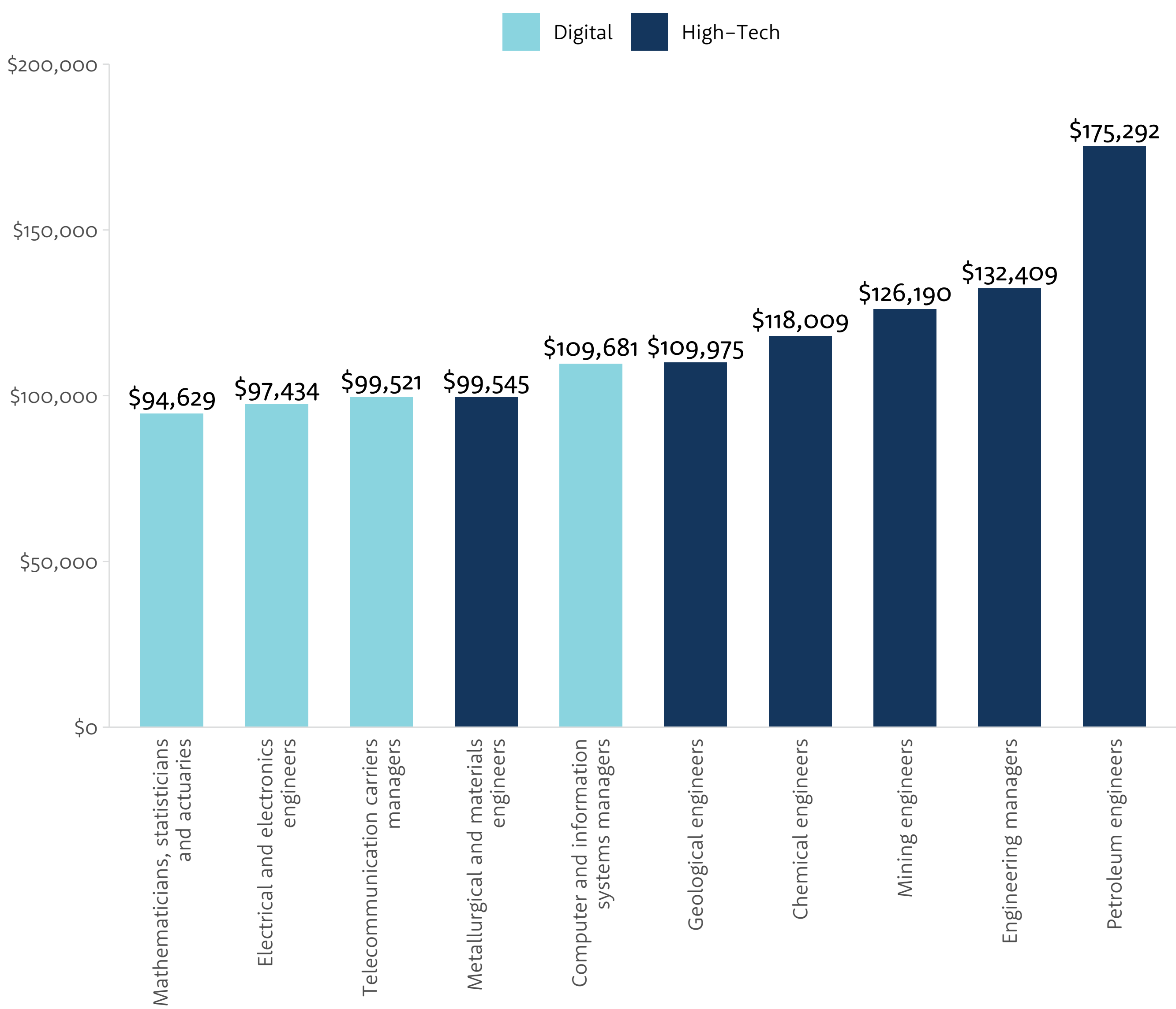
Occupational Group	Salary
Digital	$66,000
High-Tech	$90,000
Non-Tech	$45,400

In 2016, tech workers were paid considerably more than non-tech workers. High-tech occupations earned the most, earning on average $45,000 more than non-tech occupations. Digital occupations earned on average nearly $21,000 more than non-tech occupations.

Pay in tech occupations is the highest amongst engineers, in particular, those working in the resource sector. In 2016, petroleum engineers earned the highest salary at $175,292, followed by engineering managers at $132,409 and mining engineers at $126,190.

Figure 4:

Top 10 Tech Occupations by Average Earnings in Canada, 2016



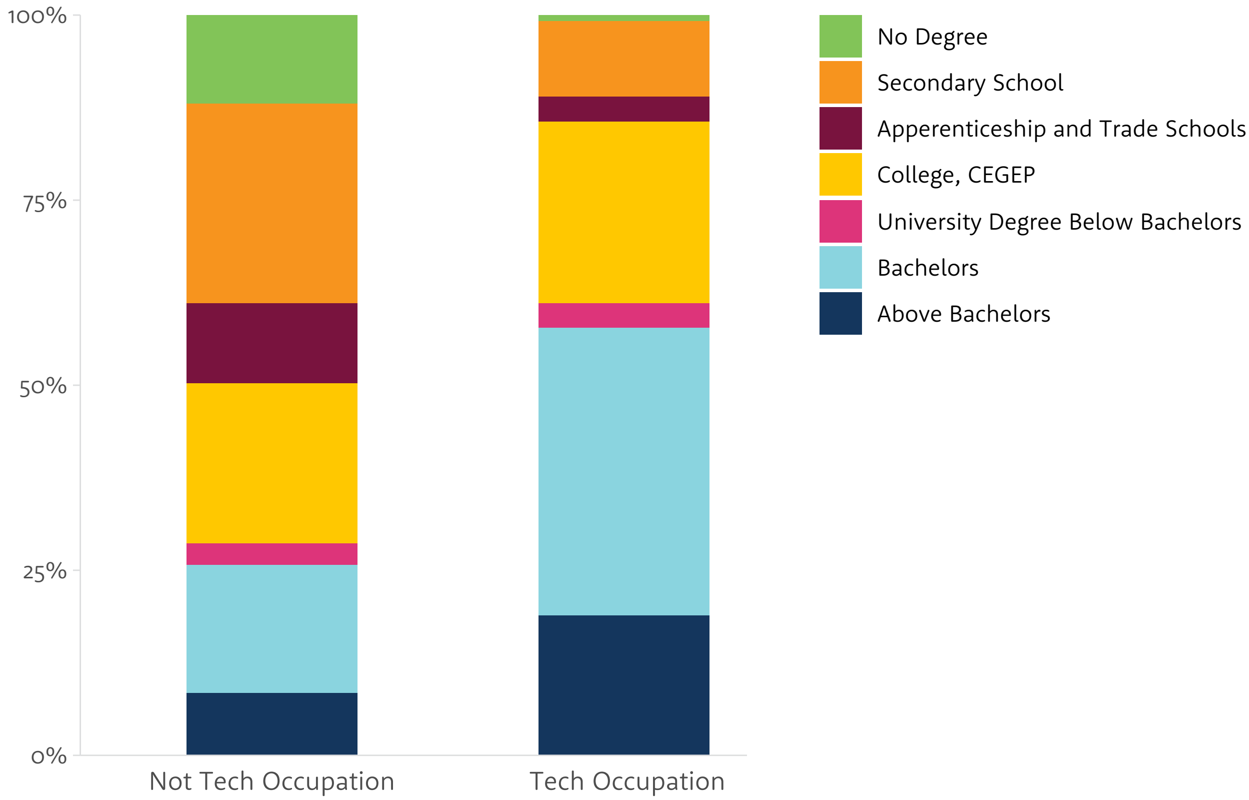
Source: 2016 Canadian Census

EDUCATION

Tech workers have higher levels of formal education on average than non-tech workers. The majority of tech workers (57.8 percent) held at least a Bachelor's degree in 2016, and only a minimal number (0.8 percent or around 14,000 people) held no degree or diploma. Workers in non-tech occupations, on the other hand, were less likely to hold at least a Bachelor's degree (25.7 percent), and 38.9 percent had either no degree or held only a secondary school diploma.

Figure 5:

Educational Composition of Tech Workers in Canada, 2016



Source: 2016 Canadian Census, BII+E Analysis

AGE

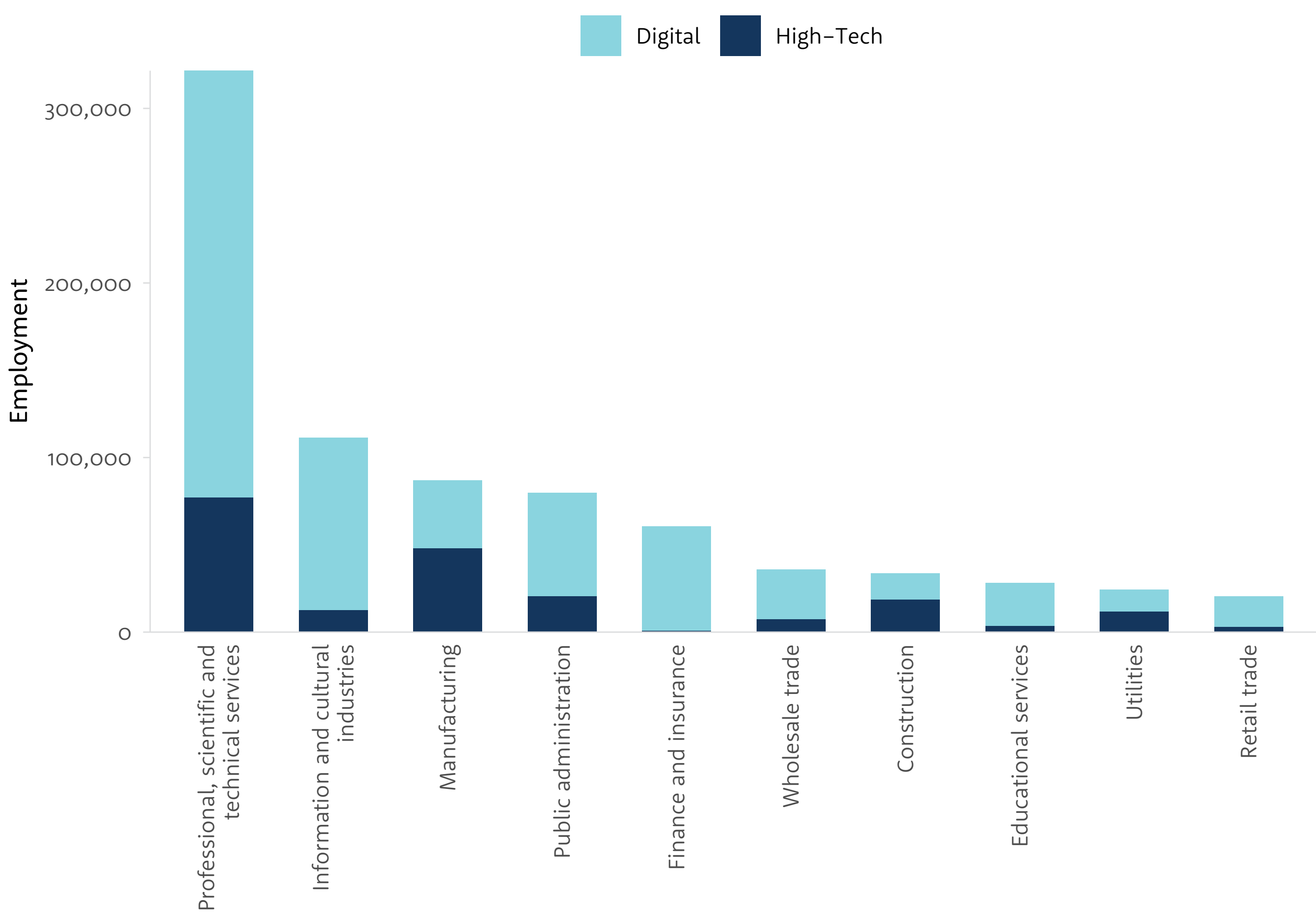
Nearly 53 percent of tech workers in 2016 were between the ages of 25 and 44, while over 38 percent were between 45 and 64.

Age Group	# of Tech Workers	Share of Tech Workforce	Participation in Tech	Pay in Tech	Pay in non-Tech Occupations
15 – 24	57,000	5.9%	2%	$26,400	$15,500
25 – 44	514,000	52.8%	6.5%	$72,100	$45,300
45 – 64	373,000	38.3%	4.9%	$92,000	$52,300
65 and over	28,000	2.9%	2.6%	$67,900	$38,000

INDUSTRIES

Figure 6:

Number of Tech Workers Employed by Industry Groups



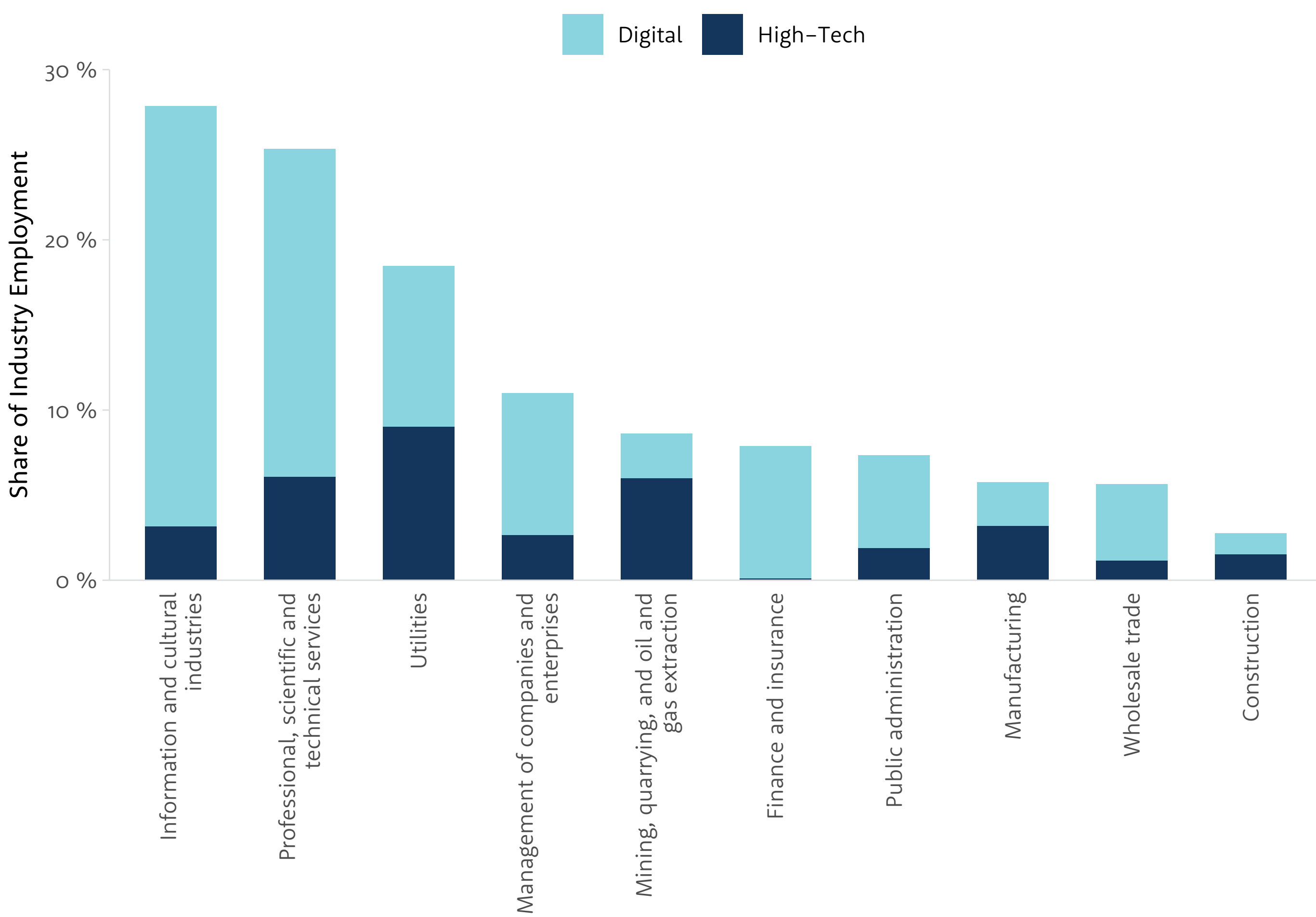
Source: 2016 Canadian Census, BII+E Analysis

Among industries, the greatest number of tech workers are in *Professional, Scientific, and Technical Services*, distantly followed by *Information and Cultural Industries*. The makeup of tech workers varies by industry. For instance, *Manufacturing* employs a large number of engineers and other high-tech workers. Meanwhile, the relatively large number of tech workers in *Public Administration* and *Finance* is driven by their large digital workforce, particularly Information Systems Analysts and Consultants, which accounted for about 21,000 workers in each industry.

