Further and Further Away

CANADA'S UNREALIZED DIGITAL POTENTIAL

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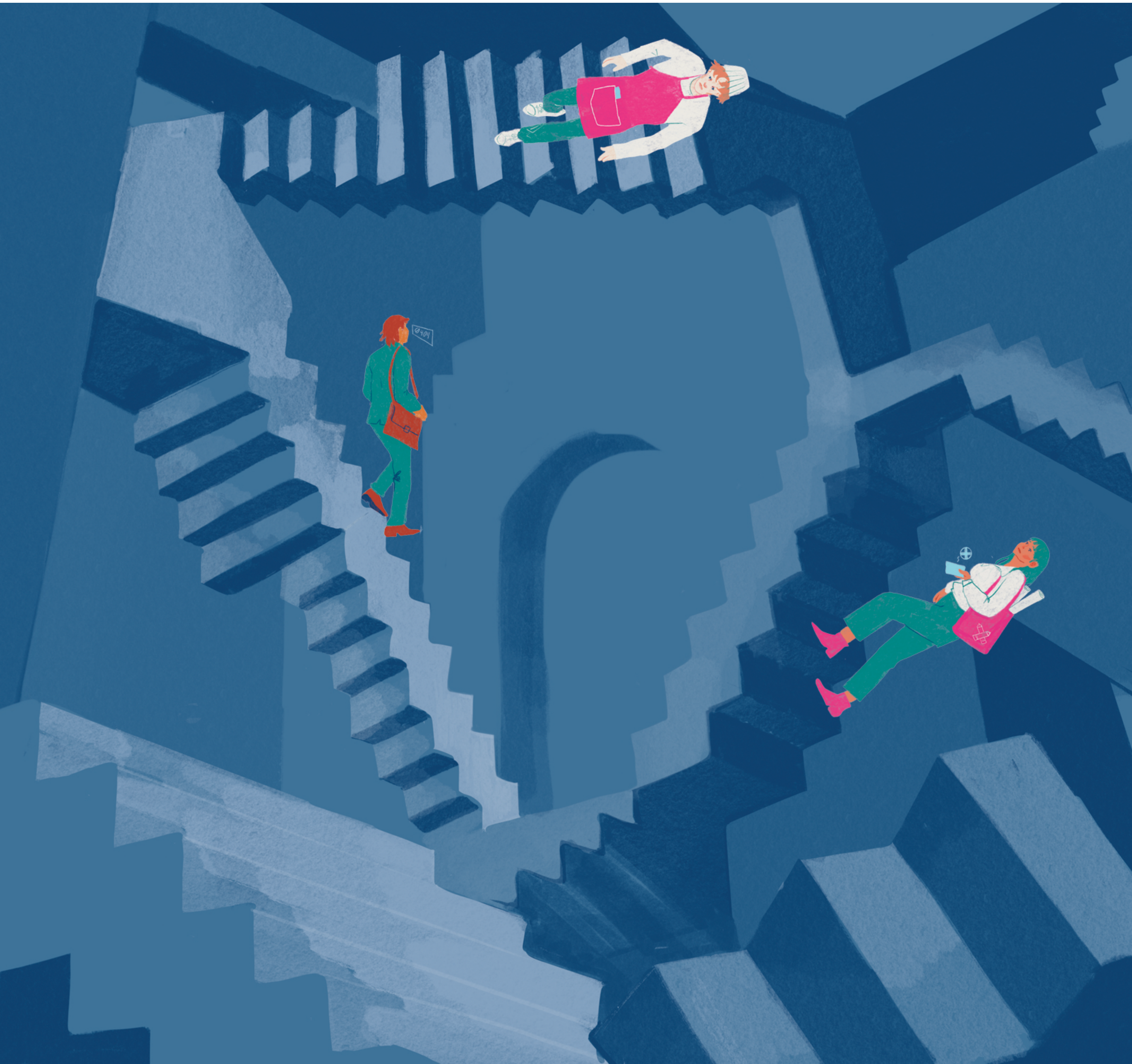

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Table of Contents

Executive Summary

TECHNOLOGY ADOPTION in the labour market will only continue to intensify. But *how* businesses and workers use technology—and to what degree—stands to play a central role in our capacity to innovate successfully, and grow the Canadian economy across new and legacy industries.

In our 2018 report, *Better, Faster, Stronger*, we explored the dual challenge of lagging technology adoption and disrupted labour in Ontario. We then identified strategies on how businesses can adopt new technologies to stay competitive, while ensuring workers are equipped with the skills they need to adapt and thrive in a changing labour environment.

Building on this research, we examine the manner in which technology and tech adoption has impacted tech workers and their jobs across 500 occupations in Canada. Using individual-level data from four Canadian census waves spanning from 2001 to 2016, along with a defined analytical framework of worker productivity and hourly pay, we set out to understand how the impact of technology adoption has changed tech work over the 15-year study period. This report covers up to 2016, as this is the most recent dataset from Census Canada available.

Using regressional analysis, we also identify specific inequities in pay and labour participation faced by workers belonging to identity groups that have been historically marginalized in Canada. Our research has found that systemic labour market inequities continue to persist, and, in some cases, have gotten worse, in that there are new inequities in 2016 that did not exist in 2001.

The results of the report overwhelmingly show that Canada is lagging behind on nurturing, developing, and using our digital talent. Pay gaps and the continued marginalization of participation in tech work has shown that those who create and use technologies in Canada do not represent those who live and work here. Without their participation, we risk missing out on valuable insights, talent, and experience that can shape future technologies.

Top five takeaways

1. **Jobs requiring the highest level of digital intensity were associated with higher salary increases.**
From 2001 to 2016, tech workers in jobs requiring the highest level of digital intensity had an average 32 percent increase in salary, while workers who were classified to be in the lowest level of digitally intensive work had a 14 percent salary increase over the same time period.

2. **Women are increasingly being excluded from tech work.**
In 2001, a woman had a 6.29 percent chance of being a tech worker. In 2016, this same probability decreased to 4.91 percent. Conversely, a man had a 20 percent chance of being a tech worker, a number that remains unchanged between 2001 and 2016. The gender participation gap is equivalent to (or in later years, larger than) the participation gap of tech workers who do not possess a university degree. The effects of intersectionality are just as significant. An Indigenous woman without a bachelor's degree, for example, has only a one percent chance of entering the tech workforce.

3. **The gender pay gap persists and is compounded by intersectionality.**
Our research reveals that men make an average of $3.49 per hour more in pay in comparison to women. Further, having a visible minority identity (averaging across all identities) lowers one's pay by $3.89 per hour.

   These associations between identity and salary are compounded, in that an immigrant woman with a visible minority identity engaging in tech work without a university degree in Canada is, on average, expected to make $8.94 per hour less than a white, non-immigrant man without a university degree. If this man also had a university degree, this gap widens to $18.50, highlighting the labour market cost of inequity in access to education.

4. **There are pay inequities amongst immigrants working in tech that did not exist before.**
In 2001, there was no observable pay gap between immigrant and non-immigrant tech workers, but from 2001 to 2016, a pay gap emerged, to an average of more than $5.70 per hour (in 2016 dollars) after controlling for other observable characteristics.

   When we control for factors such as experience, education, and sex, the immigrant pay penalty in tech is in fact larger in magnitude than the gender pay gap.

5. **Jobs associated with routine-based tasks have decreased in digital intensity.**
An analysis of all 500 Canadian occupations from 2001 to 2016 shows jobs that were predominantly associated with routine work have decreased in digital intensity. Conversely, jobs characterized as requiring a high degree of cognitive skills, coupled with non-routine work, saw a marked increase in digital intensity over the studied time period.

Introduction

IN RECENT DECADES, the Canadian economy has seen unprecedented changes and growth, as new technology and innovation continuously gets adopted. It has long been acknowledged that innovation is the only way to ensure long-term economic competitiveness and to improve living standards. At the same time, mass adoption of technology often brings about disruptions, which are not equitably distributed or felt.

We first discussed this notion of a dual challenge in technological adoption in Lamb, Munro & Vu (2018), especially to those companies and workers employed in the manufacturing and financial services sectors in Southwestern Ontario. On one side, we saw that the relatively slow pace at which Canadian businesses have been adopting technology since the beginning of the millennium has deep consequences for long-term competitiveness (especially in light of globalization and international competition) for Canadian companies. On the other side of the challenge, we also saw many workers being left out of the conversation on how increased automation will affect them, leading to worker concerns being ignored, creating further friction in how technologies are adopted across the province.

In that previous work, we cautioned against a worst-of-both-worlds outcome, where companies do not adopt technologies, and when they do, do so without appreciating the impact it has on the workforce.

Subsequent research (such as Lamb Munro 2020 and Goldsmith 2021) further established that while Canadian businesses have continued to adopt technology, the pace at which they do has stagnated. And while we have also conducted work that focuses on identifying short-term support considerations for those who are disrupted out of their job in transition to a new career, we have not been able to focus on the long-term changes workers in Canada have experienced due to technological adoption, and how different groups of people in Canada has been impacted by such changes.

When Canada can unlock all of its talent, it can be a formidable force in shaping not just the country's future, but beyond it

In this present work, we delve deeper into the question of whether Canada has fully appreciated and made use of its digital talent base, both in terms of whether the country has excluded any talent from engaging in digital work, and whether the economy has made use of all the talent from those currently engaging in technology work. Specifically, our questions include:

- How has the Canadian economy used digitized labour, and has the way with which digital workers' talents are used shifted over the past 15 years?
- Have there been shifts in patterns of inequity that surround technology, and technology work, in the past 15 years?

To answer these questions, we rely on a broad set of data, but primarily focus on person-level data from four waves of the long-form Canadian census[1], spanning 15 years from 2001 to 2016 each covering at least 25 percent of those who live in Canada. This wealth of data, accessed through a Statistics Canada Research Data Centre, will allow for a deep look into how digital adoption has impacted workers in Canada over almost the past two decades.

The picture that emerges out of this exploration is one that makes it clear that Canada has not only failed to close labour market inequities (meaning those who are involved in creating technology of the future does not represent Canada as a whole), but in many instances, the way those already in technology work are used has been worsening. In some instances, Canada has introduced new labour market inequities that did not exist in 2001.

While this is a cautionary tale, we also stress the dynamism that surrounds Canada's technology workforce. When Canada can unlock all of its talent, it can be a formidable force in shaping not just the country's future, but beyond it.

Technology Adoption

Differential adoptions within Canada, its people, workers, and companies

BEFORE WE CAN understand how digital technologies have impacted workers in Canada, we need first to establish the pace of digital adoption that has occurred in Canada, for both peoples within it, and the companies operating within the country.

The pace of digital technology adoption has been rapid. While at the turn of the twenty-first century, less than seven in ten people in Canada did not use the internet for personal reasons, by 2018, more than nine in ten people in Canada did.

Table 1
Consumer digital adoption in Canada: the case of the internet

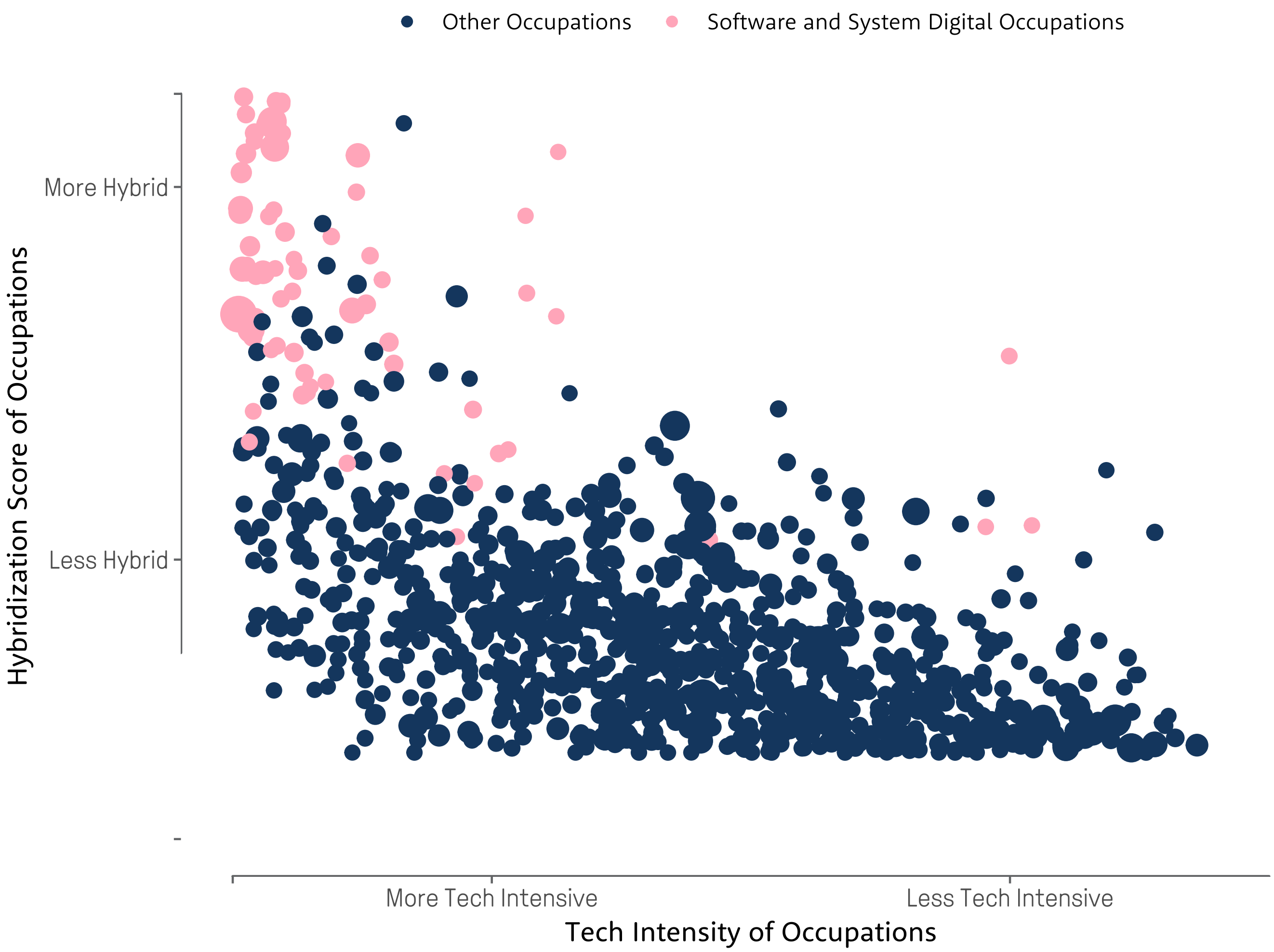
Year	Share of Canadians with personal use of internet within 12 months
2005	67.9 percent
2007	73.2 percent
2009	80.03 percent
2010	80.3 percent
2012	83.4 percent
2018[2]	91.3 percent

This shift is not only reflected in Canadians' personal lives, but also in their professional lives. Increasingly, skills involving digital technology are becoming important to success in the labour market. While knowledge of coding and programming are still specialized, in 2018, over one-third of online job postings in Canada required knowledge of a digital technology (Vu, Lamb, Willoughby 2019). At the same time, not all occupations require the same level of digital intensity, or hybrid skills, implying there are also cross-industry differences in how digital technology is used.