Information and Cultural Industries have the highest concentration of tech workers at 28 percent, primarily digital. *Utilities* had the highest concentration of high-tech workers at 9 percent, while the *Finance and Insurance* sector's tech workforce is almost entirely digital.

Figure 7:

Share of Tech Workers by Industry Groups



Source: 2016 Canadian Census, BII+E Analysis

CITIES

The top five cities by tech worker employment were Toronto with 238,000, Montréal with 140,000, Vancouver with 82,000, Ottawa with 69,000, and Calgary with 63,000.

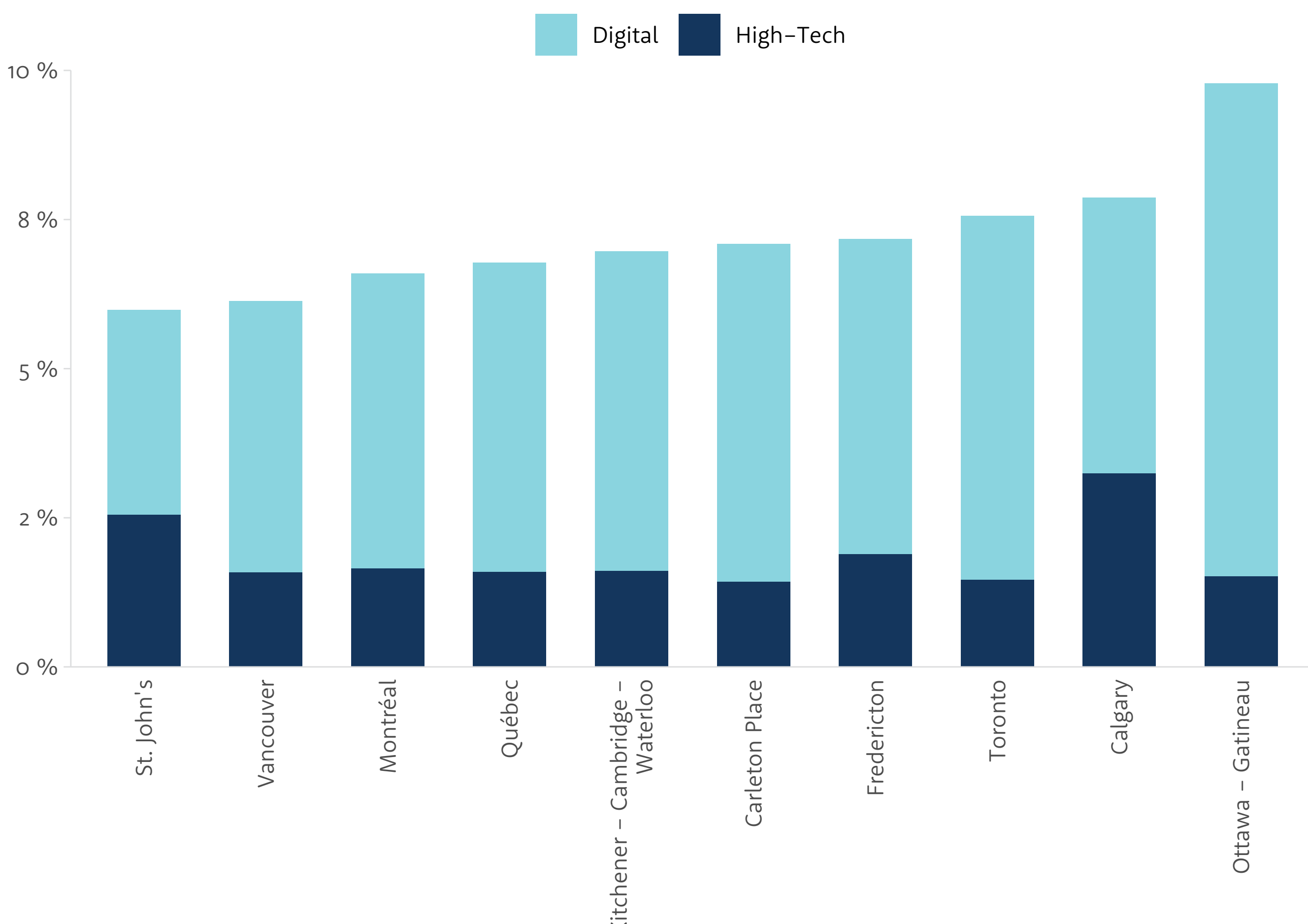
The cities across Canada with the highest concentration (proportion of the labour force occupied by tech workers) were Ottawa with 9.8 percent, Calgary with 7.9 percent, Toronto with 7.6 percent, Fredericton with 7.2 percent, and Waterloo Region with 7 percent. Digital workers make up the majority of tech workers in these cities; however, Calgary also has a large share of high-tech workers, presumably the result of a large number of engineers working in the region's resource sectors.

Between 2006 and 2016, Toronto and Montréal saw the largest absolute increase in the number of tech workers, with the cities adding 53,000 and 33,000 tech workers over the 10-year period, respectively. Meanwhile, Kitchener-Waterloo and Fredericton saw the largest increase in the concentration of tech workers over the same 10-year period. Kitchener's tech employment grew from 5.5% of their total workforce to 7 percent, while Fredericton's grew from 6 percent to 7.2 percent.

Learn more about your city's tech workforce with our data visualization for every city in Canada.

Figure 8:

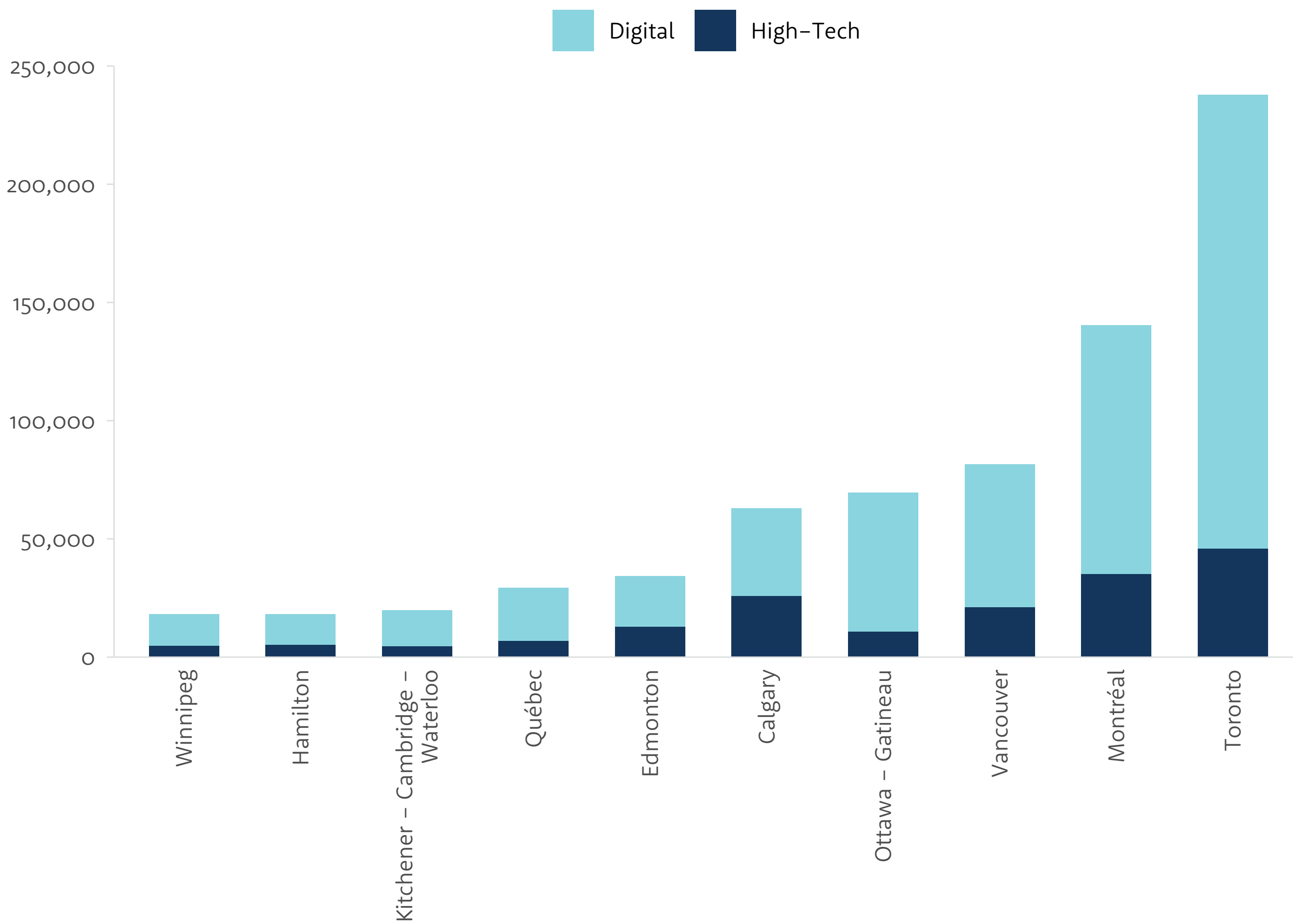
Concentration of Tech Workers by Cities in Canada



Source: 2016 Canadian Census, BII+E Analysis

Figure 9:

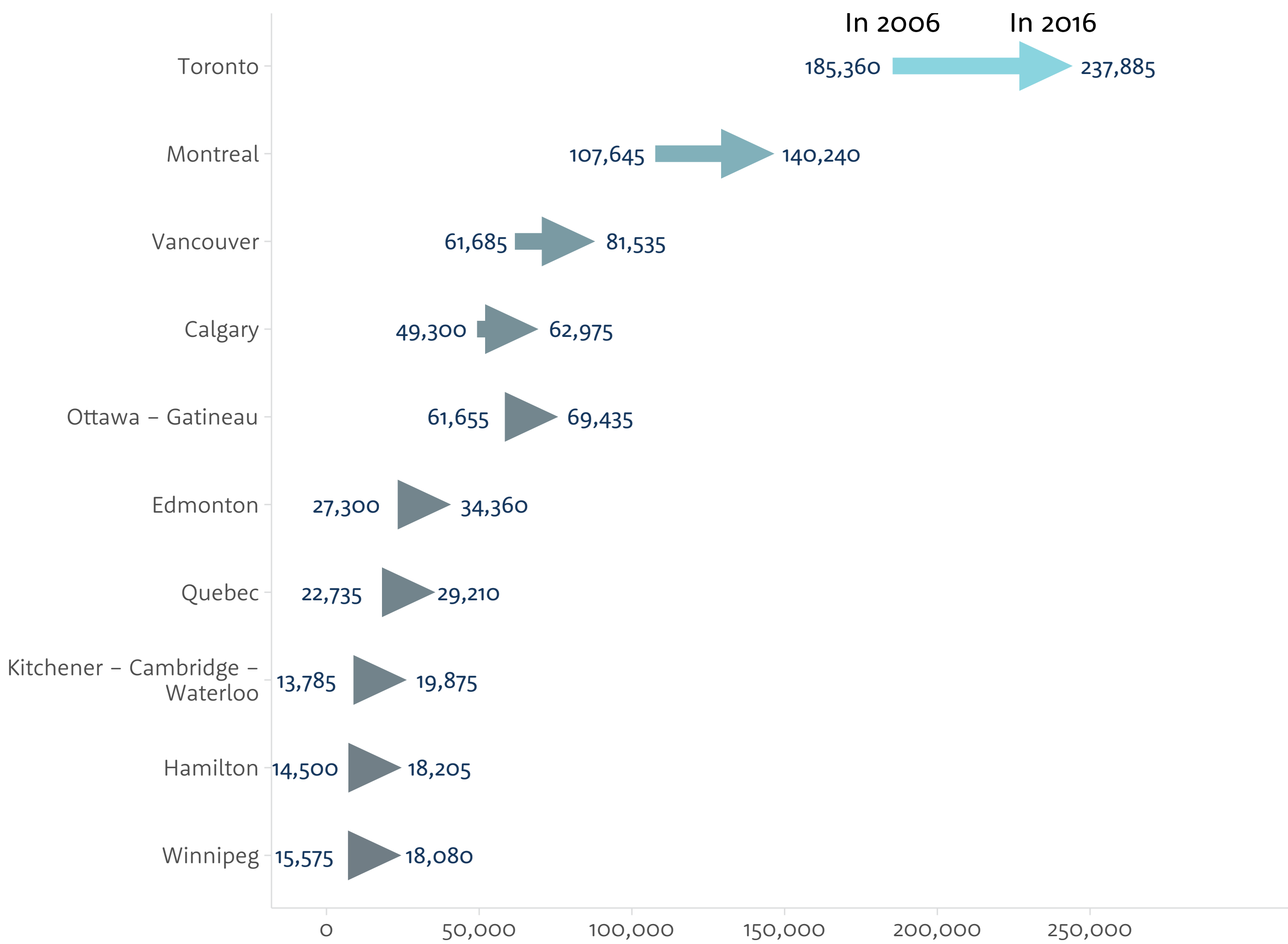
Tech Occupations Employment by Canadian Cities



Source: 2016 Canadian Census, BII+E Analysis

Figure 10:

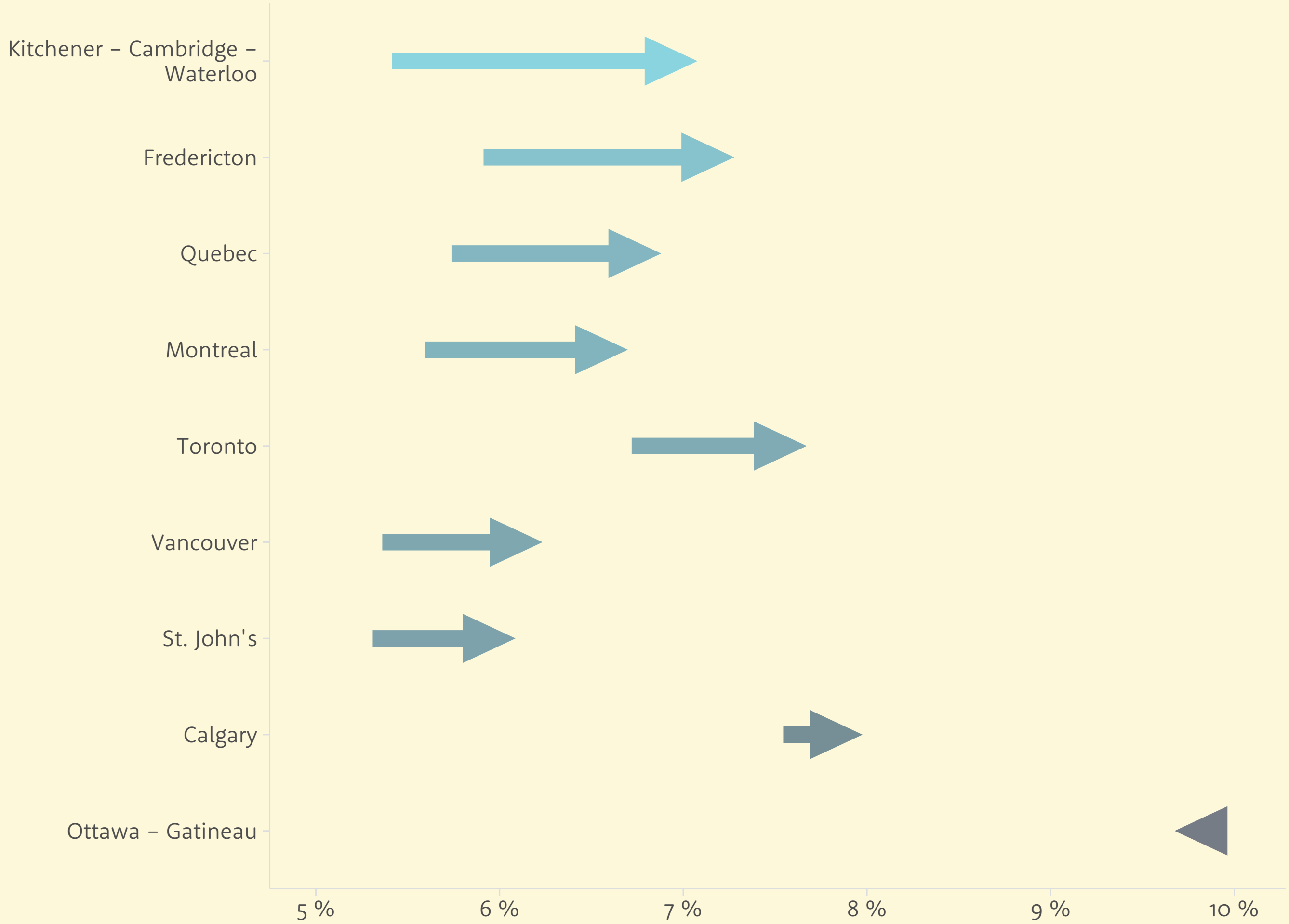
10 Years Change in Tech Occupations Employment for Canadian Cities, 2006-2016



Source: 2016, 2006 Canadian Census

Figure 11:

10 Years Change in Share of Employment for Canadian Cities



Source: 2016, 2006 Canadian Census

PART 2: DIVERSITY IN TECH OCCUPATIONS

In this section we examine diversity among tech workers, looking specifically at the earnings and participation of women, visible minority groups, immigrants and Indigenous Peoples.

WOMEN ARE UNDERREPRESENTED, AND RECEIVE LOWER SALARIES IN TECH OCCUPATIONS

Our findings

There are serious participation and earnings disparities between men and women in tech.

Men are four times more likely than women to be in a tech job; and over the past 10 years, growth in the number of tech workers has been primarily driven by an increase in the share of male tech workers between the ages of 45 and 64. There is also a stark pay gap between men and women in tech occupations, with women earning on average $7,300 less than their male counterparts.[6]

Women in tech occupations are more likely to hold a Bachelor's degree or higher. However, when comparing women and men in tech with a Bachelor's degree or higher, the simple pay gap is much higher at $19,570. The pay gap between men and women is greater for older workers, which might indicate that pay differentials increase as careers progress or might reflect an improvement in pay equity in recent years.

Context

These findings unfortunately do not come as a surprise. It has long been the case that gender representation and earnings in tech occupations are far from equal. A significant body of research suggests that barriers to entering tech roles begin early in life for women: influences from families, teachers, role models, and cultural stereotypes can impact women's decisions to engage in subjects that set them up for tech roles later in life. There is also evidence pointing to a male-dominated culture in science, technology, engineering and mathematics (STEM) education, and to discrimination in hiring or on the job. These barriers can steer women away from STEM majors, and impact their career opportunities and trajectories in tech. While women have long surpassed men in attaining a bachelor's degree or higher, they remain underrepresented in STEM education programs.[7] These trends continue into the labour market in the form of lower participation in science and tech occupations. Previous studies have also highlighted that women tend to be paid less, both within the same occupations and across occupations. Furthermore, the gender pay gap grows as careers progress and salaries increase, resulting in particularly stark differences at the top of the wage distribution.

Gender participation in tech occupations

Labour force participation among women in Canada has been steadily increasing. In 1983, 65.2 percent of Canadian women between 25 and 54 participated in the labour market. By 2015, this figure had rose to 82 percent. Canada now has the lowest gender participation gap of all G-7 countries. In 2016, women made up 48 percent of the labour market, compared to 45 percent in 1991.

Despite these trends, in 2016 there were 584,000 more men in tech occupations than women. **Men were almost four times more likely than women to work in a tech occupation**.

Table 1:

Tech Workers by Gender

Gender	# of Tech Workers	Share of Tech Workforce	Participation in Tech
Men	778,000	80%	7.8%
Women	194,000	20%	2.1%

FOR THE PAST 10 YEARS, GROWTH IN TECH OCCUPATIONS HAS PRIMARILY BEEN DRIVEN BY AN OLDER MALE COHORT

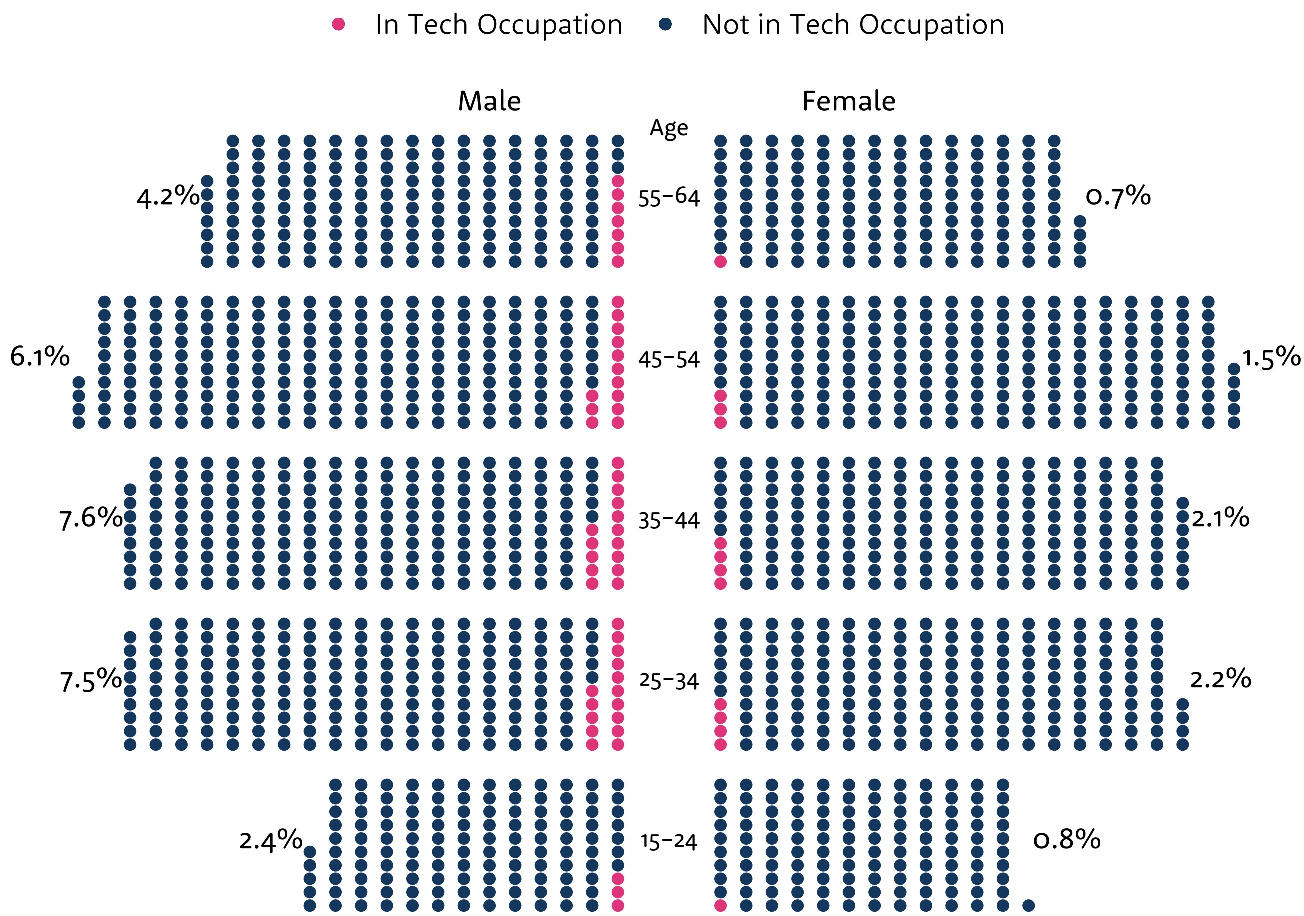
Women have dramatically increased their participation in the labour force writ large. But the participation rate among women in tech occupations was much lower than men across all age groups.

As a result, growth in the number of tech workers from 2006 to 2016 was primarily driven by an older male cohort (see full methodology in Appendix B). Tech workers between the ages of 45 and 64 years old accounted for nearly 90 percent of the 189,000 person increase in tech workers across the Canadian economy. Men in this age range were responsible for 79 percent of the total growth, adding nearly 129,000 tech workers.

Women participate at lower rates in tech, for all age groups

Figure 12:

Employment in Tech Occupations by Age and Sex, 2016



Source: 2016 Canadian Census, BII+E Analysis,
Note: Each point represents 1,000 people

Table 2:

Age and gender contribution to tech job growth, 2006 to 2016

	Age						
Sex	15-24 Years	25-34 Years	35-44 Years	45-54 Years	55-64 Years	65-74 Years	Total effect
Male	-7% (-12,800 workers)	5.4% (9,900 workers)	13.1% (24,000 workers)	33.9% (62,000 workers)	36.5% (66,800 workers)	7.6% (13,900 workers)	89.5%
Female	-1.4% (-2,600 workers)	-2.8% (-5,100 workers)	-5.6% (-10,200 workers)	7.9% (14,500 workers)	11.3% (20,700 workers)	1% (1,800 workers)	10.5%
Total effect–Age	-8.4%	2.6%	7.5%	41.8%	47.8%	8.6%	

The largest differences in participation among men and women in tech occupations were for those aged 25 to 44. While a large cohort of younger workers are entering tech occupations, women between the ages of 25 and 44 saw an overall decrease in their share of tech occupations from 2006 to 2016. During this period, the total number of women in the labour market aged 25 to 34 increased, but without a corresponding increase in the number of women working in tech occupations.

Further research is needed to explain these trends. Are fewer younger workers entering tech occupations? Or is this simply reflective of broader demographic trends, in particular, an aging population?

Men earn significantly more than women in tech occupations and this pattern is consistent across different demographic groups

Men are not only much more likely to work in a tech occupation than women; they also earn higher salaries than their female counterparts. With an average salary of $76,200, men in tech occupations earn on average $7,300 more than women in tech occupations.

Table 3:

Gender differences in pay for tech occupations

Sex	Pay in Tech	Pay in non-Tech Occupations
Male	$76,200	$49,500
Female	$68,900	$39,400

However, women in tech occupations experienced a higher tech pay premium, earning 74.6 percent or $29,500 more on average than women in non-tech occupations. This compared to men in tech occupations who earned 54 percent or $26,700 more than men in non-tech occupations. On average, the pay gap between men and women in tech occupations is smaller, by approximately $3,000 per year, compared to the pay gap in non-tech occupations.

The average pay gap between men and women in tech occupations gets larger the more education a worker has

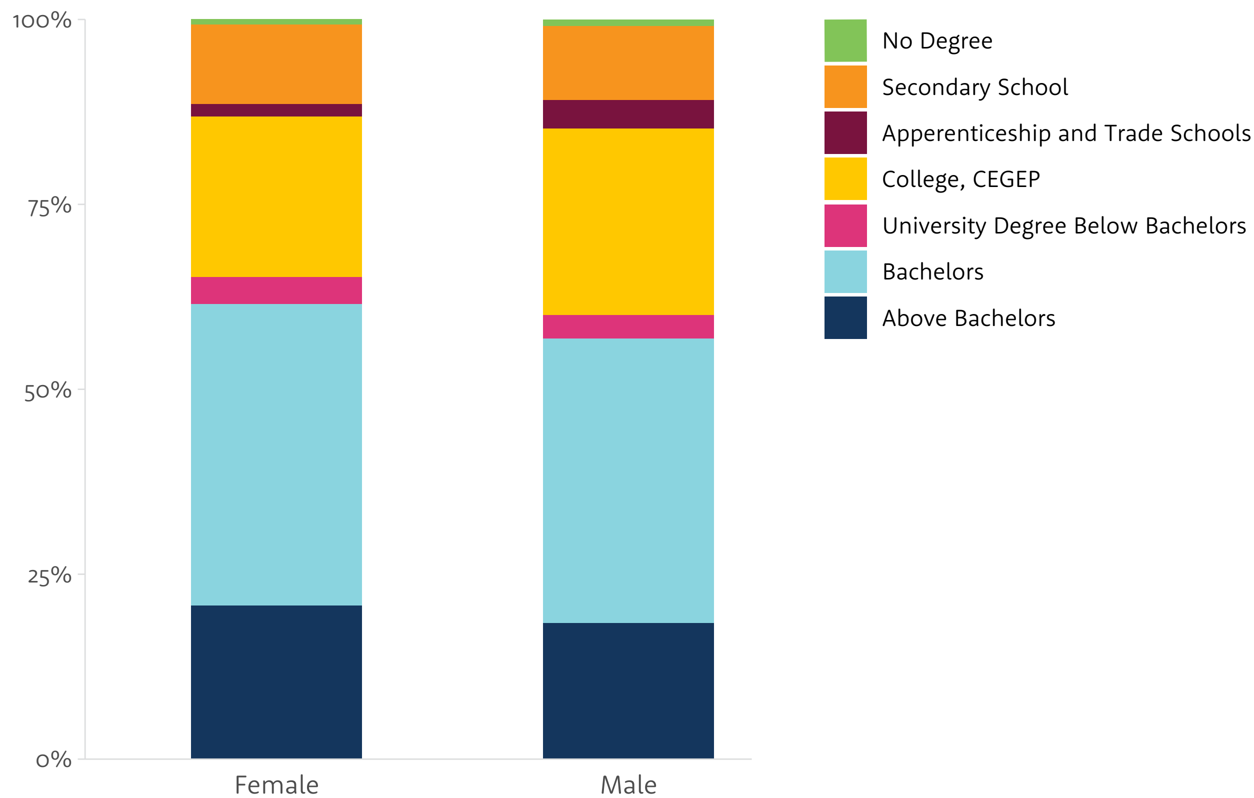
Within tech occupations, there are some notable gender differences when it comes to educational attainment and fields of study. However, preliminary analysis suggests the gender pay gap gets larger with more education.