The rapidity with which technological change has occurred in the digital space is worth noting. In 2005, only 64.8 percent of businesses had a website, by 2019, 81.8 percent of businesses did.

The rapidity with which technological change has occurred in the digital space is worth noting. In 2005, only 64.8 percent of businesses had a website, by 2019, 81.8 percent of businesses did. In 2012, while only 35.2 percent of Canadian businesses used social media, by 2019 that number rose to 60.9 percent.

Figure 1
Hybridization of digital jobs

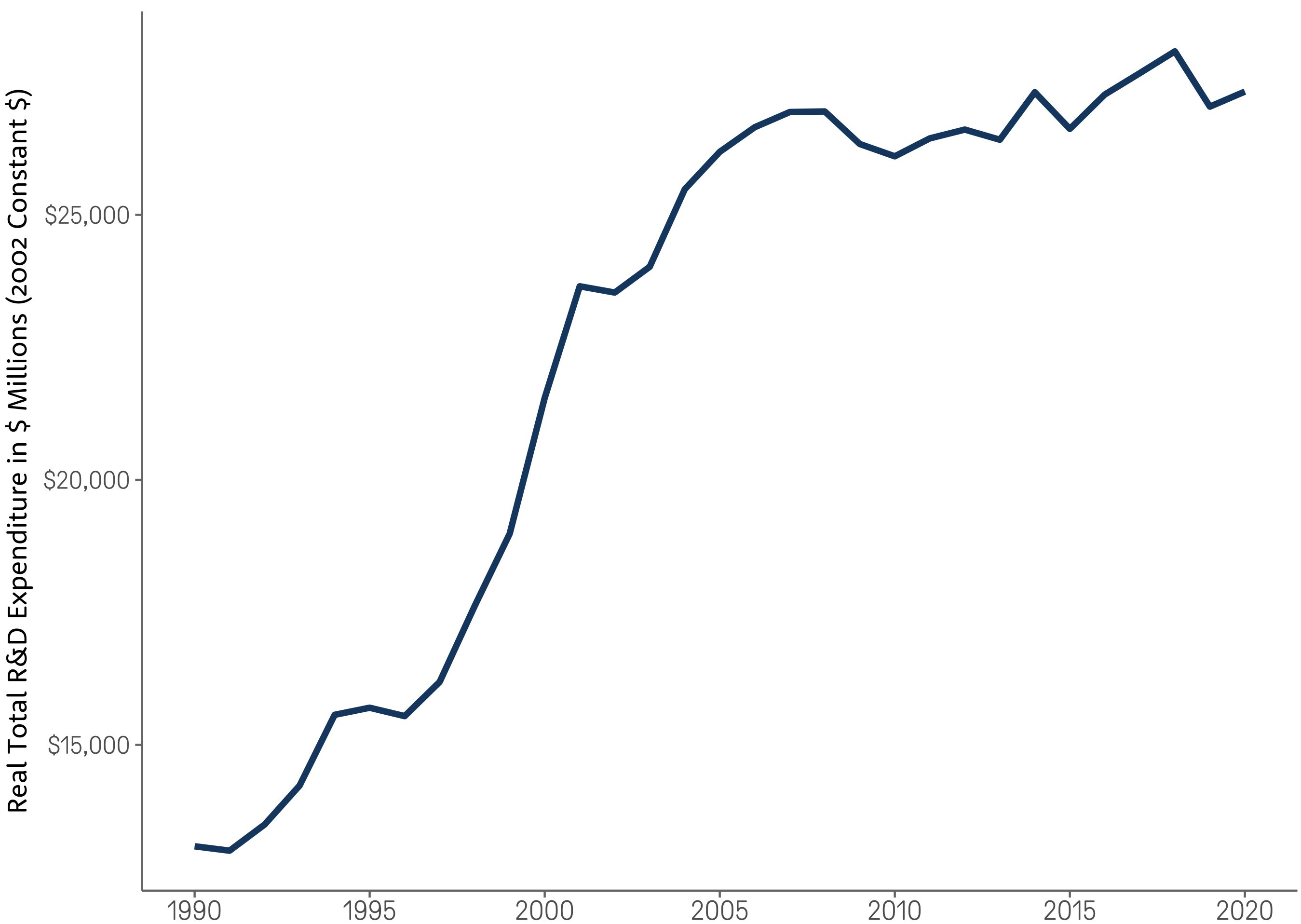


Source: Author Calculations, from Vu, Lamb, Willoughby (2019)

While recent trends look promising, there are signs of trouble ahead. Without a robust ecosystem creating new technologies to adopt, and without developing talent who deeply understand these newest technologies, many Canadian companies will likely face a ceiling in technological adoption. And while digital adoption has kept pace, business expenditures on research and development (R&D), or the resources devoted in creating and commercializing new technology, has stagnated in Canada for over two decades:

Figure 2

Almost two decades of stagnation—total expenditure in R&D in Canada



Source: Current Dollar data from Statistics Canada Table 27-10-0273-01, deflated using Statistics Canada Table 18-10-0005-01

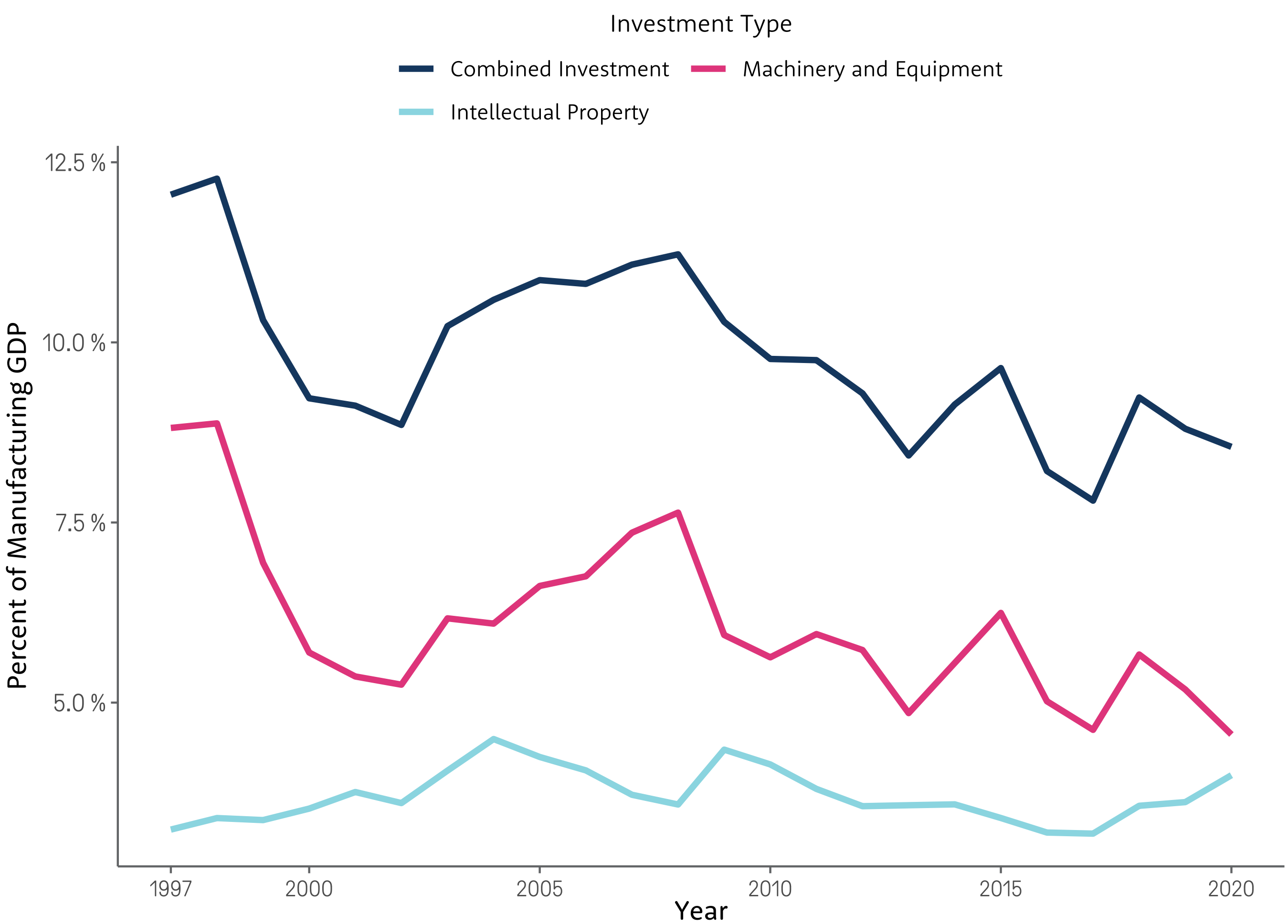
This stagnation, when combined with the simple fact that Canada has continuously grown its GDP over the same two decades, means that we have devoted less and less of our economy to innovation activities. These declines in investments are seen throughout the economy, even in manufacturing, an industry that drove a large wave of technology adoption in the 90s (Lamb, Munro, Vu 2018).

Not even scale-up firms, the type of firm known for its investment in growth and innovation, has been immune from these trends. The rate at which scale-ups invest in developing new technology has consistently declined in recent years, even while being much more likely than non-scale-ups to be investing in R&D. And while technology scale-ups in particular have not seen declines in R&D investments, they also have not increased it either.

While there are early signs that the pandemic disruption had a modest positive impact on R&D spending, the long period of stagnation in investment in R&D and its consequence on technological creation, and therefore technological adoption, will in turn have an impact on the digitalization of work in Canada. In particular, we want to understand how

Figure 3

Investment in the manufacturing sector, Ontario 1997-2016

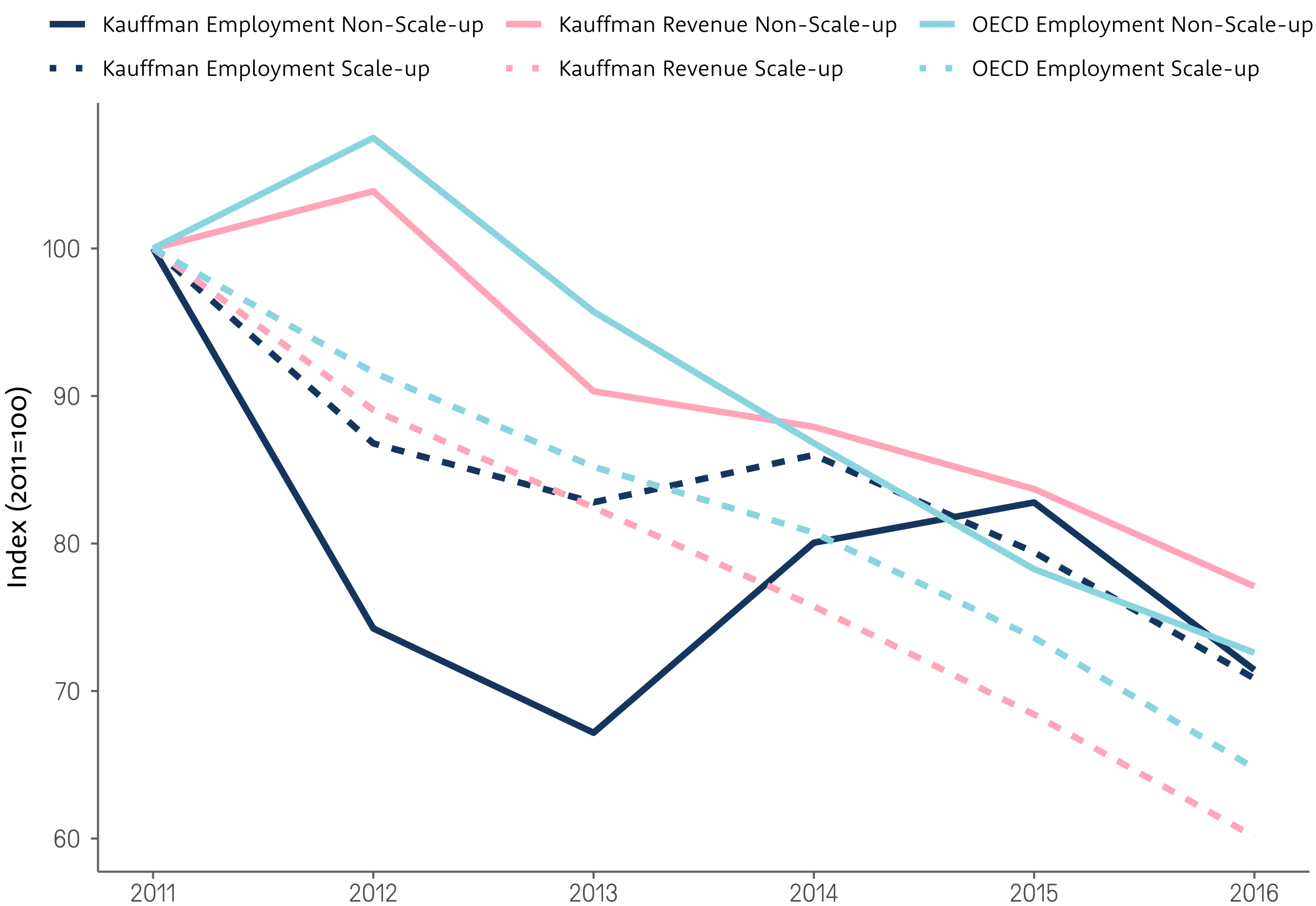


Source: Statistics Canada CANSIM 031-0005 & 379-0030, reproduced from Lamb, Munro & Vu (2018)
Note: Manufacturing includes NAICS 31-33.

such changes have prompted structural shifts in employment patterns across the country. We specifically do not focus on the changes that occurred since the onset of the COVID-19 pandemic, as many of these changes are still ongoing, and we wish to focus on medium- to long term changes that occurred prior to the pandemic. As a result, we focus on the 15-year period between 2001 and 2016 for much of our analysis.