Differences in education for women and men in tech occupations

There are two critical differences between men and women in tech occupations when it comes to education. First, a higher number of men (34.5 percent compared to 23.4 percent of women) in tech occupations received their education through colleges, apprenticeships or trade schools. Women are more likely to hold a Bachelor's degree or higher (61.5 percent compared to 56.9 percent of men), which is consistent with broader trends in higher education enrolment.

Figure 13:

Educational Composition by Sex, Tech Occupations, 2016



Source: 2016 Canadian Census, BII+E Analysis

Second, men and women tend to specialize in different fields. Looking at the top three areas that tech workers have majored in highlights these differences. 43.9 percent of men in tech occupations majored in *Architecture, Engineering, and Related Technologies*, compared to 25.3 percent of women. In contrast, *Business, Management, Marketing, and Related Studies* is a more popular area of concentration among women in tech occupations, with just over 15 percent majoring in these fields, compared to 10 percent of men in tech occupations. Interestingly, the share of men and women in tech occupations who majored in "mathematics, computer science and informational sciences" is roughly equivalent.

Differences in educational attainment do not explain the simple gender pay gap in tech occupations

Despite differences in educational attainment between men and women in tech occupations, the simple pay gap is, in fact, larger for tech workers with a bachelor's degree or higher.

We use a regression framework (see Appendix C) that draws on aggregated-level data to separate the effect of education and sex on pay and explore how they interact with each other. While this by no means constitutes a full exploration of the gender pay gap in tech occupations, it illuminates an interesting dimension of this gap.

The simple pay gap between male and female tech workers without a bachelor's degree is about $7,500. For those with a bachelor's degree or higher, however, the pay gap grows to about $19,600. Additionally, a man with a bachelor's degree or higher earned $27,400 more than a man without a bachelor's. By comparison, women with a bachelor degree or higher earned only $15,000 more than women without a bachelor's.

Table 4:

Pay by gender and degree

	Below bachelor's degree	Bachelor and above
Male	$67,600	$95,100
Female	$60,200	$75,500

Table 5:

Does education explain the simple gender pay gap?

Parameter	Estimate (without standard error)
β_0 Earnings for men without a bachelor's in tech occupation	$67,600
β_1 Earnings difference between men and women in tech without a bachelor's	-$7,500
Earnings for women without a Bachelors in tech	$60,200
β_2 Difference in earnings for men in a tech occupation with a bachelor's, compared to men in a tech occupation without a bachelor's	$27,400
Earnings for men with a bachelor's degree or higher in a tech occupation	$95,100
β_3 Difference in the bachelor's premium for women compared to men	-$12,100
Earnings for women with a bachelor's degree or higher in a tech occupation	$75,500
Earnings difference between men and women in tech with a bachelor's degree or higher	-$19,600

The simple gender pay gap also gets larger the longer workers are in tech occupations

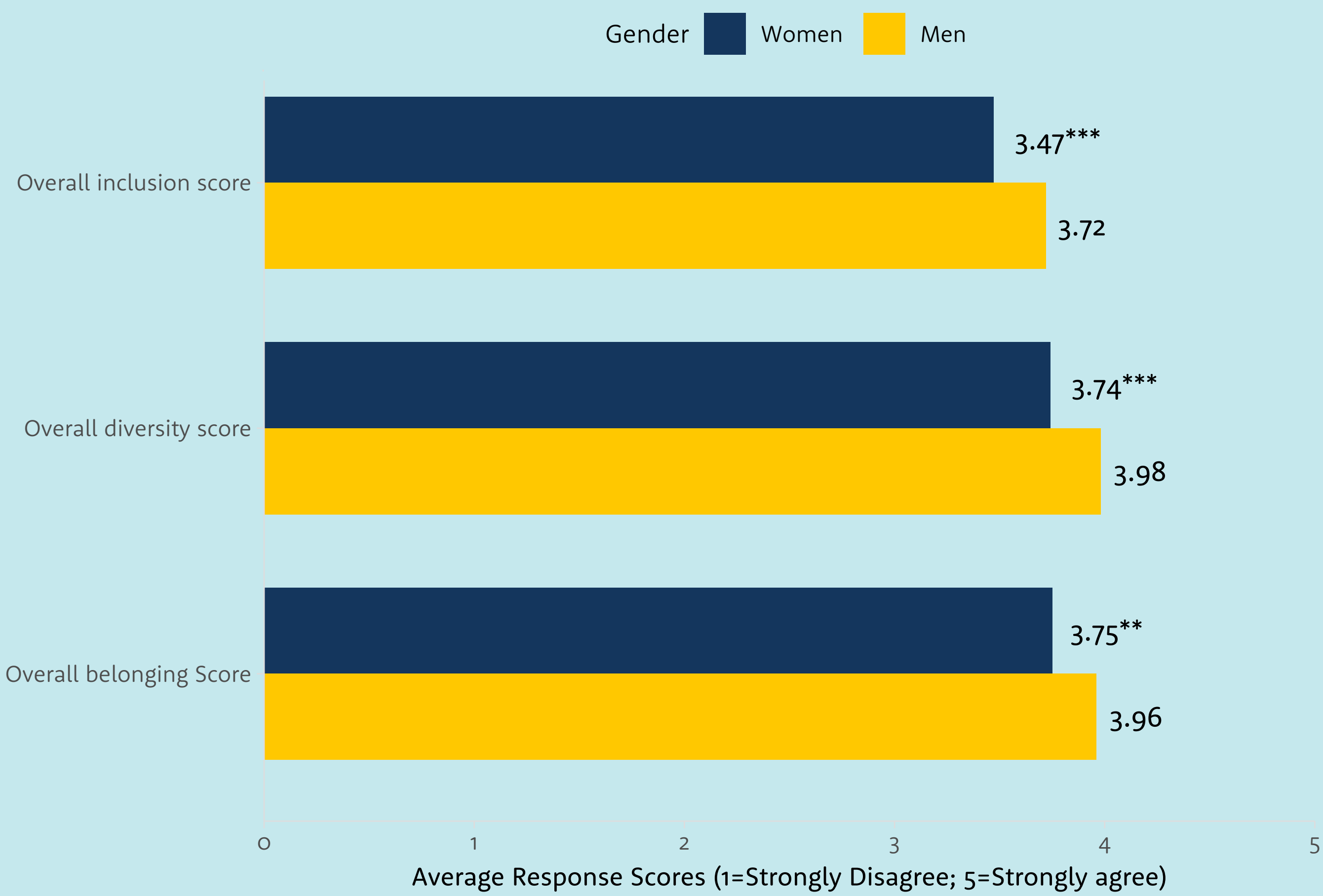
Similar to participation rates, the simple pay gap between men and women is larger for older tech workers (45 to 64 years old), at $11,600, while for younger tech workers (25 to 44 years old) it is $8,600. This could signal, consistent with other studies, that the gender pay gap increases as individuals progress through their careers, gaining experience and in some cases seniority. However, it could also indicate that the simple pay gap in tech occupations is shrinking over time, with younger tech workers experiencing smaller pay gaps than their older counterparts. Further investigation is needed to understand this relationship.

MaRS DIVERSITY, INCLUSION, AND BELONGINGS SURVEY: WOMEN REPORT LOWER LEVELS OF DIVERSITY, INCLUSION AND BELONGING IN TECH

In 2018, MaRS, Feminuity, and Fortay conducted a survey to examine diversity, inclusion, and belonging in Toronto's tech sector. While its focus on workers in Toronto's tech sector differs from this report's focus on tech workers across Canada's economy, the results of this survey help to illuminate some of the challenges facing women in tech.

Figure 14:

Toronto Tech sector DIB Scores by Respondent Gender



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level; ** at the 5% level; * at the 10% level; N = 425*

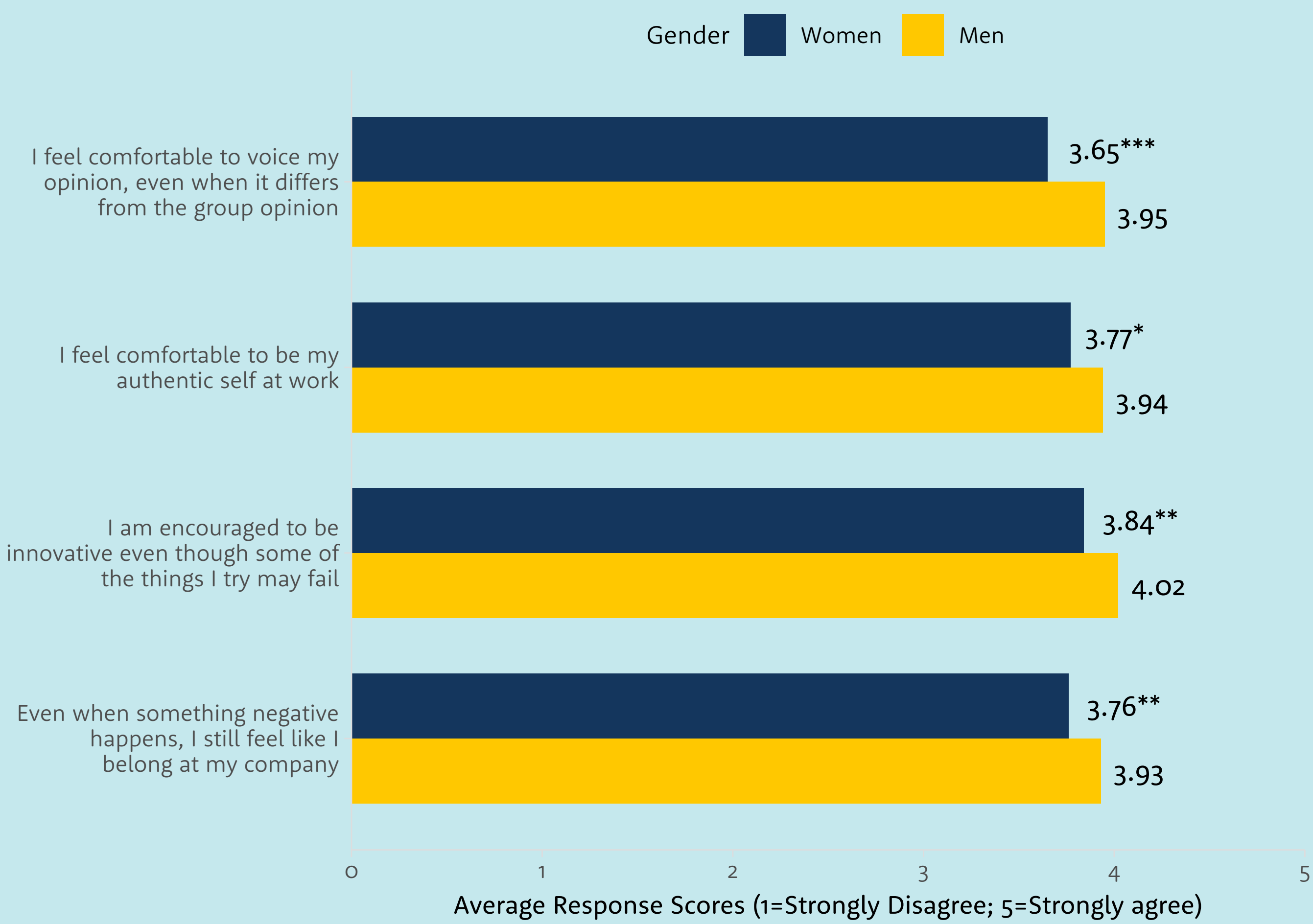
Overall, women in Toronto's tech sector reported lower levels of diversity, inclusion and belonging compared to men.[8]

This lower sense of belonging among women in Toronto's tech sector includes feeling less comfortable being their authentic self, voicing an opinion (in particular one that differs from the group consensus), being innovative even if it means failing, and feeling a sense of belonging even if something negative happens.

Additionally, women in Toronto's tech sector also feel less engaged in decision-making processes at work and are more likely to believe that the division of labour and the distribution of salaries and benefits are unfair.

Figure 15:

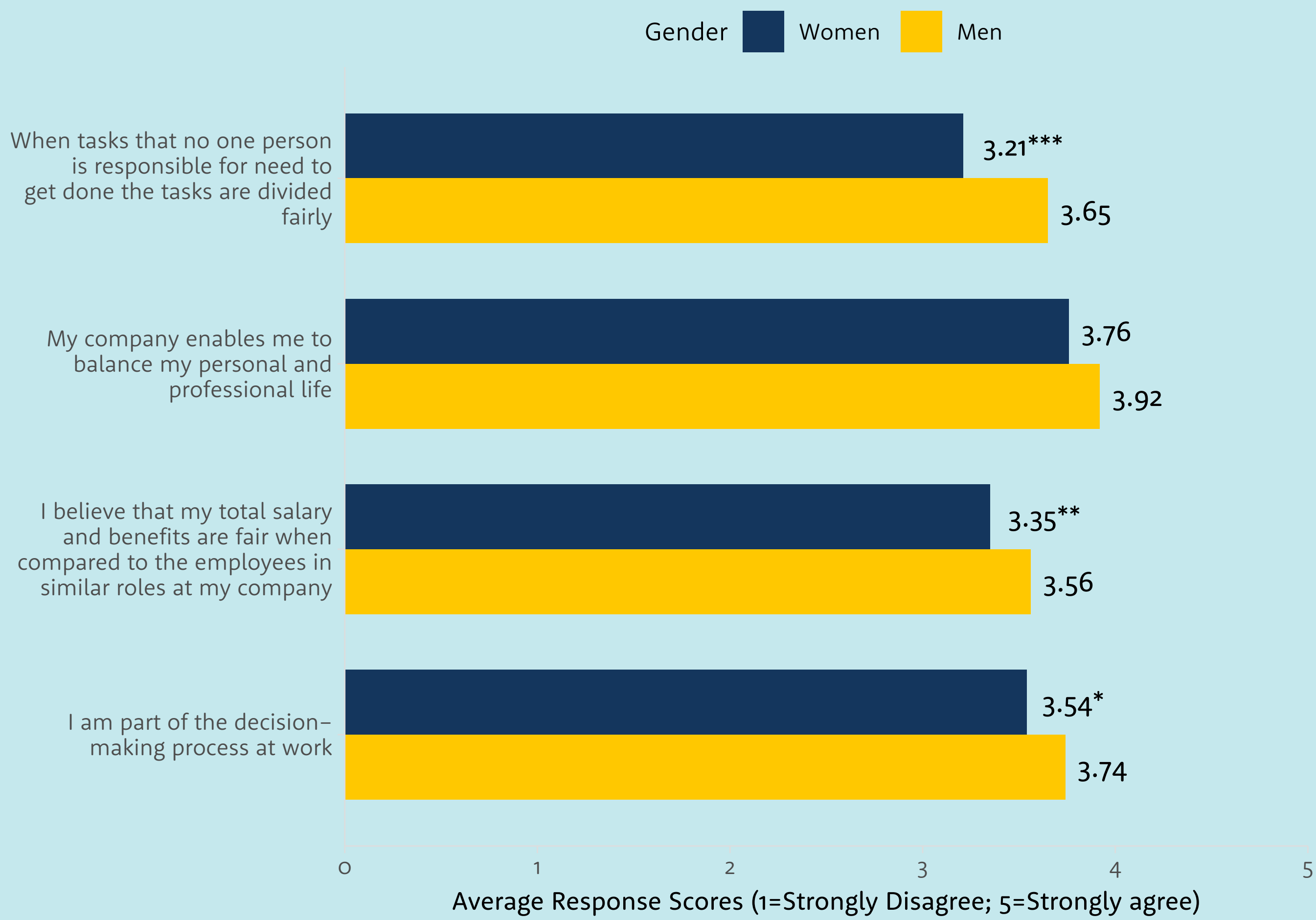
Toronto Tech Sector Belonging Scores by Respondent Gender



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

Figure 16:

Toronto Tech Sector Inclusion Scores by Respondent Gender



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

TECH WORKERS ARE DIVERSE, BUT SOME GROUPS ARE UNDERREPRESENTED AND EARNINGS ARE NOT EQUAL

Our findings

Diversity in Canada's tech occupations is, in general, high relative to the Canadian labour market as a whole; however certain groups are underrepresented and receive less pay. Visible minorities made up 31.9 percent of Canada's tech workers and were more likely to work in tech occupations than non-visible minorities. In addition, 37.6 percent of Canada's tech workforce are immigrants, and immigrants are twice as likely to work in tech careers compared with non-immigrants. However, participation rates for Black, Filipino, and Indigenous populations are low. There is also a significant pay gap for most visible minority groups—particularly for Black tech workers—relative to White and non-Indigenous tech workers.

Context

Our findings align with existing, predominantly US-focused, research on diversity in tech occupations, which has highlighted that there are significant barriers faced by certain demographic groups, in particular, Black and Hispanic workers.[9] Studies have shown, for example, that teachers have lower expectations of Black students, particularly when it comes to math, and many underrepresented minorities are less likely to have strong beliefs in their mathematical abilities.[10] Even when Black and Hispanic students major in tech-oriented degrees, they are less likely than their White and Asian counterparts to pursue a career in tech.[11] Some suggest this is the result of biases in recruiting, negative perceptions of the work culture, and encounters with racism on the job. In a study of individuals who voluntarily left tech occupations, "men of colour" were most likely to leave because of perceived unfairness, and nearly one quarter of underrepresented "men and women of colour" who left tech jobs experienced stereotyping, twice the rate of their White and Asian counterparts.

Our findings also reflect Canada's digital divide, which is reinforced by uneven access to technology and training. In particular, many rural and remote communities, including Indigenous communities, lack consistent access to the training programs, high speed and reliable internet, and digital tools that are vital to building and maintaining digital literacy and the advanced skills needed to be competitive in tech fields.

VISIBLE MINORITY TECH WORKERS

Visible minorities are more likely than non-visible minorities to work in tech occupations. 7.6 percent of all visible minorities participated in tech occupations, collectively representing approximately 294,000 people, compared to 4.4 percent of non-visible minorities, representing 641,000 people. Those identifying as Chinese, West Asian, Arab, and South Asian were the most likely to work in tech occupations out of all visible minority groups. On the other hand, those identifying as Filipino or Black had the lowest participation rates in tech occupations.

For most visible minority groups in tech occupations, however, average pay is much lower than for non-visible minority tech workers. This difference in pay is particularly stark for Black tech workers.

Average pay across all visible minorities in tech occupations was $76,300, which is more than $37,000 higher than the average pay that visible minorities received in non-tech occupations. However, it was $3,100 lower than for non-visible minorities in tech occupations. Black tech workers were the lowest paid out of all visible minority groups. Their average salary was $63,000 in 2016, over $13,000 less than the average across all visible minority groups in tech occupations, and over $16,000 lower than non-visible minorities in tech occupations.

Table 6:
Visible Minorities in Tech Occupations

Visible Minority	# of Tech Workers	Share of Tech Workforce[12]	Participation in Tech	Pay in Tech	Pay in non-Tech Occupations
Not a Visible Minority	641,000	68.6%	4.37%	$79,400	$46,800
All Visible Minorities	294,000	31.4%	7.65%	$76,300	$38,700
South Asian	79,000	9.2%	8.92%	$74,000	$40,100
Chinese	91,000	9.8%	11.94%	$79,700	$42,700
Black	24,000	2.6%	4.27%	$63,000	$35,900
Filipino	16,000	1.7%	3.4%	$69,000	$37,400
Latin American	16,000	1.7%	6.08%	$72,900	$35,700
Arab	19,000	2%	9.14%	$70,000	$36,000
Southeast Asian	10,000	1.1%	6.06%	$72,300	$35,900
West Asian	13,000	1.4%	10.14%	$69,000	$33,300
Korean	6,000	0.6%	6.39%	$68,100	$34,700
Japanese	3,000	0.3%	6.37%	$84,400	$45,300

Visible minority women in tech

Disparities in pay are even starker for women tech workers belonging to visible minority groups. For the most part, women receive lower compensation than men across all visible minority groups, receiving, on average, $10,900 less than their male counterparts in tech occupations. However, non-visible minority and Chinese women, with average salaries of $71,480 and $73,430 respectively, do earn more than many visible minority men in tech, notably Black, West Asian, and Korean men.

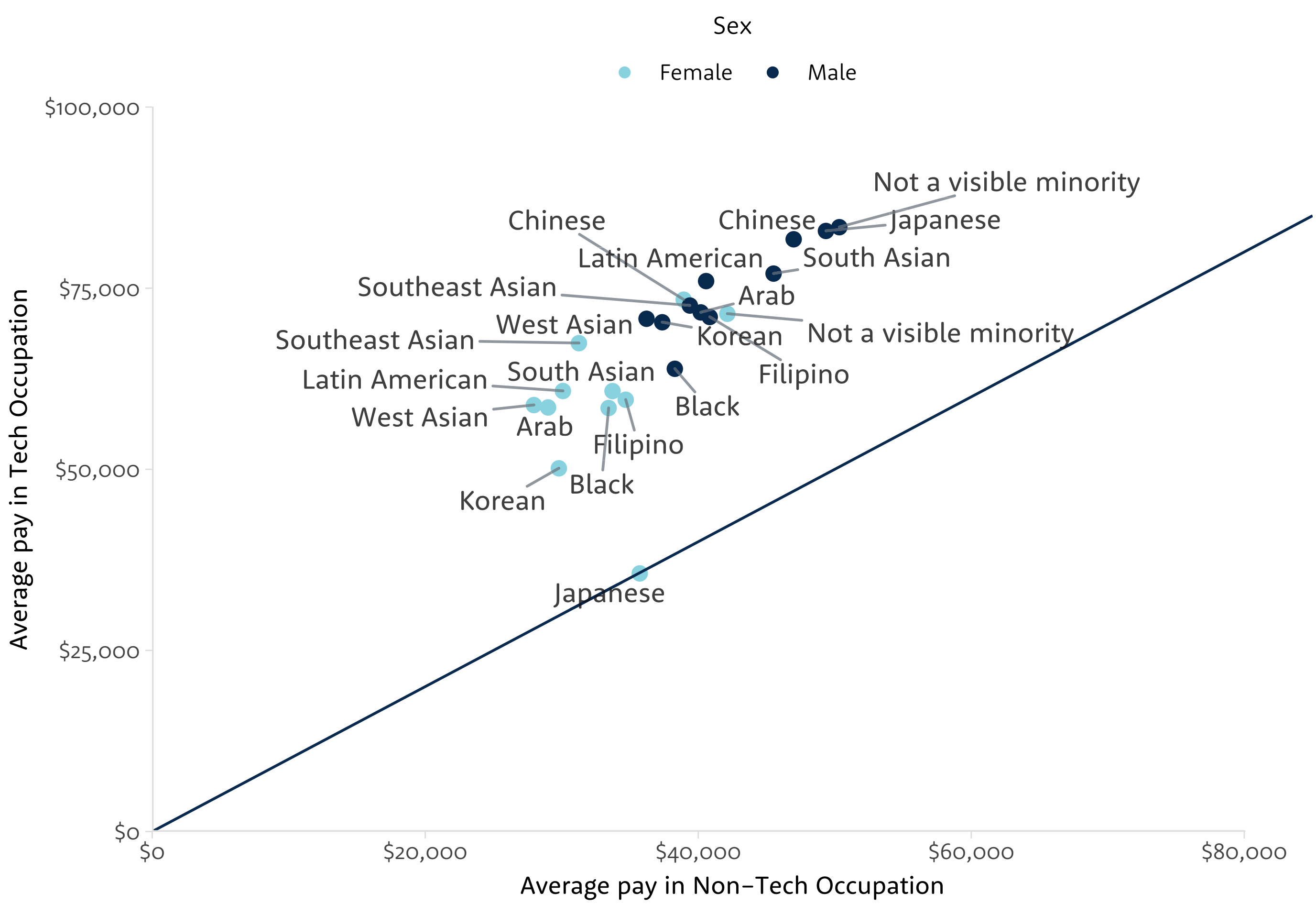
Amongst women in tech occupations, visible minority women earn less than all non-visible minority women. Women who identify as Korean (average salary $50,150), West Asian (average salary $58,880), Black (average salary $58,480), Arab (average salary $58, 550), and Filipino (average salary $59, 620) earn the least in tech occupations.

However, for both men and women across visible minority groups, there is a pay premium for working in tech occupations that on average 20.6 percent higher than the pay received by each group in non-tech occupations.[13]

With the exception of Chinese women, all women from visible minority groups participated in tech occupations at rates lower than men from the same visible minority groups. Participation rates are highly correlated with the average salary for men and women across visible minority groups, as shown in Figure 18.

Figure 17:

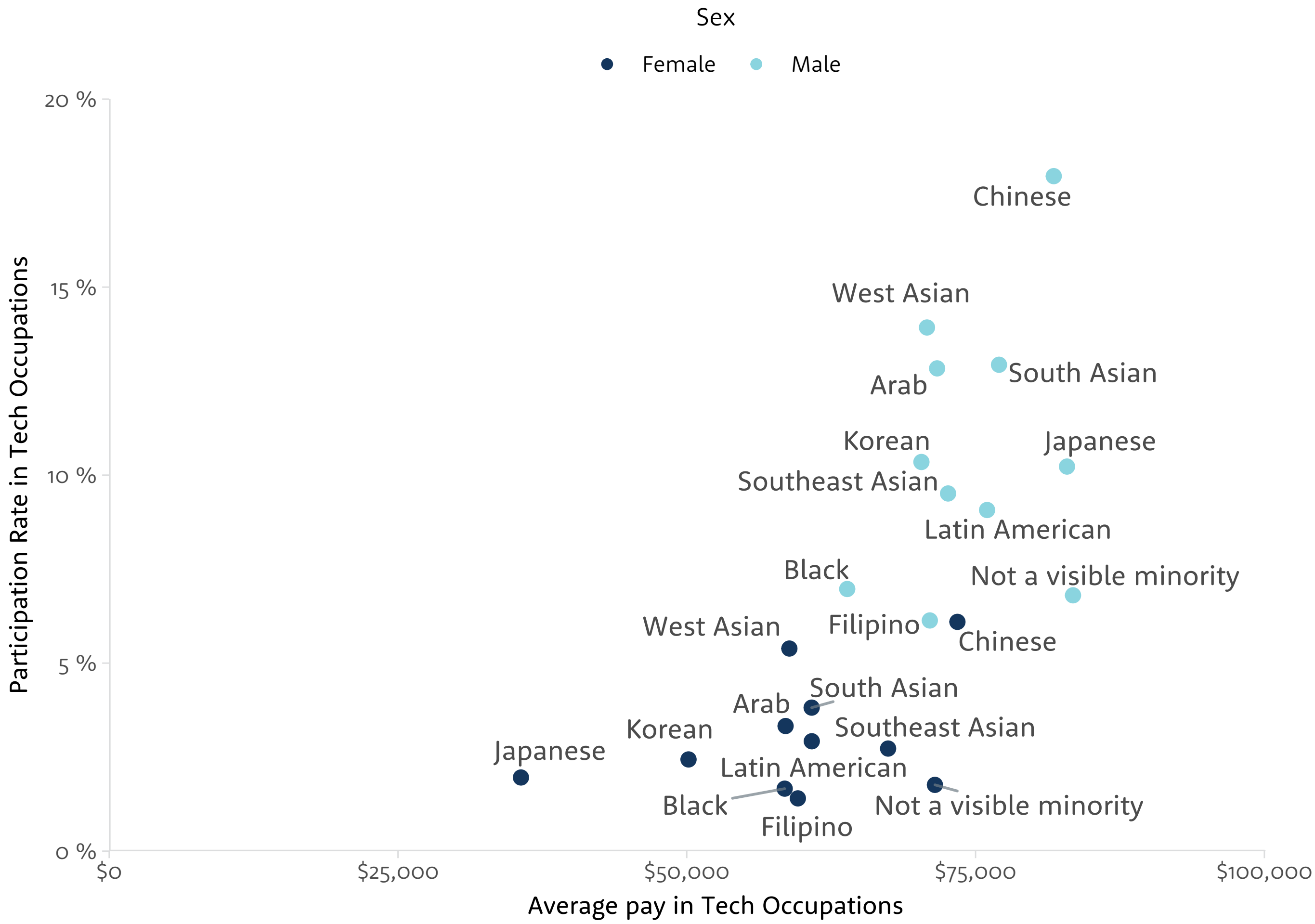
Pay Difference between Tech and Non-Tech Occupations by Visible Minority Identities and Sex



Source: 2016 Canadian Census
Note 1: Each point represents a Visible Minority – Sex pair
Note 2:Drawn With 45 Degrees Line

Figure 18:

Pay and Participation by Visible Minority and Sex



Source: 2016 Canadian Census
Note: Each Point Represents a Visible Minority – Sex pair