This is the backdrop with which we understand how technology has impacted workers in Canada. Before we delve in analyzing how these business trends have impacted workers, we briefly discuss the analytical framework, as well as the data we use in this study.

Figure 4
Trend in share of R&D spenders in Canada



Source: NALMF, Authors' Calculations

How researchers have understood the impact of digitalization on work

Work that focuses on digitalization and its implication on labour is not new. In Vu, Denney (2021), we provide a comprehensive knowledge synthesis on how its impact has been understood and measured. We will provide a very high-level summary here.

While discussions on the potential negative impact of new production technology on workers have been analyzed since the advent of the industrial revolution (such as those that are explored in Ricardo (1821), recent developments in research have focused especially on the proliferation of personal computers, which largely accelerated in the 1980s.

Within this research, a crucial question involved identifying the features of work that make it resilient in the face of technological change. This question arises from the fact that in all waves of technological change, we observe some workers being negatively impacted, while others flourish. There is also the potential for entrenching existing inequalities, and creating new polarization within the labour market.

Researchers have also observed that in many economies, these impacts have changed considerably. While historically, the gap due to adoption of digital technologies have been most explained by formal education attainment by workers (and the paradigm of high or low skills shown canonically in the Skill-Biased Technical Framework from Bound & Johnson (1992), recent patterns have pointed to a more nuanced view, that identifies a middling out, where occupations that exist in the "middle skill"[3] part of the spectrum decline, such as those shown in Goos, Manning (2007), or Green, Sand (2013) for a Canadian-focused study.

And while much of the past research in this area has focused on how technology tends to replace jobs, we focus here on how technology has changed jobs. We don't fully lose sight of the differential impact that technological adoption has had on different peoples (especially those who experience negative labour market outcomes from such changes), but we attempt to contribute to understanding the extent to which digitalization of work has benefitted workers, especially with a distributional lens—do those who benefit the most from the digitalization of the economy reflect the people living in Canada?

Analytical Method

A focus on hourly wage and efficiency wage

THERE ARE MANY ways to measure and compare different individuals' income. However, what we are most interested in, is the extent to which digital technology has impacted worker productivity across time (and its associated impact on income). Within this context, we want to focus on hourly pay instead of annual employment income, as a worker could command a higher annual income on the virtue of working more hours, instead of working more productively for each hour they work. In other words, conceptually we want to focus on a concept called **efficiency wage**, or the wage paid to a worker for each **efficiency unit** of work they do. **Efficiency unit** can be understood as a discrete task involved in doing work.

In one context relevant to this report, we do estimate efficiency wages and use that to compare differences between workers, but the method we employ can only be used to calculate such wages at the aggregate level, and not at the individual level. As a result, we will specify when we discuss findings that implicate efficiency wage, and use hourly wages as the base unit of analysis (especially in discussing factors that impact individual workers).

It is important to understand the difference between the two. A decline in efficiency wage can still imply an increase in hourly wage (as the worker can simply be supplying more efficiency units for each hour they work), and there are reasons to believe that in general, efficiency wages tend to decrease in the long run (while hourly wage increases).

Relative digital context, not absolute

There are two ways for an occupation to conceptually become "more digitally intensive"—one could use more technology overall, or one could use more technology as compared to other occupations. In the second instance, there are cases in which while an occupation becomes more digitally intensive, they can become less digitally intensive when compared to different occupations. As our study is concerned with comparing digitally intensive workers and less digitally intensive workers, we'll focus on the relative measure.

Regressional estimates on the direct impact of one particular attribute

Our study is also concerned with understanding the inequities that surround technology work. While previous work has explored group-differences (such as between sex[4], race, and immigration status) to characterize this inequality, this method of understanding differences treats one group as a homogenous identity, and doesn't account for within-group differences that could be partly responsible for the differences we observe. As a result, to isolate the impact of a particular facet of one's identity (or more precisely, the social consequences, due to forces of discrimination such as sexism, racism, of those identities), we use regressions, a statistical tool that allows us to isolate the direct impact of, for example, being a woman, has on technology pay (having controlled for other factors like education level, experience, and race).

Elasticity

A useful way to understand the importance of digital labour across different sectors is by estimating a property known as the **elasticity of substitution.** An elasticity of substitution intuitively measures how many non-digital workers are needed to replace a loss of one digital worker.

Formally, elasticity in economics denotes the relative responsiveness of a factor to a change in the price of that factor. An elasticity of substitution is the ratio between two factors of productions' elasticities. That is, in this context, the elasticity of substitution can be understood as the response in the relative share between the two kinds of workers (digital and non-digital) in response to the relative change in prices between the two kinds of workers: that is, how will a company adjust the ratio between digital workers and non-digital workers they employ to respond to an increase in the pay associated with digital worker (relative to non-digital worker).

Taken another way, it looks at the way a specific company is differentially using digital labour compared to non-digital labour. The smaller the elasticity, the more non-substitutable digital labour is compared to non-digital labour, or that it takes more non-digital labour to replace one unit of digital labour.

Gallipoli & Makridis (2018) first explored estimating the elasticity of substitution between digital work and non-digital work in the US context, a framework we adopt in our analysis of the Canadian economy. In our study, what we expect to find, given technological adoption, is the relative efficiency wage between digital workers and non-digital workers to be decreasing over time. This does not mean that the wages technical workers actually get paid are decreasing—but that due to productivity increases attributable that for "comparable work" (between digital and non-digital worker), digital workers will be paid lower for each unit of comparable work they do, leading firms to substitute away from non-digital workers in the manufacturing industry. We also expect this elasticity to be lower in the service sector as a whole, due to the relatively lower efficiency gains from technological adoption.

Comparative static examples

	Digital labour	Non-digital labour
Wage	$20	$10
Share	25 percent	75 percent

Wage ratio = 2 (digital workers are paid twice as much as non-digital workers); share ratio = 0.333

Say wage ratio increases by one percent, to 2.02 (say one percent increase in tech pay to $20.2 no change in non-tech pay), elasticity of 10 means share ratio goes down to 0.2997 or now employs 23 percent tech labour compared to 77 percent non-tech labour. Note here that we're talking about "efficiency wages"—wages could increase due to actual efficiency increases.

Over time, we expect relative wages of tech labour to decrease compared to non-tech labour (tech workers become more efficient) so we expect things to become fairly inelastic.

Data

For this study, we mainly rely on individual-level data from four census waves—2001, 2006, 2011[5], and 2016, accessed through Statistics Canada's secure Research Data Centres. As the long-form census covers a substantial portion of the population, and asks detailed questions about a worker's work context (including occupation) and other identities, it provides a rich source for analysis in how work has changed over the 15-year- time span we consider, especially in how technological change has impacted workers.

Hourly employment wages are not a measure that are reported as-is in the long-form census. To derive this measure, we used the total hours worked for the reference week reported by the census respondent, multiplied by the number of weeks worked by the respondent, then dividing the respondent's income from wages and salaries by this number. We remove anyone who reported negative employment income.

In the long-form census, respondents are asked to report on their hours for a specific week in the year. The reference week for the reporting of weeks worked tends to fall onto the first week of May of the year of collection. And those who were on vacation, or were ill and did not work ordinary hours during that week are instructed to report 0 hours on that question. To understand the impact of this reporting standard, we looked at the distribution of hours worked by reported labour force status (part-time versus full-time versus no work).

As well, we rely on the assumption that the distribution of illness, as well as vacation schedule, is approximately random, conditional on one's occupation, education, and geography– the level of aggregation that we work with for this study. The geography we primarily work with for this study is Census Agglomeration & Census Metropolitan Areas, which are generated through combining census subdivisions (approximately a municipality) that has strong economic ties together (in the sense of labour commuting flows), and approximates a local labour market. It is also worth noting that there are no federal or provincial holidays that ordinarily fall in the first week of May. It's likely that within the same occupation, in the same local labour market will have similar leave offers (to stay competitive at least locally), meaning our assumption is likely to be satisfied.

Geography

In the 15-year period that we examine digital intensity trends, there were shifts in population dynamics and commuting patterns that implicated associated changes in the geographical boundaries of both the census metropolitan areas as well as the census subdivisions that make up the census metropolitan areas/census agglomeration. To ensure consistency, we use the 2016 Census Metropolitan Areas (CMAs) as the base year, and using geographical concordance at the Census Sub-division[6] (CSD) level, reconstruct the 2016 CMA for 2011 2006 and 2001 census years, so the appropriate labour markets are included in our estimates.

*O*NET—NOCCrosswalk*

In order to generate a set of measure of occupation-level digital intensity for Canadian occupations, detailed occupational attributes are adapted from the US's SOC-O*NET or O*NET database, using a crosswalk, or a tool that connects between two related but different classification systems, first introduced in Vu (2019). However, as this research spans multiple census waves, and in many ways also relies on the changing digital intensity within the same occupation over time, only having a crosswalk that only uses one specific National Occupational Classification vintage to one specific O*Net vintage was insufficient. As a result, we developed two new crosswalks that allows researchers to connect between older versions of both NOC and O*NET, which allows for occupational attributes from 2005 to be used in understanding 2006 census data, and occupational attributes from 2010 to be used in understanding 2011 census data. We are also publishing these crosswalks in a separate technical release, to allow other researchers to use this tool in other research.

Digital intensity estimates

We define and identify tech occupations using the O*NET database and closely following Vu, Zafar, Lamb from our 2019 report, *Who Are Canada's Tech Workers?* I expand on this research by using multiple versions of O*NET, and generating a new set of crosswalks, to ensure that the digital intensity of occupations in 2006 comes from O*NET measures that were collected in 2006. While O*NET only updates a selected number of occupations with each annual release, we rely on two facts that provide sufficient and meaningful levels of variation. Firstly, each year, at least 100 O*NET occupations are updated with new occupational attribute measures.

This accumulates over five years, to cover almost half of the almost 1,000 occupations in O*NET database. Secondly, as our occupational digital intensity measures rely on rank measures–that is, the relative standing of a particular occupation as compared to others, changes in the rank of one occupation necessarily have an effect on the ranking of another. This does mean, however, that we assume that the absolute measure of a non-updated occupation remains constant, but this approach still provides additional values as compared to the alternative, where we use a static measure of digital intensity in a base year that is projected onto all other years in the sample.

Specifically, to generate the digital intensity measure, we find the harmonic mean of the occupational ranking in six job attributes, spanning Skills, Knowledge & Work Activities, combining both the Importance & Level measure of O*NET.

While we tried to align the census years as closely as possible to the year in which O*NET occupational attributes are measured, this was not always possible. For the 2006 census, the O*NET version that corresponds best was version 10, collected in 2015. However, O*NET version 10 introduced new occupations, including some digital occupations (such as interactive web developer), but the initial release did not contain occupational attributes for these occupations. It wasn't until version 13 that the full occupational values for these occupations were filled. As a result, for the 2006 census year, we used version 10 occupational attributes except for those occupations for which version 10 attributes were not available, and use version 13 attributes for those occupations instead. Alternative specifications (including fully using version 13 for all occupations in 2006) did not significantly alter results.

A Recent History of Digitized Work in Canada

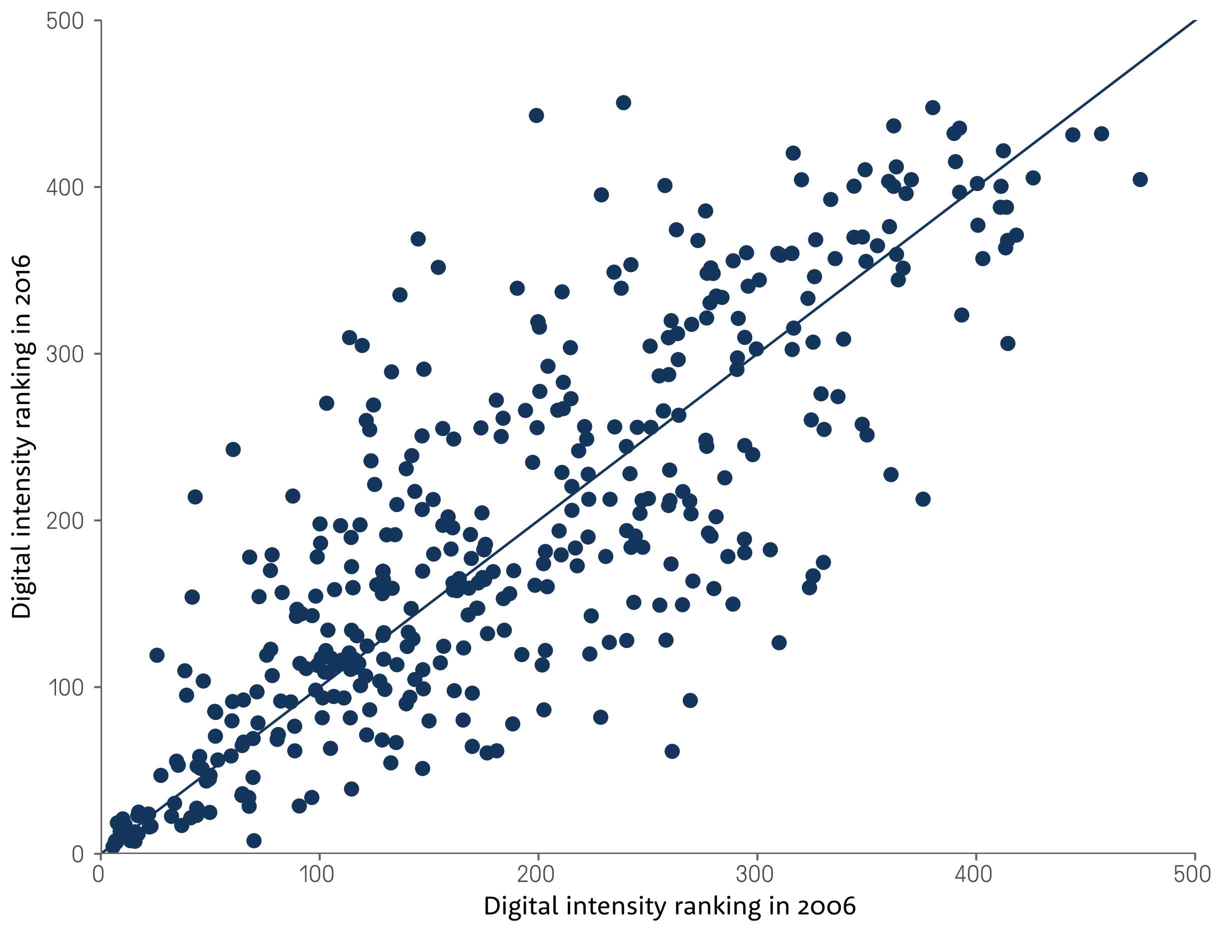
Changes in the tech intensity of Canadian jobs

In order to discuss how technology has impacted work and workers in Canada, we must first directly characterize how the content of Canadian work has changed digitally over time. As it is difficult to account for the pace of technological change, as well as methodological changes in how scores for each occupation are generated, we focus on comparing how the relative technology intensity across occupations have shifted over time. This allows us to focus especially on whether some occupations have digitized faster than other occupations. We also expand this analysis and extend it to 2021 in Abuallail & Vu (2022), while here we focus on the main period of interest—changes up to 2016.