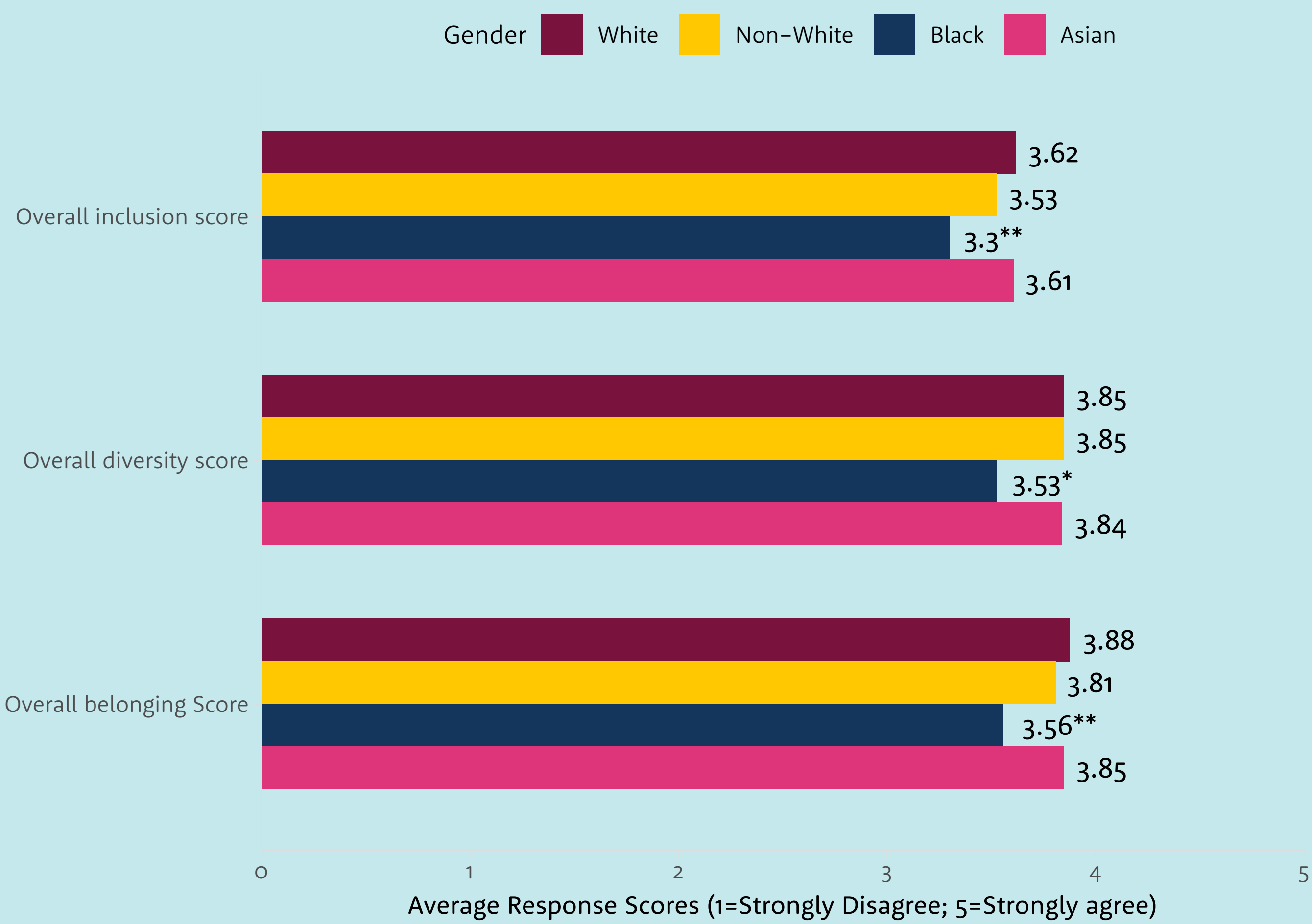
SIMILAR TO WOMEN, BLACK WORKERS IN TORONTO'S TECH SECTOR REPORT LOWER LEVELS OF DIVERSITY, INCLUSION AND BELONGING

Once again, drawing upon the survey conducted by Feminuity, MaRS, and Fortay, we see similar trends. Black workers in Toronto's tech sector reported lower levels of diversity, inclusion and belonging.

Of those surveyed, Black workers in Toronto's tech sector were less likely to feel that those who are different can thrive at their company compared to White, Asian, and other visible minorities. They also reported feeling less involved in the decision-making process at work; and in line with our findings, they were more likely to feel that their salaries and benefits are unfair compared to other employees in similar roles.

Figure 19:

Toronto Tech Sector Dib Scores By Repondent Race



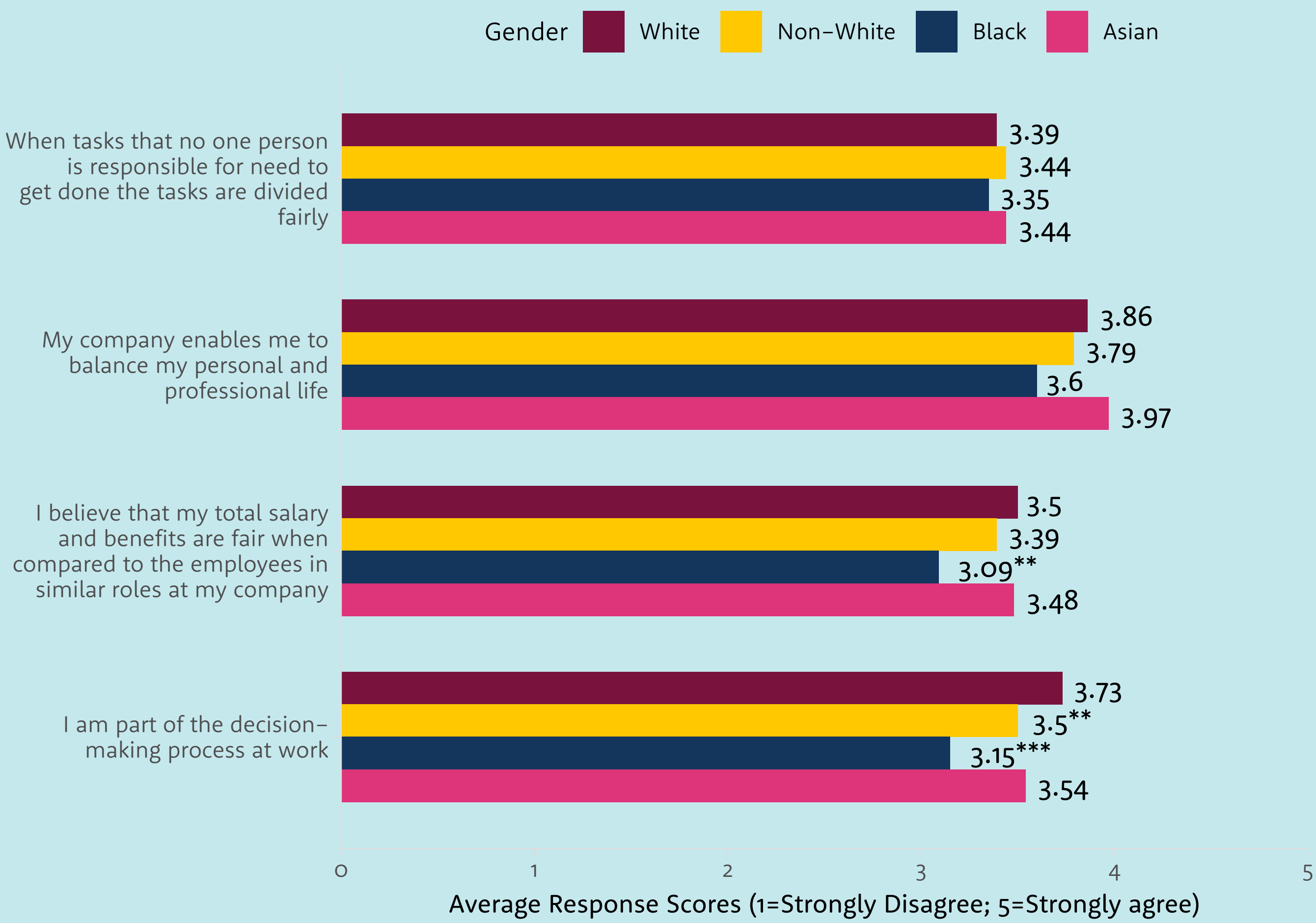
Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

Similar to women, surveyed Black workers in Toronto's tech sector feel less of a sense of belonging than their White, Asian and Non-White counterparts. They feel less comfortable being their authentic self at work, and feel less like they belong when a negative situation arises.

Black workers in Toronto's tech sector were also less likely to feel that their company comprised of a diverse workforce and provided equal opportunities for all workers.

Figure 20:

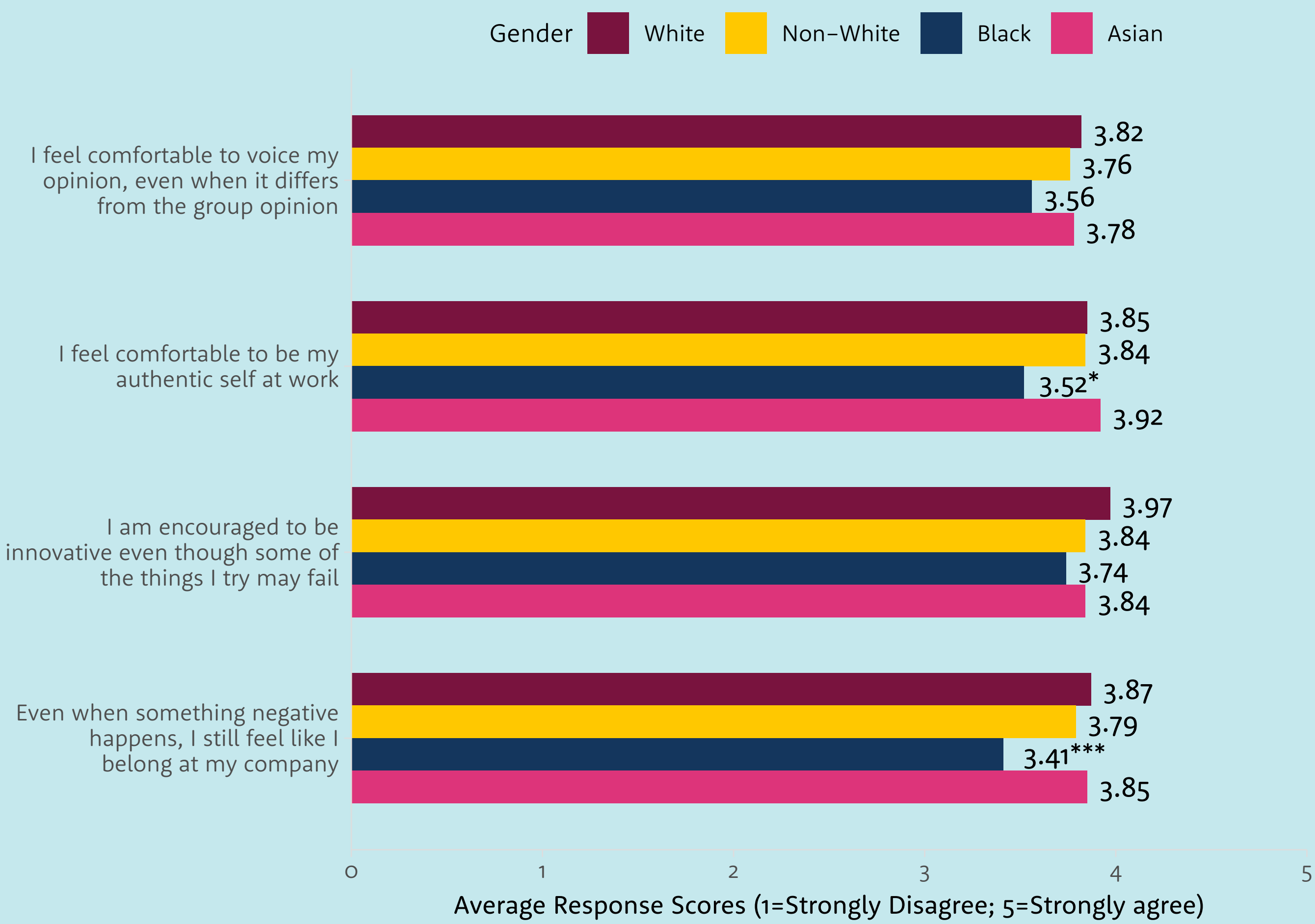
Toronto Tech Sector Inclusion Scores By Respondent Race



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

Figure 21:

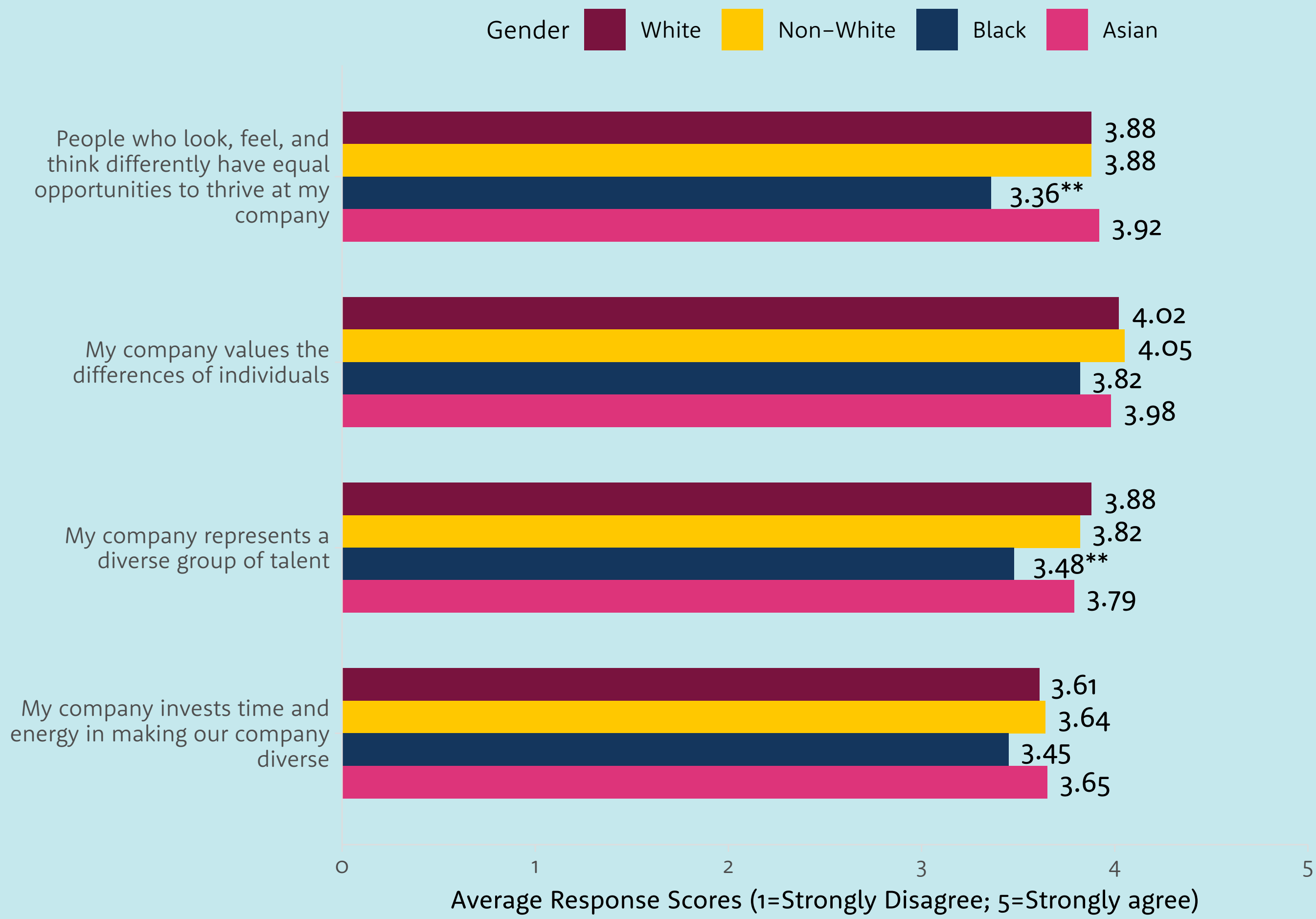
Toronto Tech Sector Belonging Scores By Respondent Race



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

Figure 22:

Toronto Tech Sector Diversity Scores By Respondent Race



Source:MaRS Discovery District analysis using survey dataset powered by Fortay and Feminuity
*Note: *** denotes statistically different from men score at the 1% level;*
*** at the 5% level; * at the 10% level; N = 425*

INDIGENOUS PEOPLES IN TECH OCCUPATIONS

Among enumerated Indigenous Peoples in Canada, participation in tech occupations in 2016 was much lower (at 2.2 percent or 13,000 people) when compared with individuals with non-Indigenous identities (at 5.2 percent or 921,000 people). When this participation rate is examined by the three major groups of Indigenous Peoples in the 2016 Census (First Nations, Inuit, and Métis), significant differences arise. Individuals identifying as Métis had the highest participation rate in tech occupations (2.3 percent or 7,000), comprising half of all those identifying as Indigenous in tech occupations. Those identifying as First Nations and Inuit had lower rates of participation (1.6 percent and 1.3 percent respectively).