Figure 5 shows the degree to which relative digital intensity (that is, the digital intensity of an occupation as measured relative to all other occupations) across all 500 occupations in Canada has shifted over the 2006-2016 period. Several features stand out. The occupations closest to the origin are those that are most digitally intensive. As can be seen by the fact that these occupations are clustered around the 45 degree line, occupations that were highly digital in 2006 tended to be similarly digitally intensive in 2016: that is, highly digital occupations remained highly digital.

Figure 5

Change in relative digital intensity, Canadian Occupations 2006-2016

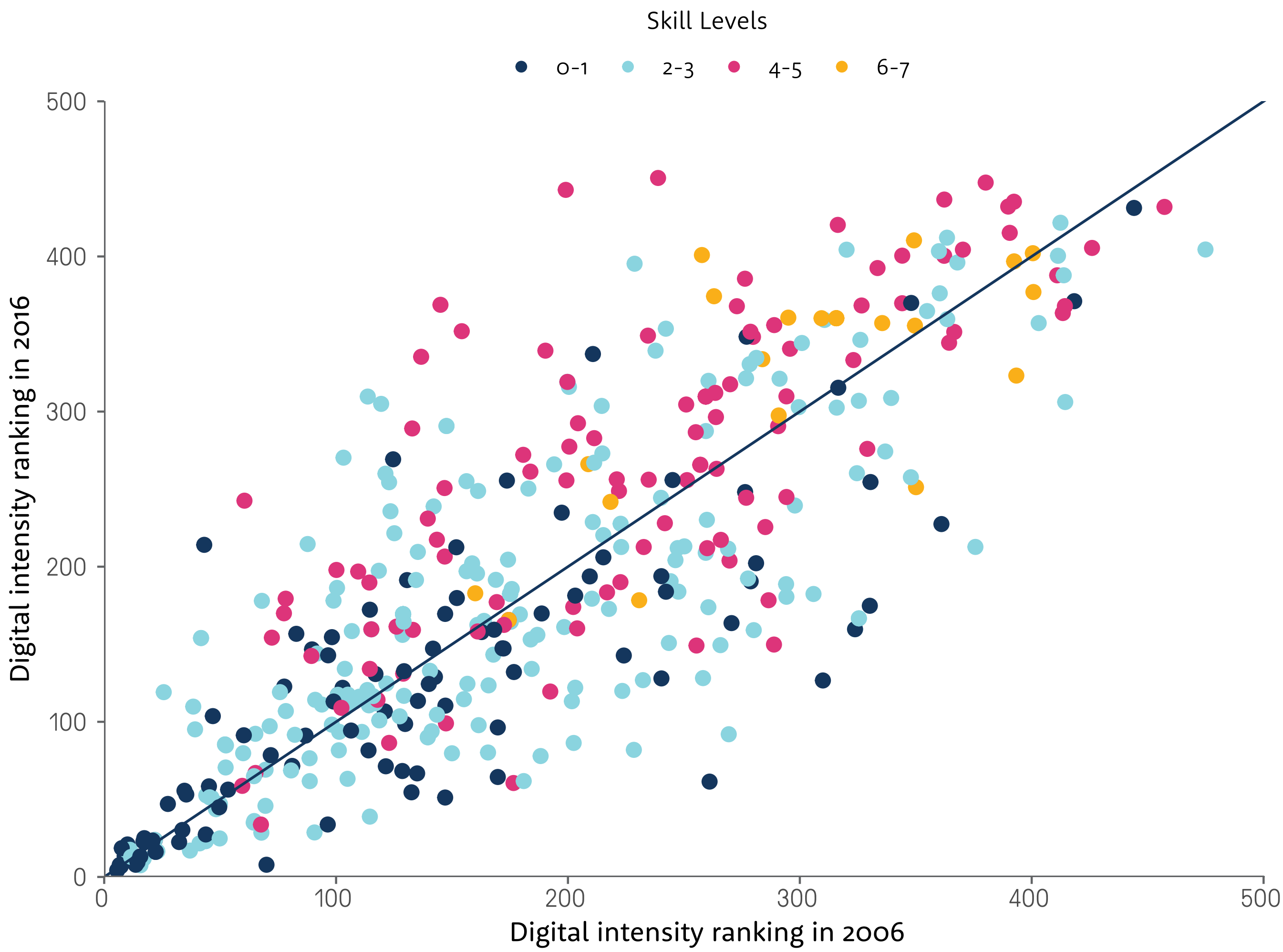


Source: Author Calculations

Another way to explore this change is by grouping occupations by different skill levels. Employment and Social Development Canada classifies occupations as belonging to eight skill levels, that are further grouped into four skill groups: the range goes from the first skill group, (0-1) comprising occupations that usually require a university degree, to skill group 4 (6-7) comprised mainly of occupations where on-the-job training is provided that is sufficient to do the work. When different skill levels are overlaid, it becomes clear that those in the 0-1 skill levels (managerial or professional—those that are associated with non-routine cognitive skills) broadly saw high levels of digital intensity in 2016 as compared to 2006. In contrast, those working in skill levels 4-5 broadly showed lower digital intensity in 2016 as compared to 2006.

Figure 6

Change in relative digital intensity, Canadian Occupations 2006-2016, Skill Levels



Source: Author Calculations

Shifts in labour market inequities in tech

While the make-up of the group of most digitally-intensive occupations have not changed significantly, we also examine here whether the make-up workers in these occupations has changed over time. In previous work, we documented significant differences across worker characteristics such as "race and gender" in participation in tech work, and we extend that analysis here for the 15-year period from 2001-2016.

We focus particularly on understanding how each worker characteristic impacts the chances that they will work in a tech occupation, after controlling for all other factors. Characteristics analyzed are age, marital status, race, Indigenous identity, sex[7], education level, immigration status, and province of residence.

In this discussion, we will focus on the profile "white, unmarried non-immigrant man in his 30s with a university degree living in Ontario" to explore how changing one or more of these characteristics impacts the probability of being a tech worker. We use this approach as a way to understand the impact of labour market barriers faced by identities that we know to have been excluded from the technology sector, since individuals have little agency over how society and the labour market perceives their gender, race, or age. While we use "John Doe" to refer to the base profile for ease of reference, we avoid attributing specific names in this comparative exercise to recognize the shared barriers many face. The following table shows the probability that John works in a technology occupation:

In 2001, a woman with every other characteristic similar to "John" had a 6.29 percent chance of being a tech worker. In 2016, this same probability was only 4.91 percent.

Table 2
Base probability of John Doe (a white, unmarried non-immigrant man in his 30s with a university degree living in Ontario) being a tech worker.

Year	Probability
2001	19.1 percent
2006	17.9 percent
2011	21.3 percent
2016	19.9 percent

Being a woman (without changing any other characteristics, including educational attainments or experience) reduces this probability substantially. Incredibly, however, the participation gap is larger in 2016 than compared to 2001. In 2001, a woman with every other characteristic similar to "John" had a 6.29 percent chance of being a tech worker. In 2016, this same probability was only 4.91 percent. Conversely, a man had a 20 percent chance of being a tech worker, a number that remains unchanged between 2001 and 2016.

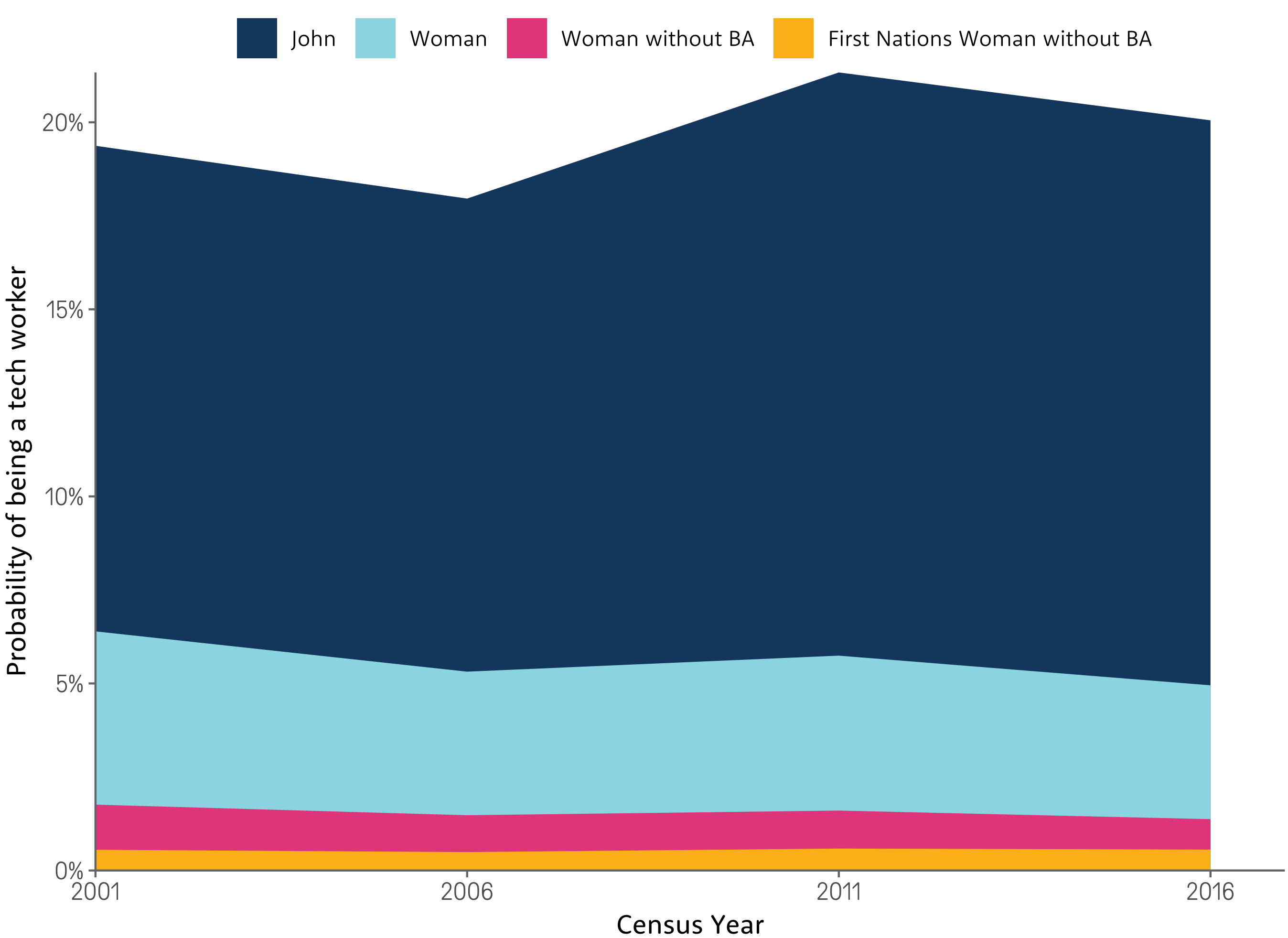
The gender participation gap is substantial, and is equivalent to (or in later years, larger than) the impact that not having a university degree has on one's probability of being a tech worker. In 2001, had John not had a university degree, his probability of being a tech worker was 5.28 percent (a 14 percentage point, or 72 percent reduction). This trend was consistent across the years such that in 2016 he still only had a 6.22 percent chance of being a tech worker without a university degree.

John's ethnic identity also impacts the probability that he is a technology worker, though the picture is deeply nuanced. If John had a First Nations identity[8] (without changing any other characteristics), their chance of being a tech worker in 2001 was 6.84 percent, and 9.12 percent in 2016. However, given many of the exclusions John would face still in Canada, this effect would be further compounded, for example by the fact that they would be less likely to have been afforded an opportunity to attain a university degree. This would have further reduced his chances of being a tech worker in 2001 to 1.89 percent, and 2.61 percent in 2016. In creating policies and programs that address labour market barriers for marginalized communities, it's important to understand how these effects compound. While there would have been variations had John been Inuit, Metis, or other Indigenous identities (as compared to being First Nations), the barriers they would face would largely be the same.

Figure 7 demonstrates how this compound effect works by comparing John's probability of being a tech worker, to workers increasingly different from him:

Figure 7

Effect of specific identity to probability of being a tech worker in Canada



Source: Census microfiles, author calculations

The compounding effect of multiple intersectionalities, and how that impacts participation in technology work can immediately be seen, where First Nations women without a bachelor's degree have less than a 1 percent chance of being a tech worker. This shows that any policies that aim to increase inclusivity in the technology sector must tackle multiple issues. It also reminds us that the impact of solving representation issues from just one facet of identity may only have limited impact in improving representation within technology work.

However, on average, had John belonged to a visible minority community (in Canada, visible minority identities are separated from indigenous identities), it would have either had no impact (in 2016), to a slightly higher chance of being a tech worker (in 2001).While this appears encouraging, we know that there is large heterogeneity across different visible minority identities, as this category groups many different backgrounds together, from East and South-east Asians, South Asians, Hispanic people, and Black Canadians. This fact by itself obscures important barriers that Black Canadians, for example, face in technology, something we documented previously in Vu, Zafar & Lamb (2019).

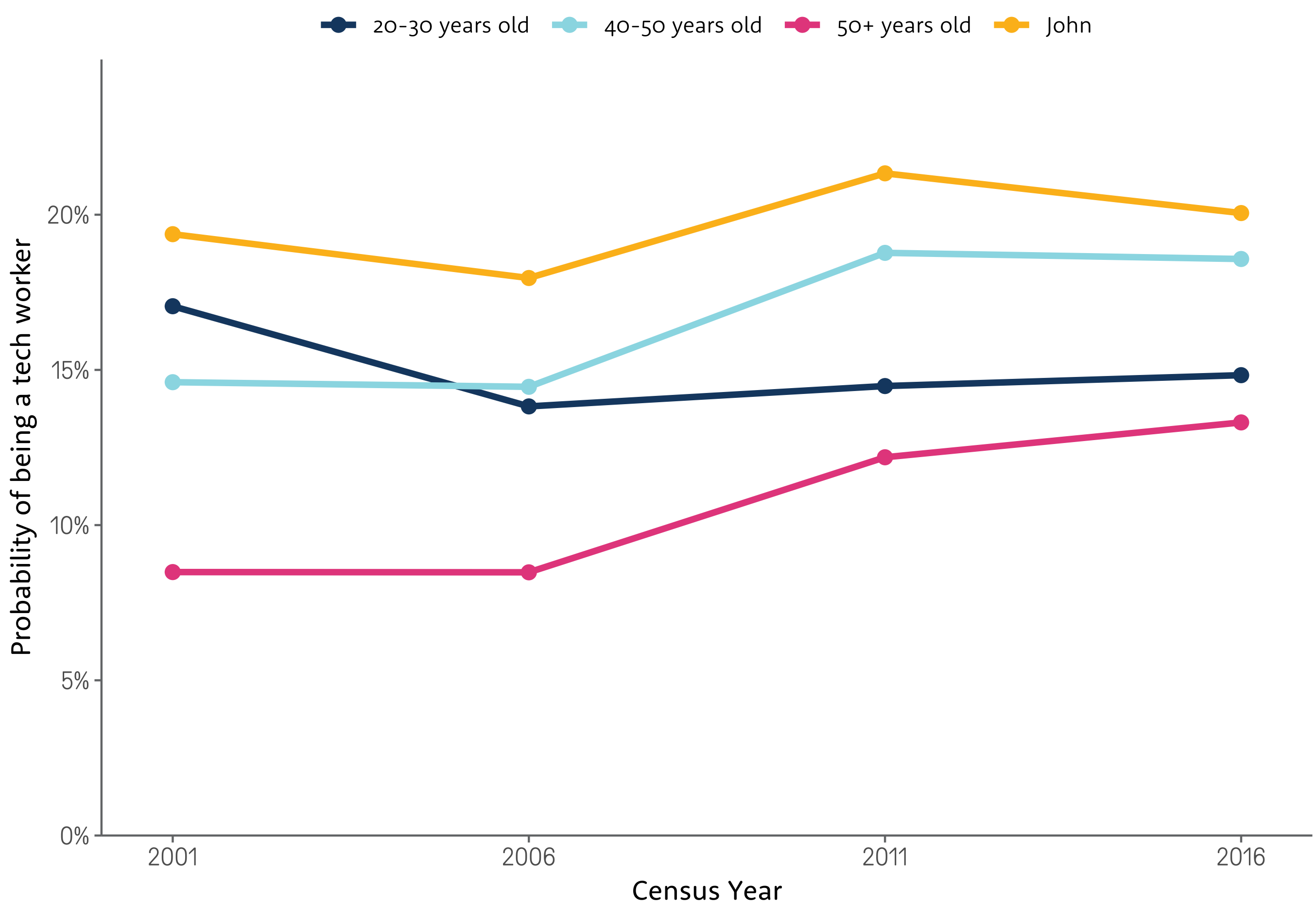
Had John been an immigrant, their chances of being a tech worker in 2001 would have increased to 25.2 percent and in 2016, 26.8 percent. This is a largely consistent trend we see in research, and likely reflects the nature of the modern immigration system Canada employs, focusing especially on high-skilled immigrants. The full picture of the experience of being an immigrant tech worker in Canada is more complicated, a fact we return to when we discuss the impact of specific characteristics on wages in tech occupations.

The compounding effect of multiple intersectionalities, and how that impacts participation in technology work can immediately be seen, where First Nations women without a bachelor's degree have less than a 1 percent chance of being a tech worker.

Over this period, there was also an aging of the technology population in Canada—while being 30-40 years old made one most likely to be a tech worker, the proportion of younger workers declined from second to third place, while the chance of a worker being over 40 years old increased over the 15-year period between 2001 and 2016.

Figure 8

Effect of age on probability of being a tech worker in Canada



Source: Census microfiles, author calculations

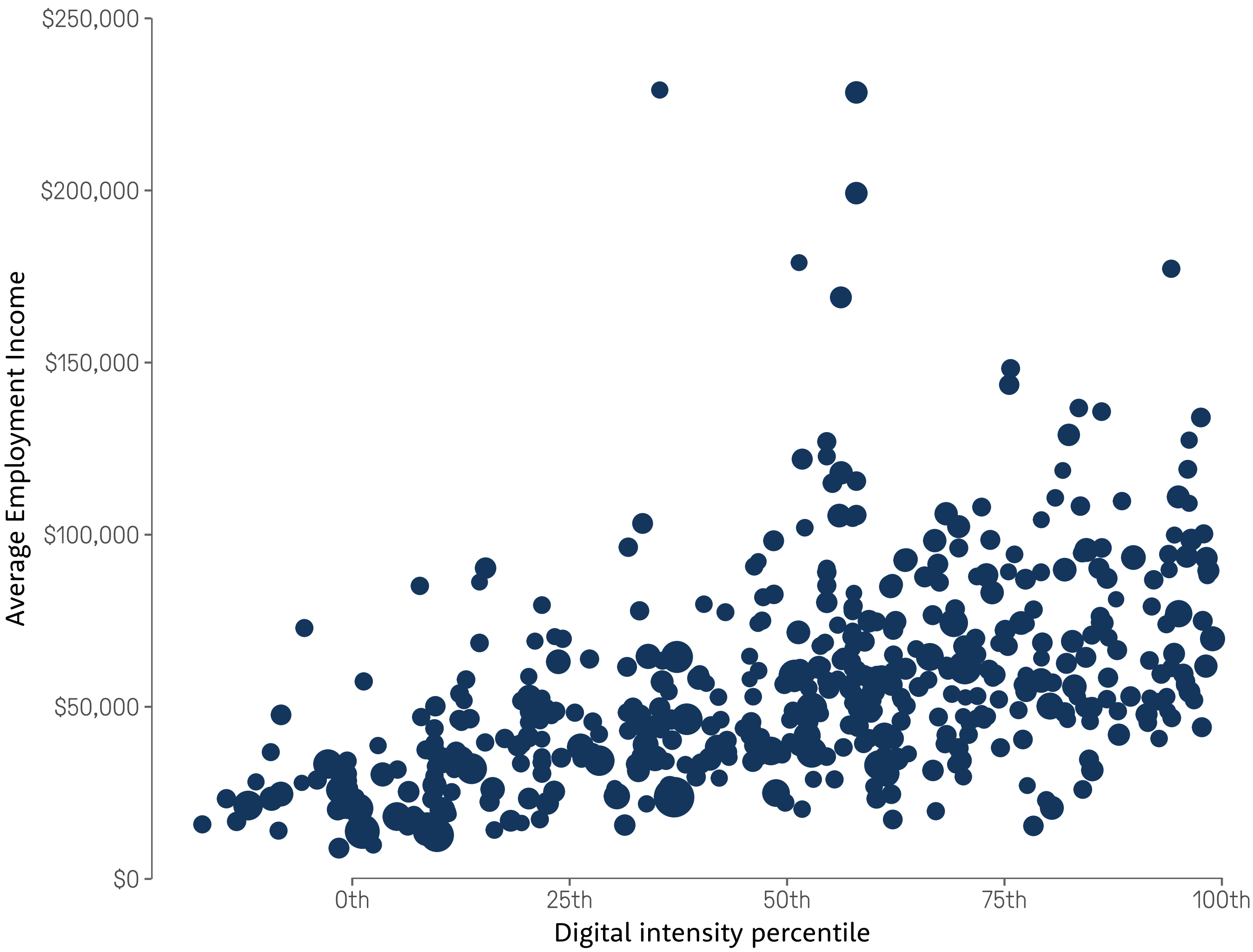
How pay in technology work has shifted

The simple wage premium

One aspect of the examination of the impact of digitalization of work, is understanding the pay differential associated with working in a more digital occupational context. As Figure 9 shows, higher digital intensity is associated with higher wages.

Figure 9

Pay and size for occupations for different digital intensities, 2016



Source: Census data combined with author analysis of O*Net data

However, when we focus on how the distribution of wages across the digital intensity distribution (from high to low) has shifted over the years, we note that while average wage (in real, or inflation-adjusted terms) have increased for all workers, the pay gap between more digitally-intensive workers and less digitally-intensive workers seems also to have became larger– while those working in the first digital intensity quantile saw a wage growth of around 14 percent, those working in the fourth (or the most digitally intensive quantile) saw a wage growth of 32 percent. We explore this idea of wage polarization in a later section.

Figure 10:

Wage across digital intensity spectrum across the years, 2001-2016

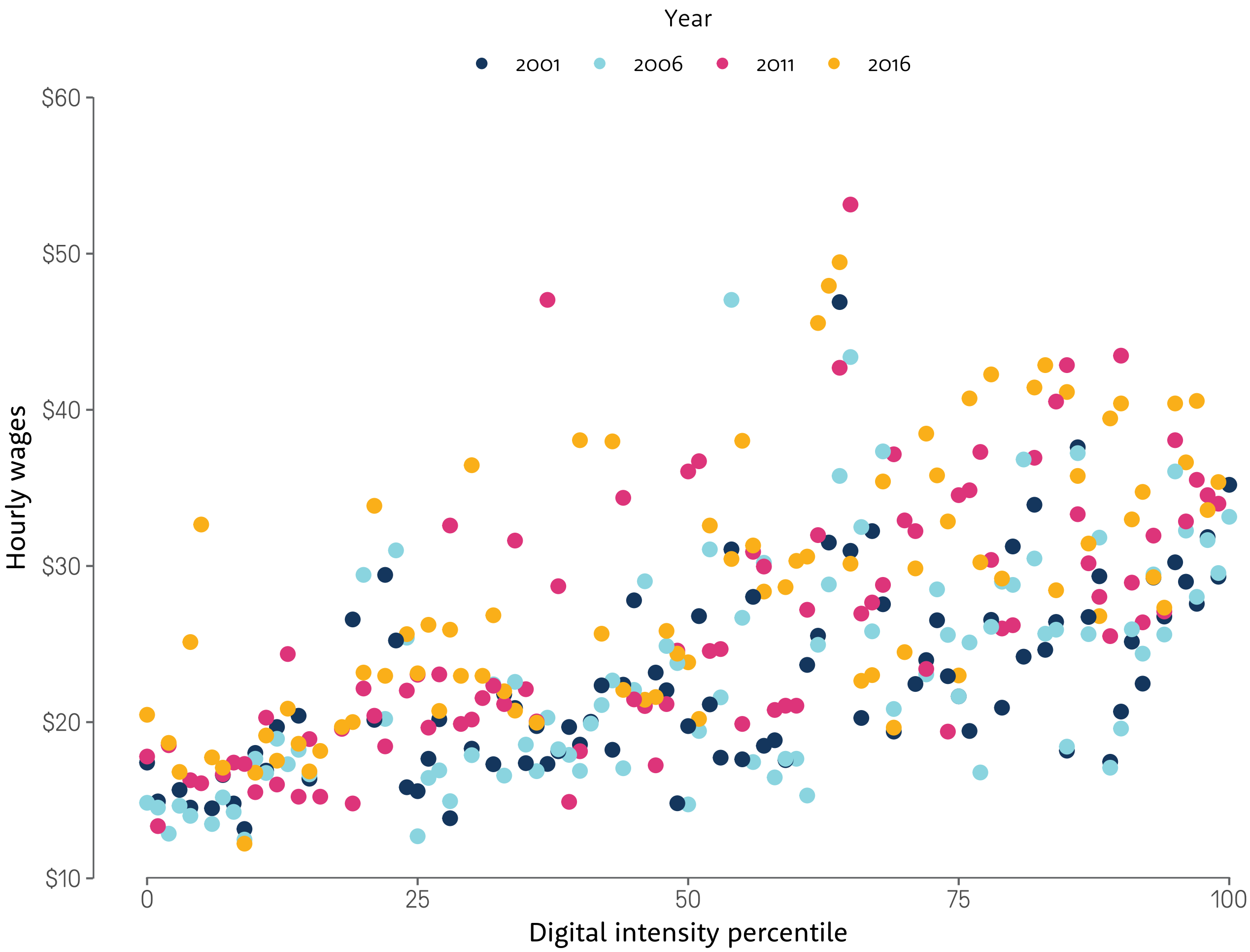


Table 3

Wage quantile for different quantile of digital intensity (Constant 2001 dollars)

Quantile	2001	2006	2011	2016
First (0th—25th)	$18.2	$17.53	$18.15	$20.78
Second (25th- 50th)	$19.61	$19.62	$24.49	$30.25
Third (50th—75th)	$24.90	$26.47	$29.44	$31.68
Fourth (75th—100th)	$26.84	$27.62	$32.95	$35.50

Men experience an average $3.49 per hour increase in pay, compared to women... an average of over $7,200 in annual income.