Furthermore, those identifying as Indigenous Peoples in tech occupations were paid much less than non-Indigenous tech workers—ranging from $30,000 lower on average for Inuit tech workers, to $3,400 lower for individuals identifying as Métis. However, for both First Nation and Métis, average salaries were higher in tech than in non-tech occupations.

Census and the Indigenous Peoples in Canada

For the Indigenous Peoples in Canada, data collection, use, and ownership can be a complex and controversial issue. Historically, data collected from Indigenous communities has been used to their detriment, helping to perpetuate inequality and discrimination.[15]

Due to this historical context, many Indigenous communities have refused Census enumeration from the government of Canada, leading to incomplete data in the Census. We acknowledge that this may have resulted in important omissions from the data presented in this report. In 2016, 14 reserves and settlements were not enumerated; however, this represents a decrease relative to the 2011 National Household Survey, where 31 reserves were not enumerated (due in part to forest fires) and the 2006 Census, where 22 reserves were not enumerated.[16]

Table 7:

Indigenous Peoples in Tech Occupations

Aboriginal Identities	# of Tech Workers	Share of Tech Workforce[14]	Participation in Tech	Pay in Tech	Pay in non-Tech Occupations
Non-Aboriginal identities	921,000	98.5%	5.2%	$75,100	$45,400
First Nations	5,900	0.6%	1.6%	$64,000	$36,000
Inuit	300	0.03%	1.3%	$45,000	$38,800
Métis	7,000	0.7%	2.3%	$71,700	$43,000

As is the case for other demographic groups, Indigenous women working in tech occupations earned less than their male counterparts. Out of the 300 enumerated Inuit tech workers in 2016, there were no women identified.

Table 8:

Salaries of Indigenous Tech Workers

Sex	First Nations	Métis
Male	$65, 680	$73,350
Female	$52, 270	$55,990

IMMIGRANT TECH WORKERS

Table 9:

Immigrants in Tech Occupations

Immigration Status	# of Tech Workers	Share of Tech Workforce	Participation in Tech	Pay in Tech	Pay in Non-Tech Occupations
Non-immigrant	584,000	62.5%	4.1%	$78,200	$45,700
Immigrant	351,000	37.5%	8.6%	$82,500	$43,900

Immigrants in Canada are well represented in tech occupations. In 2016, immigrants made up 37.5 percent of tech workers, representing around 351,000 people. They were also twice as likely as non-immigrants to be tech workers—almost 9 percent of immigrants are in tech occupations compared to four percent of non-immigrants. Additionally, immigrant tech workers received slightly higher pay on average than non-immigrant tech workers. They also experienced a higher pay premium for working in a tech job compared to a non-tech job.

Immigrant men received compensation on par with non-immigrant men in tech occupations. Immigrant women receive the highest pay-premium for working in a tech occupation, but still earn less than non-immigrant women in tech.

Immigrant women experienced the highest premium for working in a tech occupation, earning 93 percent or $33,900 more than immigrant women not in tech occupations. At 3.55 percent, immigrant women also worked in tech occupations at a rate more than twice that of non-immigrant women (1.64 percent).

Immigrant men are paid better than non-immigrant men in tech occupations, earning on average $5,700 a year more, while in non-tech occupations their earnings are similar. Immigrant men are also much more likely to work in tech occupations compared to immigrant women, with participation rates of 12.1 percent and 3.5 percent, respectively.

Table 10:

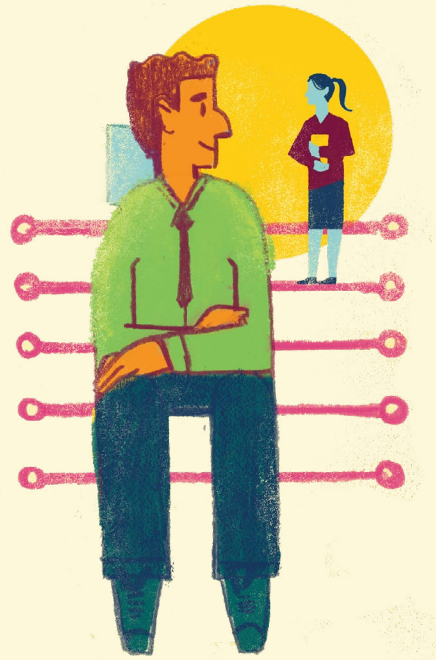
Technology premium for immigrant workers

Immigrant Status	Sex	Average Pay in Tech	Average Pay outside of tech
Immigrant	Male	$85,800	$51,700
	Female	$70,300	$36,400
Non-immigrant	Male	$80,100	$49,800
	Female	$70,300	$41,500

Table 11:

	Immigrant	Non-Immigrant
Male	66% ($34,100) higher earnings than non-tech	61% ($30,400) higher earnings than non-tech
Female	93% ($33,900) higher earnings than non-tech	69% ($28,800) higher earnings than non-tech

CONCLUSION



Canada's tech talent is a vital engine of economic growth. In 2016, there were 935,000 tech workers in Canada, and this number is likely to grow. They tend to be highly educated and earn significantly higher salaries than the rest of the labour force.

At first glance, tech workers are also diverse. They come from many different backgrounds and can be found working in cities and industries across Canada. In aggregate, visible minorities and immigrants participate in tech occupations at higher rates than their non-immigrant and White counterparts.

However, significant disparities exist. First, women are four times less likely to work in tech occupations than men, and even when they do they are paid substantially lower salaries. These differences persist across demographic groups. Second, despite high participation rates overall, visible minorities earn less than non-visible minorities in tech occupations and certain groups are notably underrepresented. Black workers have the lowest rates of participation and the lowest pay. Third, available data indicates that Indigenous Peoples are both underrepresented and paid less relative to non-Indigenous counterparts in tech occupations.

As Canada continues to bolster its tech economy, it has an opportunity to draw from a wider talent pool that is more reflective of Canada's diversity, while also ensuring that different groups' experience in tech is much more equal. Creating an environment in which people have access to, and are encouraged to participate and progress in tech occupations, regardless of who they are or where they live, is essential not only to promote greater inclusion and equity, but also to fuel the discovery new technological frontiers, to help Canada's companies succeed, and to drive economic growth.

VIEW AND DOWNLOAD THE DATA FOR THIS REPORT, AND FOR YOUR CITY!

Using our accompanying data visualization, you can learn more about tech workers in your city. All data for this report and open source code for key elements of our methodology are available on GitHub. We encourage analysts, researchers and others to improve and build upon this work.

APPENDIX A: DEFINING THE TECH OCCUPATIONS

To analyze tech workers, we must first define them. While the software developer has an iconic place in our modern image of tech, our definition aims to be more holistic and capture the pervasiveness of technology across industries and occupations.

Many groups around the world have attempted to define the tech sector in different ways. These include national statistical bureaus and academic researchers. We scanned these definitions to inform and contextualize our own approach.

Definitions used by different groups differ based on two main factors. First, different nations use different occupational classification systems, leading to frictions in applying one nation's definition to another. Second, there is no sure way to measure an occupation's technological intensity. The table below explores some of the approaches taken in the past to define technical occupations.

Organization	Country	Method
US Bureau of Labour Statistics (BLS)[30]	US	Based on work performed, as well as skills and education needed to classify occupations into 1 of 20 STEM occupational groups
US Bureau of Economic Analysis (BEA)[31]	US	Starting from the ICT definition, BEA consulted experts and included goods and services that are a member of either (a) digital-enabling infrastructure, (b) e-commerce, or (c) digital media. Using this goods and supply-table, the BEA includes industries that produce these goods and services as the digital industries.
Brookfield Institute for Innovation + Entrepreneurship (2016)[32]	Canada	Examine 4 criteria (Use of technology, R&D, STEM knowledge, producing high-tech goods) with any occupation satisfying at least 3 criteria considered to be tech.
Brookings Institution (2017) [33]	US	Use the O*Net Skill: "Interacting with Computers" and Knowledge: "Computers and Electronic" to calculate digitization scores for all occupations
Anderberg et. al. [34]	US	Examine technological intensity of an occupation, by looking at the frequency of technology use, type of job in which technology is used, purpose of technology used, as well as the highest level of technology available for that occupation to group occupations in 5 technological intensity groups
Chapple et. al. [35]	US	Focused on occupational categories of "scientific and technical occupations" in occupational classifications and validated the selection with industry experts, while excluding assistant level occupations.
Gallipoli et. al. [36]	US	Selected 12 skill measures from US O*NET database to identify skill content of different occupations.

In this appendix, we detail the full methodology we employed, as well as robustness checks involved in defining tech occupations. We first identify tech occupations based on their requisite skills.

We rely on the US Department of Labour's O*NET database to identify the skill content of different occupations. The O*NET database collects detailed information on 974 occupational groups (as of April 2018). It includes a common taxonomy on important occupational attributes, such as skills, knowledge, and abilities.

Specifically, we crosswalk O*NET occupations to Canada's 500 National Occupational Categories (NOC) occupations[37] at the 4-digit level and use the resulting skills, knowledge, and work activities to identify whether each 4 digit NOC is considered a tech occupation. This crosswalk is available on the corresponding GitHub repository for this report.

To accomplish this, we first identified "tech skills" by following two principles:

1. The skills, knowledge, and work activity must relate directly to technology use or technology creation.

2. If an occupation has a strong requirement for any of the previously identified tech skills, it will qualify as a tech occupation.

The first principle allows us to focus on occupations that directly interact with technology in a meaningful way, and the second principle allows us to identify core tech skills. The important consequence of the second principle is the exclusion of certain scientific skills and knowledge often associated with tech occupations such as Biology. An occupation with a high requirement of knowledge of biology does not automatically qualify an occupation to be unambiguously tech.

Using these principles, we identified six skills, knowledge and work activities (SKW) as defined by O*NET that we consider to be tech skills:

+ **Interacting with Computers:** Using computers and computer systems (including hardware and software) to program, write software, setup functions, enter data, or process information.

+ **Computers and Electronics:** Knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming.

+ **Programming:** Writing computer programs for various purposes.

+ **Technology Design:** Generating or adapting equipment and technology to serve user needs.

+ **Engineering and Technology:** Knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services.

+ **Telecommunications:** Knowledge of transmission, broadcasting, switching, control, and operation of telecommunications systems.

For each of these SKWs, O*NET produces two measures: level (the complexity at which one is required to know the SKW), and importance (how vital the SKW is to an occupation). An SKW's level is measured on a 1-7 scale, with specific anchor points (unique to each SKW) to delineate the scale. SKW's importance is measured on a 1-5 scale, of 1 being "Not at all important" and 5 being "Very important".

Due to the specificity of the anchor levels attached to each SKW, direct comparison between different SKWs is difficult. Further, even within the same SKW, the difference in skills is not consistent (e.g., the distance between a level 1 and level 2 in the skill "Mathematics" is not the same as the distance between a level 4 and level 5 in the same skill).

Therefore, we focus on the ordinal scale (whether one number is more significant than another) rather than the cardinal scale (by how much is one number larger than another).

As a result, we first rank all occupations using each of the SKWs considered, then aggregate the resulting six rankings into one composite measure. For the individual ranking, we first multiply each SKW's level and importance. Combining these two measures is O*NET's recommended way of using them, as it incorporates both the complexity and the importance of a particular SKW to an occupation. However, O*NET also recommends normalizing the two scales before combining them, as the two measures have different ranges. We do not do that here as we are not interested in cardinal measures. Instead, after multiplying the raw scores, we use them to rank each occupation for each of the six tech skills we selected.

Regarding the aggregation methods, we devised three possible methods to do so, and discuss each method's features.

AGGREGATION METHODS

Arithmetic mean

Arithmetic mean may be the most common form of aggregating and averaging multiple measures on the same scale.[38] This measure simply adds all observations together and divides them by the number of observations observed:

$$\textbf{For } x_i, i \in \{1, 2, ...n\}$$

$$\bar{x}_A = \frac{1}{n}\sum_{i=1}^{n} x_i$$

In the context of aggregating rankings, it penalizes particularly low rankings, while making it difficult for a high rank in another skill to compensate. It thus rewards ranking consistently in all categories of skills considered.

Geometric mean

Geometric mean takes the n-th root after multiplying all of the inputs:

$$\textbf{For } x_i, i \in \{1, 2, ...n\}$$

$$\bar{x}_G = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$$

In the context of aggregating rankings, geometric means reward particularly high ranks and punish particularly low ranks. The geometric mean is the exponential of the arithmetic mean, and as a result, dramatizes the effect of the arithmetic mean.

Harmonic mean

Harmonic Mean is defined as the reciprocal to the arithmetic mean of the reciprocals of the inputs:

$$\textbf{For } x_i, i \in \{1, 2, ...n\}$$

$$\bar{x}_H = n\frac{1}{\sum_{i=1}^{n} \frac{1}{x_i}}$$

In the context of aggregating rankings, harmonic means reward a high rank while not punishing a low rank.[39] Due to the reciprocal calculation, a one rank difference between rank one and two affect the mean as much as a 100 rank difference between rank 100 and rank 200.

For our selection of the aggregation method, we look at the second principle we defined above. An occupation that ranks well in just one skill should qualify that occupation to be a tech occupation. As a result, we select the harmonic mean, which rewards one particularly high rank very well, while not penalizing low ranks too severely.

MODEL DEPENDENCE

To choose a specific aggregation method it is essential to examine the level of model dependence, or how sensitive the resulting set will be to a change in the aggregation method. In this case, as we are aggregating rankings, there are three broad cases that we can fall into:

1. **Highly (positively) correlated rankings:** In this case, the six rankings that we consider are highly correlated, which means that they move together. As a result, rankings are likely to be consistent across different SKWs, implying that different aggregation methods will generate similar results.

2. **No correlated rankings:** In this case, none of the six rankings correlate with each other (pair-wise). This implies that a high ranking in one SKW does not indicate other SKWs' rankings. As a result, we expect there to be a high level of model dependence without a common cause.

3. **Some correlated rankings:** In this case, some rankings are correlated with each other, while others are independent from the rest. In this case, model dependence is likely to exist, but the cause can be isolated to those rankings that are independent.

It is important that we explore the correlation structure of multiple rankings together, not just the pair-wise correlation matrix to identify "blocks" of skill rankings that move together. For this purpose, we employ a technique called Principal Component Analysis (PCA).