Labour market inequities in tech: wage edition

This simple understanding of wage structure obfuscates a number of different factors. It is important that while focusing on hourly pay (as we stated in the methodology section) allows us to focus on pay differentials that exist among different groups, it does not allow us to focus on broader labour market inequities. For example, due to the expectations for child-rearing falling disproportionately on women, this might show up in the gender pay gap in the differing hours men and women work. While these types of labour market inequities are important to focus on, for this study, we are particularly interested in understanding the gaps that exist between work contexts that are comparable.

Furthermore, we know that within the labour market, workers with particular characteristics are more disadvantaged than others, and previous research has indicated that the tech sector is not immune to such issues that impact pay equity. To specifically isolate the impact of the digital aspect of work, these factors need to be controlled, something we do in the proceeding section. Broadly speaking, we use data for each individual, and compare the hourly wage (thus controlling for the hours worked) after controlling for a number of individual characteristics such as a worker's educational background, their gender, immigrant status, and race. Importantly, we also control for their age, which we use as a proxy for their experience.

When the impact of having a specific identity on hourly pay in tech work is explored, important patterns emerge— the first is the importance of experience and a university degree, both of which are vitally important in determining hourly pay for tech workers. Those without a university degree and experience are likely in their early careers (proxied for by age here) and earn just under the hourly minimum wage set by many provinces in Canada.

However, significant differences still exist between different identities, something we first identified in Vu, Zafar & Lamb (2019). Being a man is associated with a $3.49 per hour increase in pay in 2022 dollars, or, assuming a 40-hour work week[9], a difference of over $7,200 in annual income, compared to being a woman. Having a visible minority identity (averaging across all identities) lowers one's pay by $3.89 per hour, or almost $9,500 in annual income. Being an immigrant is associated with a $5.03 lower pay per hour, or over $10, 400 less in annual income.

These differences here are additive–that is, an immigrant woman with a visible minority identity engaging in tech work without a university degree in Canada, on average, is expected to make $18.5 per hour less than a white, non-immigrant man with a university degree, or over $38,000 in annual income. If this man had a university degree, he would make on average $8.94 per hour more.

Having a visible minority identity lowers one's pay by $3.89 per hour, or almost $9,500 in annual income.

Of particular note here is the negative pay from being an immigrant. Vu, Zafar & Lamb (2019) demonstrated that the pay of an immigrant tech worker is higher than that of a non-immigrant, without controlling for any other factors. However, once factors such as experience, education, and sex is controlled for, the immigrant pay penalty in tech is in fact larger in magnitude than the gender pay gap.

Previously, in Vu, Zafar & Lamb (2019), we were only able to look at the conditional differences between different groups (that is, female tech workers as a whole compared to male tech workers), and while controlling for various factors (such as experience—proxied by age) reduces the observed gap, it doesn't fully eliminate it, implying labour market outcome differentials, and the existence of important equity issues in the tech sector in Canada. This is consistent with other findings to this effect.

Once factors such as experience, education, and sex is controlled for, the immigrant pay penalty in tech is in fact larger in magnitude than the gender pay gap.

Table 4

Technology pay gap based on identity in Canada

Identity	Hourly wage (2001 constant $)	Inflation adjusted 2016 wages	Inflation adjusted 2022 wages	Yearly equivalent 2016	Yearly equivalent 2022	Gap 2016	Gap 2022
Base identity (30-40 year old unmarried white man with a university degree)	$31.49	$41.31	$48.23	$85,931.13	$100,328.31	NA	NA
Being a woman	$29.21	$38.32	$44.74	$79,709.57	$93,064.38	-$6,221.55	-$7,263.93
Not having a university degree	$21.52	$28.23	$32.96	$58,720.01	$68,558.16	-$27,211.11	-$31,770.15
Being BIPOC	$28.53	$37.42	$43.69	$77,837.65	$90,878.82	-$8,093.48	-$9,449.49
Being an immigrant	$28.21	$37.01	$43.21	$76,978.09	$89,875.25	-$8,953.04	-$10,453.06
Having 10 more years of experience (being 40-50 years old)	$37.33	$48.97	$57.17	$101,856.13	$118,921.43	$15,925.00	$18,593.12
Being married	$35.61	$46.72	$54.54	$97,168.13	$113,448.00	$11,237.00	$13,119.68
Young unmarried Immigrant non-white man with a university degree	$14.462	$18.97	$22.15	$39,463.21	$46,075.01	-$46,467.92	-$54,253.30

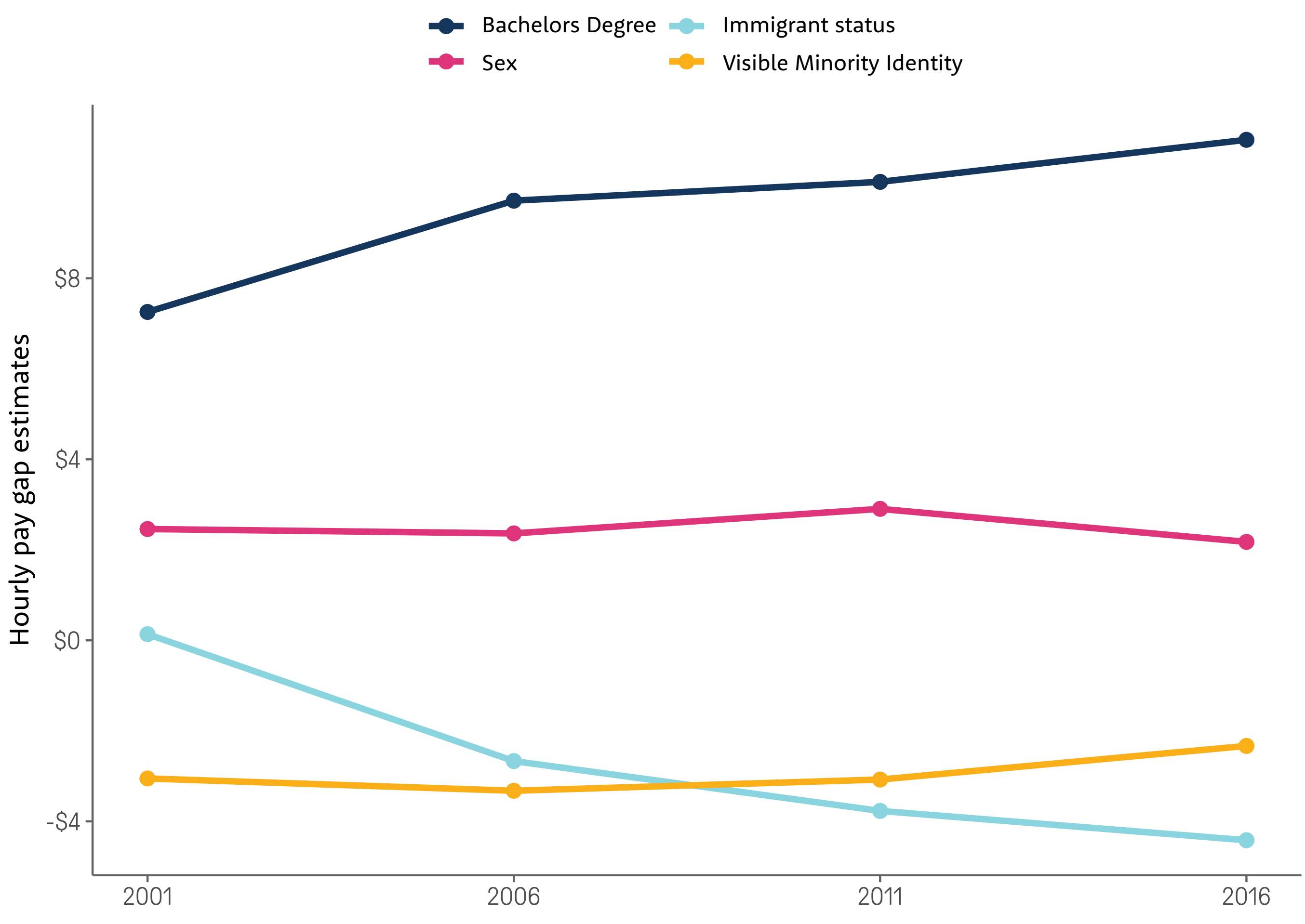
In exploring these differences, we also explored whether there were pay differences for tech workers across different provinces. Our analysis shows that after controlling for demographic make-up, there weren't any, except for tech workers in Alberta, which was likely due to the very specific nature of tech work (mostly concentrated in the energy sector), earned $13 per hour higher than tech workers elsewhere in Canada. Once the likely demographic characteristics of these workers are taken into account, this wage gap likely gets larger in magnitude.

There is also interest in running this pay-gap model for each of the census years that we have in the data (2001-2016) to see how these pay gaps have evolved over time.

The premium in technology pay for those with a bachelor's degree has increased in the past 15 years.

Figure 11

Evolution of pay gap in tech over time, selected characteristics



Source: regression estimates using census microfiles from 2001, 2006, 2011 and 2016

There are several interesting characteristics at play. The first notable one is that the premium in technology pay for those with a bachelor's degree has increased in the past 15 years. The gender pay gap has remained fairly consistent over the sample period, though the estimate in 2016 is not statistically significant. However, given the participation barrier women face in tech jobs that we outlined in the previous section, there is a non-trivial chance that this is driven by changes in the number of women in the tech sector (changes in women who remain in tech work, as opposed to those who leave), as opposed to the actual elimination of a pay gap.

Most interesting is the pay gap that immigrant tech workers incur. In 2001, there was no observable pay gap between immigrant and non-immigrant tech workers, but over the 15-year period, this gap has continued to widen, to over $4.40 per hour (in 2001 dollars, or $5.70 in 2016 dollars) after controlling for other observable characteristics. This widening gap stands as an important challenge, as Canada increasingly relies on highly skilled immigrants in tech, to ensure new workers in Canada can equitably access the labour market.

In 2001, there was no observable pay gap between immigrant and non-immigrant tech workers, but over the 15-year period, this gap has continued to widen, to over $4.40 per hour.

The only gap that seems to have improved is the pay gap visible minority tech workers face; however, this obscures important heterogeneity in this side group. We know from previous research for example, that Black tech workers still face significant barriers in the technology sector in Canada, where among the visible minority identities, they face the largest pay gap.

In the data, we do not observe pay penalties that are specifically associated with different Indigenous identities. In previous work (Vu, Zafar, Lamb 2019), we discussed the issues with using census (or any data collected by the government of Canada) to understand issues impacting Indigenous peoples in Canada, and also noted the important trends impacting different communities of Indigenous peoples (that goes further than a simple First Nations-Metis-Inuk delineation we conduct here). The lack of a gap specifically associated with Indigenous people also does not mean Indigenous peoples working in tech jobs aren't paid lower salaries—this is a fact we documented previously. We discuss the implication of this pay result in conjunction with the significant barrier that Indigenous peoples face in accessing technology jobs later, especially in implications for Indigenous economic empowerment policies.

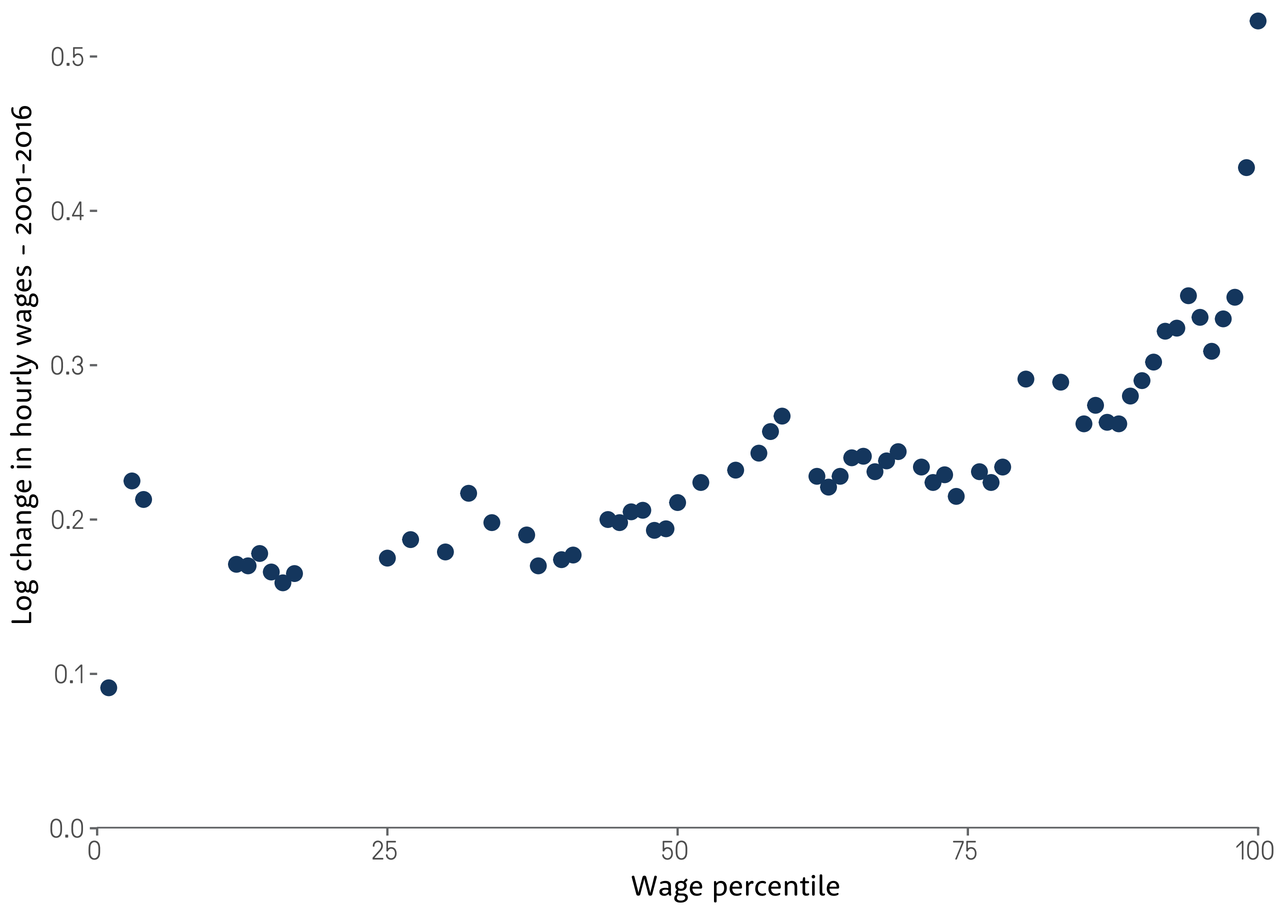
Wage polarization in Canada in the 2000s

One trend we focus on to understand the potential differential impact of technological adoption on workers in Canada, is how it has impacted wages for different income groups in the labour force. Economists, in analyzing labour markets in jurisdictions such as the US and UK, have identified the trend of job polarization, where more recent technological change (as compared to technological change that occurred previously) confers particularly negative impacts to those who are "middle skilled" –those who are involved in routine tasks for which technology can easily automate. The most recent work that explores the idea of job polarization in Canada by Green & Sand (2015) examined the dynamics of wage growth across the distribution of income levels between the 1980s and 2006, showing that job polarization has not occurred in Canada for the period beginning the the 1990s.

We updated this analysis up to 2016[10], to document largely the same trend, where job polarization, or labour market declines in the middle of the income distribution, relative to both the high and low end of the income distribution, has not been documented of occupations in the Canadian labour market between 2001 to 2016. It is important to note that this does not mean wage growth has been equitably distributed in Canada, just that the impact of technology on the labour market in Canada is likely different to other jurisdictions.

Figure 12

Changes in log hourly wage by wage percentile in Canada, 2001-2016

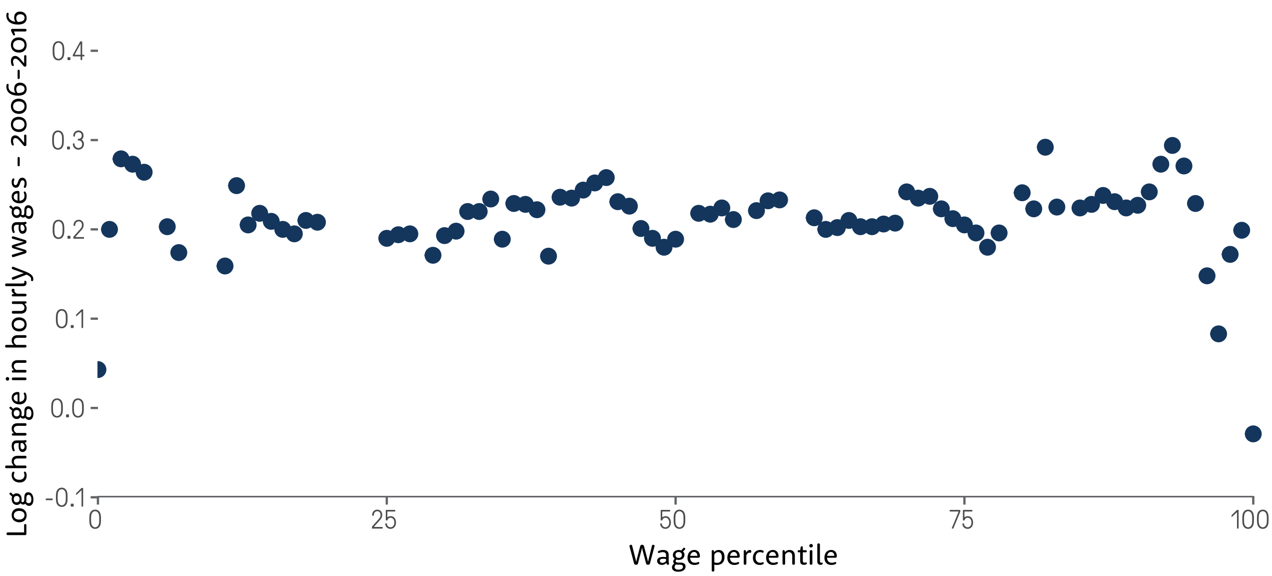


Source: Author Calculations, Census Microfiles 2001-2016

However, when we restrict the analysis to log wage growth over 2006 to 2016, a different pattern emerges where hourly wage changes in the decade are much more equally distributed across income levels. This implies the particular importance that the years 2001 to 2006 played in the observed polarization in wages.

Figure 13

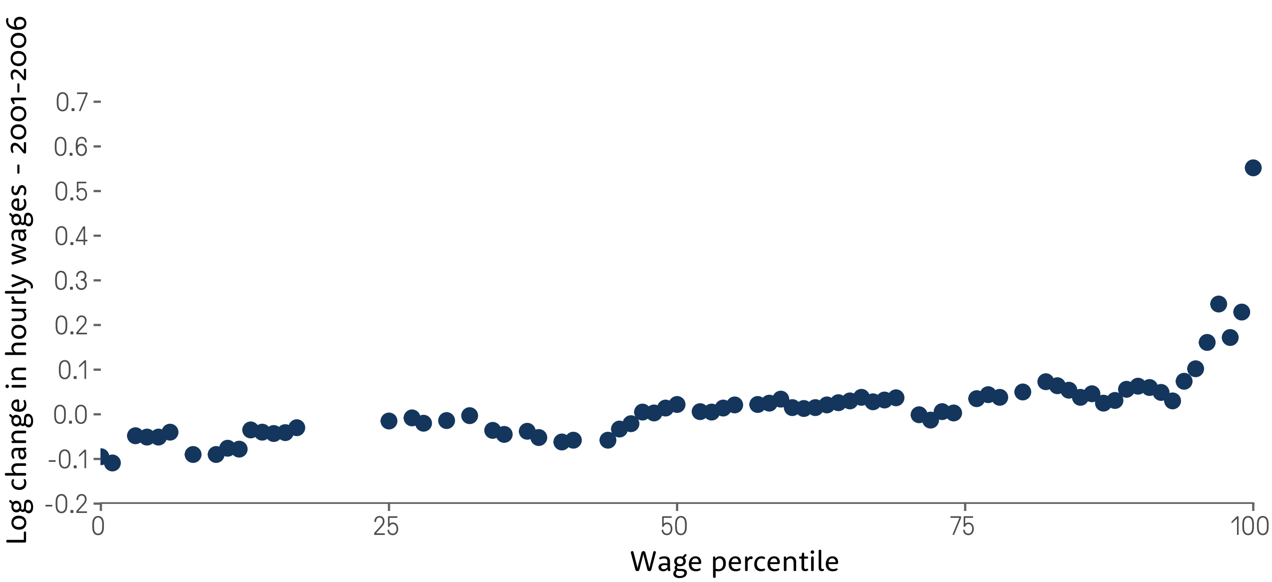
Changes in log hourly wage by wage percentile in Canada, 2006-2016



Source: Author Calculations, Census Microfiles 2006-2016

Figure 14

Changes in log hourly wage by wage percentile in Canada, 2001-2006



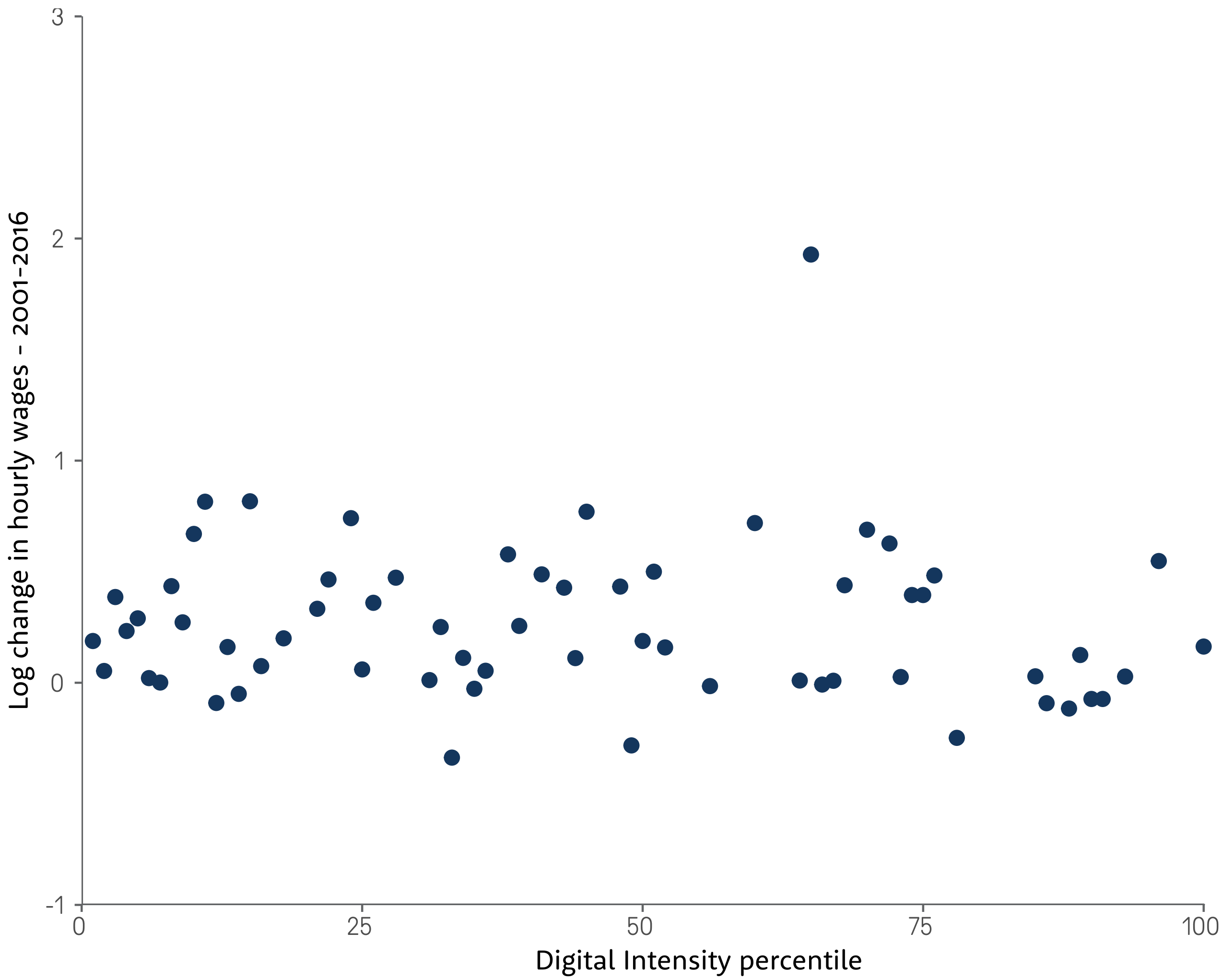
Source: Author Calculations, Census Microfiles 2001-2006

To more explicitly understand how wage distribution has evolved by different levels of digital skill requirements, we observe wage changes for each percentile of digital intensity across our sample period. At first glance, when the aggregate period between 2001 and 2016 is observed, it looks as though there are no clear patterns to the evolution of hourly wages for each digital intensity percentile.

However, when we concentrate on the period between 2001 and 2006[11] in Figure 16, a fascinating pattern emerges, where wage changes for those at the two ends of the digital spectrums is clustered, and generally positive, while those in the middle has high variance as to the wage changes they experienced. This is consistent with the idea of job polarization explored in a routine-based framework.

Figure 15

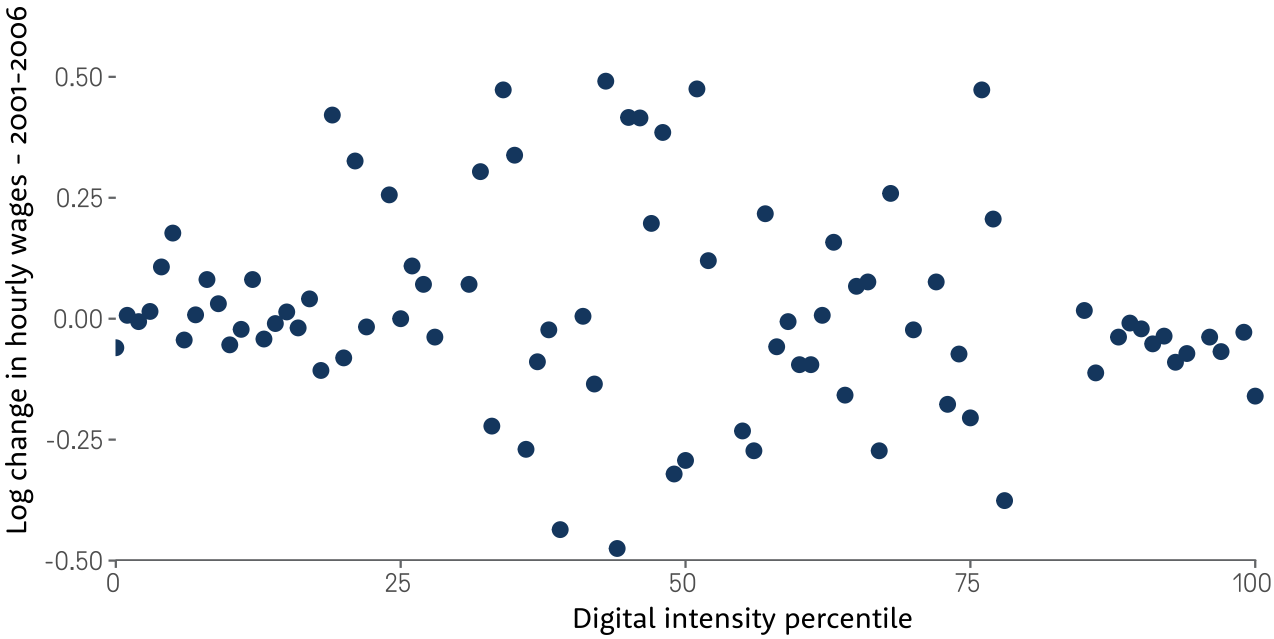
Changes in wage by digital percentile 2001-2016