PRINCIPAL COMPONENTS ANALYSIS

Principal Component Analysis (PCA) is a technique used when analyzing data with many dimensions (or variables). It is often used to reduce the number of dimensions in the data to aid with predictive models or visualization. Conceptually, PCA analyzes the data and linearly combines its dimensions (SKWs, in our case) into a smaller number of "components" that explain most of the variation in the data.[40] These components can be analyzed to see which dimensions tend to covary together.

Theoretically, for an n (observations) by m (variables) matrix of observables X, the k-th principal component is identified as a solution of the following optimization problem:

$$\max_{\vec{w}_k} \sum_{i=1}^{n} (\vec{x}_i \vec{w}_k)^2$$

Where $\vec{w}_k$ is the k-th principal component. To place a bound (and have a unique solution) on this optimization, the matrix of observables are often demeaned, and the search is restricted to the set of unit vectors. Analytically, the solution to this problem is the set of eigenvectors of the variance-covariance matrix of the matrix of observables, with the k-th principal component is the eigenvector corresponding to the k-th largest eigenvalue.

The resulting vectors define the linear transformation of the original set of variables and allow researchers to examine which set of variables covary together.

For this report, we run the PCA on the set of all NOC occupations with SKWs. The first five principal components explain 74.5 percent of the variance observed in the data. We focus particularly on the third component that explains 7.7 percent of the variation:

SKW	Coefficient in PCA3
Programming	-0.2303
Interacting with Computers	-0.1997
Computers and Electronics	-0.1976
Technology Design	-0.1658
Engineering and Technology	-0.1369
Telecommunications	-0.0455

It is clear that out of the six SKWs considered, telecommunications is the only SKW that does not covary with the other five. What this result implies then is that our definition of a tech occupation is likely to be model dependent, with telecommunications as a cause. In other words, using harmonic mean is likely to identify occupations with high requirement for telecommunications skills and none of our other selected considered skills.

Six occupations in our definition could be considered telecommunications occupations, and account for 70,000 occupations nationally, while digital occupations account for 680,000, and high-tech for 255,000.

TECH OCCUPATIONS IDENTIFIED

Using the outlined methodology, and keeping the model dependence in mind, we examined a list of ranked occupations, and selected a cut-off based on our judgement. This corresponded to the top 5 percent of occupations according to our harmonic mean of SKW ranks:

Top 5 percent of Occupations		
Computer programmers and interactive media developers	Electrical and electronics engineers	Metallurgical and materials engineers
Software engineers and designers	User support technicians	Electrical and electronics engineering technologists and technicians
Aerospace engineers	Mining engineers	Other professional engineers, n.e.c.
Mechanical engineers	Geological engineers	Audio and video recording technicians
Computer network technicians	Chemical engineers	Technical occupations in geomatics and meteorology
Computer engineers (except software engineers and designers)	Civil engineers	Petroleum engineers
Telecommunication carriers' managers	Telecommunications line and cable workers	Physicists and astronomers
Database analysts and data administrators	Industrial designers	Mathematicians, statisticians and actuaries
Web designers and developers	Broadcast technicians	Cable television service and maintenance technicians
Engineering managers	Telecommunications installation and repair workers	
Information systems testing technicians	Information systems analysts and consultants	
	Computer and information systems managers	

The following five occupations fell just below our cut-off:

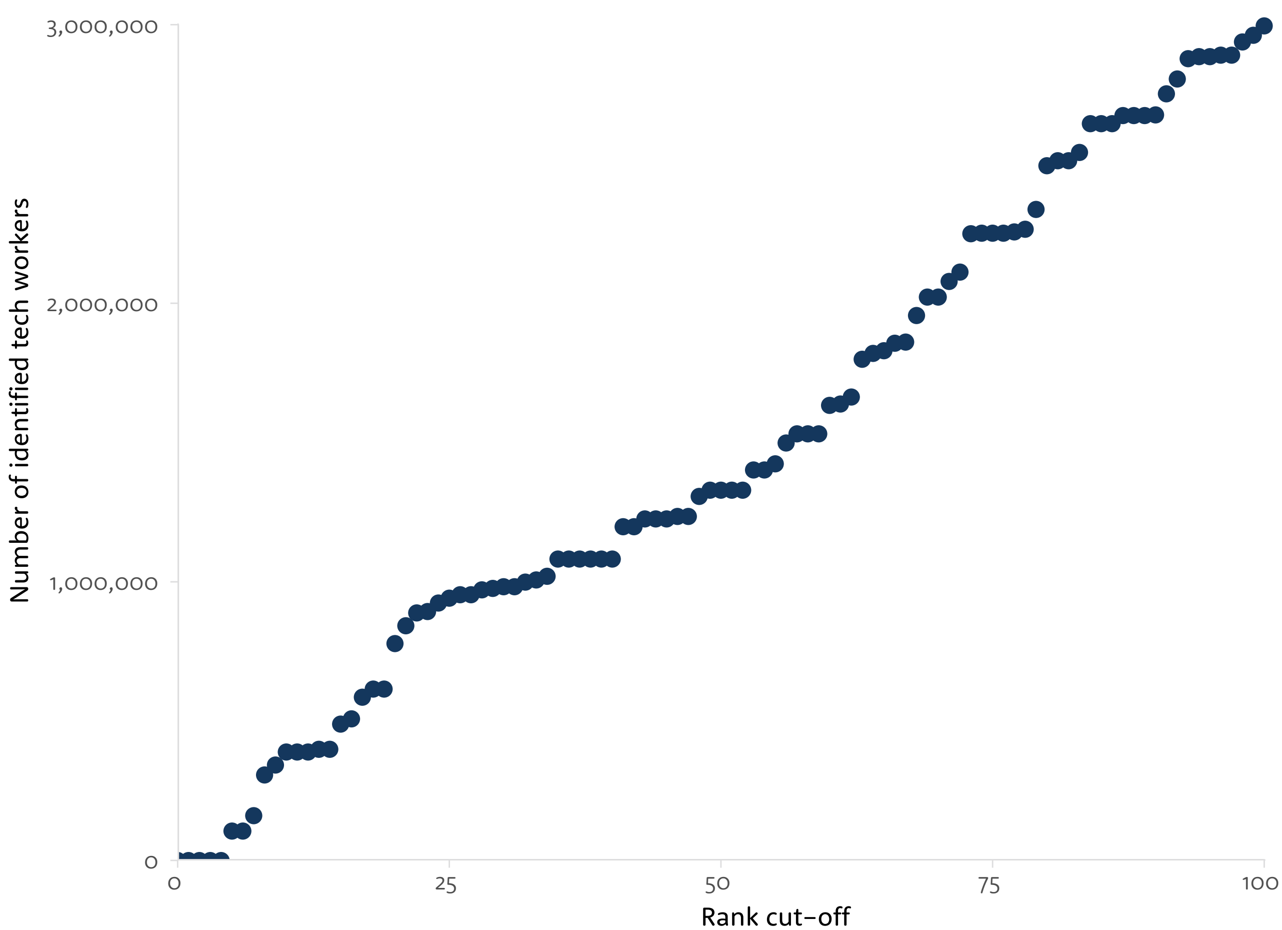
1. Statistical officers and related research support occupations
2. Managers in publishing, motion pictures, broadcasting and performing arts
3. Industrial engineering and manufacturing technologists and technicians
4. Film and video camera operators
5. Announcers and other broadcasters

To check how sensitive our findings are to this specific cut-off, we examined how the number of identified tech workers change depending on the cut-off ranks chosen.

As this graph makes clear, the number of identified tech workers remains relatively stable for ranks below 25 — implying that choosing a cut-off rank below rank 25 would not have significantly affected the report's findings. On the other hand, if a rank above rank 25 was chosen (for example, rank 20), the number of identified tech workers would have been significantly less (300,000 less). However, we see no reason to exclude any of the identified occupations from our tech occupation definition.

Figure 23:

How Number of Tech Workers Change by Varying Cut-Off for Tech



ROBUSTNESS

To gauge the robustness of our definition, we use another method to examine the skill content of an occupation. Specifically, we take the view that educational specializations train individuals to specialize in a set of specific skills unique to each such specialization. As a result, we can examine the skill content of an occupation by looking at the degree programs people working in those occupations specialize in.

To do this, we use the Classification of Instructional Programs (CIP), a taxonomy that classifies all postsecondary programs into detailed instructional program categories, to see what workers working in different occupations studied. For this exercise, we are interested in whether occupations that we identified as tech are grouped together, and if we missed any occupations with workers that have similar training to the identified occupations.

To illustrate this visually, we use a network analysis. We define a bipartite graph with the two types of nodes being major programs and occupations. An edge is defined between a major program and an occupation if there are workers in that occupation who studied that major program. The weight of the edges is the number of workers with such backgrounds. This process results in 787 nodes and 14,483 edges.

From this graph, we use a force-based algorithm (OpenOrd)[41] that pulls nodes with edges closer and pushes nodes without edges apart from each other to observe the network structure of the occupations.

When Occupational Clusters are defined through major programs that the worker in that occupation studied, there is a clear separation between tech occupations following our definition and other occupations within our sample. This is a good indication that the occupations we consider are separate and distinct in training requirements from other occupations.

Further, there is also a separation (broadly speaking) between occupations we categorized to be “digital” and “high-tech”. Digital occupations were all grouped together, indicating similar major program origins for workers within these occupations while high tech occupations were more dispersed through three main groups. The first being the engineer groupings, the second being the telecommunication groupings, and the third being that of “science” occupations.

A distinct telecommunication grouping of occupations raises an interesting point. We often consider tech to be ICT. However, recent advances in technology have increasingly made ICT a medium through which occupations in the tech sector operate, while not necessarily being tech occupations themselves.

When we exclude telecommunications from the list of skills considered while keeping the cut off harmonic rank, most telecommunication occupations were excluded from the list of tech occupations.

APPENDIX B: DECOMPOSING DEMOGRAPHIC CHANGES

Following Cortez, Jaimovich, and Siu (2017),[42] we decompose change in the share of the population who are employed in tech occupations into two main effects—changes in demographic population share, and changes in tech employment propensity. Conceptually, we are trying to understand whether tech employment among age and sex groups changed due to demographics, or the rate of tech job participation among each demographic group.

For this report, we looked at the change over 10 years, from the Census in 2006 to the Census in 2016, with our demographic cell being a Sex-Age group. This results in 12 demographic cells (2 levels in sex and 6 levels in age for each 10-year interval starting from 15-24 year olds.) We call the population participation rate at 2016 $\pi_{01}$and the population participation rate at 2006 π_{11} By construction:

$$\pi_1 - \pi_0 = \sum_i p_{i1} s_{i1} - \sum_i p_{i0} s_{i0}$$

Where ρ is the propensity of the specific demographic cell to be employed within tech and S is the share of that demographic cell in the overall population. By adding and subtracting terms, we can decompose this initial difference into three components:

$$\pi_1 - \pi_0 = \sum_i \Delta p_{i1} s_{i0} + \sum_i p_{i0} \Delta s_{i1} + \sum_i \Delta p_{i1} \Delta s_{i1}$$

The first term in this equation is the contribution to the overall change in the share of the population due to changes in the propensity for each demographic cell over the considered period, holding the population share of each demographic groups constant. We call this the **propensity effect**. The second term is the contribution of the overall change in the share of the population due to changes in the share of specific demographic cell in question, holding the propensity constant. We call this the **composition effect**. The third and final term measures the interaction between these two effects.

Note that in this instance, we're interested in the distribution of workers in technology occupations, not necessarily changes in unemployment dynamics. As a result, we use the labour force population as the base group, while not distinguishing between working and unemployed people.

APPENDIX C: REGRESSION WITH AGGREGATED DATA

Assume for a moment that the true model is as follows:

$$y_i = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \beta_3 D_{1i} D_{2i} + \epsilon_i$$

Where y_i is the dependent (e.g. income) and $D_{1i} \in \{0,1\}, D_{2i} \in \{0,1\}$; in other words, the two regressors are dummy variables of different demographic characteristics (e.g., sex, degree-level, etc.) with an additional interaction term. We assume that:

$$E[\epsilon | D_{1i} D_{2i}] = 0 \text{ (Exogeneity and zero-mean)}$$
$$E[\epsilon^2] = \sigma^2 \text{ (Homoskedasticity)}$$

In addition, that the two regressors are not collinear

We observe four aggregated, average dependent variables:

$$\bar{y}_1 = \beta_0 \text{(when } D_{1i} = 0, D_{2i} = 0\text{)}$$
$$\bar{y}_2 = \beta_0 + \beta_1 \text{(when } D_{1i} = 1, D_{2i} = 0\text{)}$$
$$\bar{y}_3 = \beta_0 + \beta_2 \text{(when } D_{1i} = 0, D_{2i} = 1\text{)}$$
$$\bar{y}_4 = \beta_0 + \beta_1 + \beta_2 \beta_3 \text{(when } D_{1i} = 1, D_{2i} = 1\text{)}$$

This is a system of four equations with four unknowns. Using the standard assumptions, we can find the point estimates for these values. In addition, if we have the variance of the mean of the dependent, we can then calculate the variance of the estimated parameter as well and perform hypothesis testing.

One drawback of this approach is that the true model cannot contain continuous variables. In addition, the usual restriction of endogeneity bias due to omitted variables are present.

For the model relating income to education and sex, we use the following decomposition technique and specification:

$$income_i = \beta_0 + \beta_1 Sex_i + \beta_2 Educ_i + \beta_3 Sex_i Educ_i + \epsilon_i$$

Where Sex is 0 for Male (base group) and 1 for Female (comparison group) and Educ is 0 for qualification below a bachelor's (base group) and 1 for qualification at or above a bachelor's (comparison group).

There are some limitations to our approach. Most important is that due to the lack of data on the variance of the income estimates, we only provide a point estimate without reporting any variances. Therefore, we cannot state whether this difference is statistically significant. However, given a large number of observations inherent with census data, there is a reasonable chance that the values we find are statistically significant. What we ought to worry about more is potential endogeneity in the data as we only observe ex-post occupational outcomes.

ENDNOTES

1. Muro, Mark; Sifan Liu, Jacob Whiton, and Siddharth Kulkarni (2017) "Digitization and the American Workforce", Brookings Institution.

2. The full ranking, aggregation and sensitivity analysis can be found in Appendix A.

3. O*NET is an occupational database maintained by North Carolina's Department of Commerce under sponsorship from the US Department of Labour's Employment & Training Administration (ETA). O*NET provides authoritative occupational information for the US, including the skills and knowledge required for an occupation, the specific tasks performed, and the tools & technologies used. O*NET is the largest and most detailed database of its kind, and tracks almost 1,000 occupational groups. In recent years, prominent research in labour economics has used O*NET's data on occupational tasks extensively.

4. Note that a higher percent change in employment does not equate to a higher change in the overall number of jobs.

5. COPS uses a slightly aggregated occupational system compared to the NOC system in our definition. Because of this, a few additional occupations are included in these forecasts that are not present in our original definition.

6. The pay gap we refer to in this report is a "simple pay gap," which does not control for other potential factors such as experience, education or occupational choice.

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18. In this context, diversity means "appreciation of differences whether it be our ethnicity, gender identity, age, disability, sexual orientation, education, or religion, just to name a few"; inclusion refers to "differences being valued and respected

as well as ensuring the right conditions are in place for each person to achieve their full potential"; and belonging is "...the feeling of security, support, and acceptance when people can be their authentic selves".

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