Source: Author Calculations, Census Microfiles 2001-2016

Figure 16

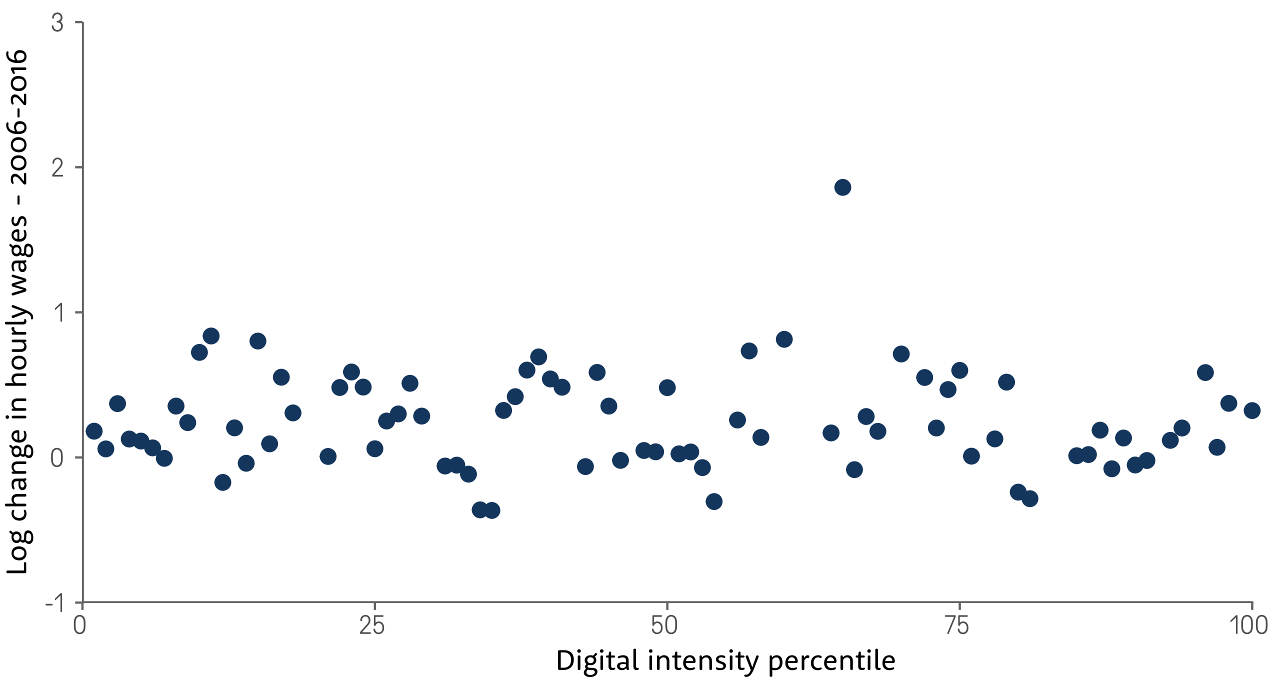
Changes in wage by digital percentile 2001-2006



Source: Author Calculations, Census Microfiles 2001-2006

Figure 17

Changes in wage by digital percentile 2006-2016



Source: Author Calculations, Census Microfiles 2006-2016

Sectoral differences in the use of digital labour

In the previous section, we extensively explored how the characteristics of digital work have shifted over 15 years in Canada. We now discuss how such talents are used in the economy, especially with the aim to understand how digital labour is used in comparison to non-digital labour. In this section, we focus on the impact of changes in efficiency wage across two broad sets of occupations, and how that affects the make-up of a particular industry.

Table 5

Elasticity of substitution between digital and non-digital workers in Canada

Industry	If elasticity doesn't change	If elasticity changes		
		2006	2011	2016
Manufacturing	~100 percent	~100 percent	~100 percent	27*
Service	5.78***	4.29***	5.74***	8.92***

While we find, expectedly, that the service industry is less sensitive to changes in a tech worker's efficiency wage (as technology workers alone cannot dominate the industry). However, our elasticity estimates imply that both industries do substitute between digital and non-digital workers. As we expect the technology efficiency wage to decrease faster than the non-technology efficiency wage in the medium run, there are important implications surrounding labour demand, as well as skill demand.

We also find, however, that while the elasticity of substitution has increased across the period for services, the elasticity of substitution has decreased in the manufacturing sector.

However, in some instances, this shift could also reflect the fact that work easily replaced by technology has all already been replaced, and those engaged in non-tech work perform non-routine tasks that are hard to substitute efficiently with technology. However, given the general context of the lack of investment in technological adoption seen by the stagnation in investments in intellectual properties, as well as machinery, we believe, with a fair amount of certainty, that we have not exhausted our technical potential and that Canadian industries (both services and manufacturing), have used technology workers less effectively than in the past.

Conclusion

The landscape of Canadian digital skills have changed immensely in the past two decades.

Digital technology has changed rapidly over the past two decades, affecting all occupational contexts and work in Canada. The rapid rise in technologies that concern storing, analyzing and making sense of immense amounts of data in particular has had a big impact on how workers interact with digital technology in their everyday work.

However, even when technology increasingly permeates our everyday life, if businesses do not adopt technology, and if Canada does not engage fully with its technological talent, we risk losing out on the immense opportunity of the digital economy. In this research, we focused in particular on the worker dimension, deepening our understanding on who we're including and excluding in the digital economy, and how well we use the talents of those we do include.

We observed the extent to which those who create technologies in Canada do not represent those who live here, and how their absence can cause us to miss out on valuable insights, talent, and experience that can shape future technologies.

Canada has yet to unlock the full potential of the digital workforce, and we leave more on the table with every passing year.

Technology workers in Canada have immense talent and potential. And yet, it seems that as a country, Canada has never been able to unlock their full promise. We examined important evidence that showed exclusion in technology work across a range of identities, including those barriers faced by women, immigrants, people with visible minority identities, and Indigenous identities. These levels of exclusion come from two sources–exclusion of participation and exclusion from equal remuneration.

We observed the extent to which those who create technologies in Canada do not represent those who live here, and how their absence can cause us to miss out on valuable insights, talent, and experience that can shape future technologies. Even when they are included in the sector, their talent is not valued in the same way, and this implies that if we are able to eliminate pay differentials that exist (alongside other labour market inequalities), we'll also be unlocking their full potential.

However, even if we are to remove all labour market inequities in technology and the wider economy, Canada will have to overcome yet another challenge—we have made poorer use of technology talent over time. As discussed in the previous section, while part of this can be driven by the fact that "what can be automated has been automated", the evidence we have gathered on Canada's investment in technological and adoption and R&D, as well as in technological adoption, tells a different story, where the stagnation in such investment means that not only have we not harnessed technology workers' full potential, we are leaving more and more on the table with each passing year.

This has important consequences for Canada's long term prosperity, especially in light of demographic factors including an aging population. While important investments have been made in Canada since 2016 to tackle this issue, available data shows that we have yet to see the impact of such investments in important areas, such as investment in R&D activities, or productivity growth. And while future research should focus on the impact the pandemic has had, especially from the perspective of the forced adoption of digital technology, that alone is not enough. We are not able to be truly successful unless we also make an effort to address labour market inequities that leave out important voices from this economy.

It has long been argued that Canada has been lagging behind international competitors when it comes to business digital adoption. In this research, we demonstrate that Canada is also lagging behind on nurturing, developing, and using our digital talent. While in future work, we will endeavor to explore specific aspects of the immense challenge we face, especially in examining if there are ways to close this gap, we stress the importance of Canadian policy makers taking action to benefit fully from the power of the digital economy.

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Appendices

Appendix A— Theoretical model of the role of digital workers in the Canadian economy

IN THIS APPENDIX, we outline the theoretical model used in understanding the economy, and explore the implications, constraints, and assumptions this implies for our main estimation exercise. The model is taken from Gallipolli & Makridis (2018), which in itself is an adaptation of the model devised by Adao (2016). The appendix mainly focuses on the intuition behind these models, while the full technical derivation is available in the respective sources.

Workers

In this economy, each worker has different expertise in digital skills and non-digital skills. In comparing between two workers, we focus on the idea of **absolute** and **comparative** advantage. Given two skill sets, **absolute** advantage means one worker has better non-digital skills than another worker; **comparative** advantage means that regardless of absolute advantage, one worker's relative digital skill (compared to non-digital skill) is better than another.

To understand this further, imagine the case of two workers with the following features:

	Non-digital task	Digital task
Worker 1	1 hour	2 hour
Worker 2	2 hour	2.5 hour

In this case, Worker 1 has absolute advantage over Worker 2 (since they can do the same job in half the time). However, Worker 2 has comparative advantage for digital tasks, since by switching between non-digital task and digital tasks, they only add 0.5 hours to their time (which is 25 percent of the time they take to finish non-digital task), while Worker 1 will have to add one hour (or 100 percent of the time they take to finish non-digital task).

We focus on advantages here, so we can be agnostic about the precise measurement of each worker's productivity, such that as long as we know the rank order of workers, we have enough information about how they'll behave in this model. As a result, workers' comparative advantage will be expressed as a fraction of a worker's absolute advantage.

Production

Within this model, the economy produces one good, that is produced using two different kinds of labour, digital labour and non-digital labour, that is combined with a constant elasticity of substitution (that is, regardless of production size, the change in digital labour due to a change in non-digital labour wages is the same). There is no capital used in this economy, and we impose standard competitive market assumptions so that the market clears when the marginal product equals marginal cost.

Equilibrium dynamics

Within this economy, each worker, in deciding whether to be employed in a digital or non-digital task, considers and compares the pay they'll receive. This pay is dependent on two main factors. The first factor is the task-specific unit wages. Digital tasks and non-digital tasks are valued differently by design in this model, and these differences mean that each unit of digital or non-digital task will be paid a different price. The second factor is the worker-specific productivity, which we abstract away to focus on their absolute and comparative advantage, which determines how many units of each task they can supply.

This means that each worker face two wages, as follows:

> Non-digital task wages = non-digital-task unit pay x absolute advantage
>
> Digital task wages = digital-task unit pay x absolute advantage x comparative advantage

Workers then choose whichever work will give them a higher pay. To look at the full dynamic, we order every worker in this economy according to their comparative advantage, lowest on the left, and highest on the right. We can then see that there will be a point where the non-digital wage is equal to the digital wage, where to the left of this point, non-digital wage is higher, and to the right of this point, digital wage is higher. This point divides workers into two groups and incidentally will represent the share of workers engaged in each of the tasks in equilibrium.

Appendix B—All regression tables

THIS APPENDIX PROVIDES all detailed regression tables that were used to generate various graphs and tables presented in this report.

Table 1 & 2 detail results from regression models that was used to perform the pay and participation gap analysis.

Table 3, 4, 5, 6, 7 & 8 are the set of tables that were used to estimate the elasticity of substitution between digital and non-digital labours in manufacturing and services. We tested broadly between 2 stages least squared and 3 stages least squared strategy, and within each set of models, between a model that constrains the key estimate to be time-invariant, and an unconstrained model where we allow for the key estimate to be time-variant. The elasticity is then calculated as the reciprocal of the absolute value of the effective wage premium.

Table 1—Participation model

	Pooled	2001	2006	2011	2016
Intercept	**-4.703***** (0.007)	**-4.280***** (0.013)	**-4.544***** (0.013)	**-4.646***** (0.012)	**-4.816***** (0.011)
Sex	**1.448***** (0.004)	**1.258***** (0.008)	**1.361***** (0.008)	**1.493***** (0.007)	**1.572***** (0.006)
Age (30-40)	**0.333***** (0.004)	**0.156***** (0.009)	**0.311***** (0.010)	**0.471***** (0.009)	**0.365***** (0.008)
Age (40-50)	**0.141***** (0.005)	**-0.184***** (0.010)	**0.052***** (0.010)	**0.311***** (0.009)	**0.270***** (0.008)
Age (50+)	**-0.339***** (0.005)	**-0.796***** (0.012)	**-0.549***** (0.011)	**-0.199***** (0.010)	**-0.126***** (0.008)
Married	**0.064***** (0.003)	**0.013*** (0.008)	**0.060***** (0.007)	**0.057***** (0.006)	**0.104***** (0.006)
First Nations	**-1.232***** (0.056)	**-1.168***** (0.044)	**-1.107***** (0.041)	**-1.015***** (0.038)	**-0.906***** (0.029)
Metis	**-0.621***** (0.049)	**-0.699***** (0.055)	**-0.449***** (0.043)	**-0.407***** (0.038)	**-0.314***** (0.029)
Inuk and others	**-0.886***** (0.064)	**-0.983***** (0.118)	**-0.821***** (0.102)	**-0.807***** (0.096)	**-0.442***** (0.068)
Visible minority	**0.104***** (0.004)	**0.125***** (0.011)	**0.622***** (0.012)	**0.062***** (0.009)	-0.003 (0.007)
Immigration	**0.343***** (0.004)	**0.356***** (0.010)	**0.280***** (0.008)	**0.371***** (0.008)	**0.389***** (0.007)
Bachelor's degree or above	**1.321***** (0.003)	**1.338***** (0.007)	**1.320***** (0.007)	**1.320***** (0.006)	**1.320***** (0.005)
Region control	Yes	Yes	Yes	Yes	Yes
Year control	Yes	NA	NA	NA	NA
N	11,111,100	2,324,700	2,628,000	2,682,000	3,476,300

*A logistics regression with the dependent variable is whether a worker works in a technology occupation or not. ***:p<0.001; **:p<0.01, *:p<0.05*

Table 2—Pay model

	Pooled	2001	2006	2011	2016
Intercept	**12.76***** (5.02)	**17.14***** (1.301)	**23.87***** (1.841)	**31.37***** (1.997)	**31.42***** (2.896)
Sex	**2.28***** (0.707)	**2.46***** (0.774)	**2.36*** (1.105)	**2.90*** (1.149)	2.17 (1.654)
Age (30-40)	**6.66***** (0.860)	**6.94***** (0.877)	**6.07***** (1.319)	**5.59***** (1.452)	**8.19***** (2.069)
Age (40-50)	**12.50***** (0.902)	**9.88***** (0.957)	**12.78***** (1.372)	**11.65***** (1.499)	**14.73***** (2.157)
Age (50+)	**20.50***** (0.971)	**15.35***** (1.167)	**20.92***** (1.554)	**20.69***** (1.589)	**22.75***** (2.194)
Married	**4.12***** (0.645)	**2.87***** (0.715)	**3.18***** (1.009)	**4.26***** (1.044)	**5.21***** (1.493)
First Nations	-2.39 (3.698)	-3.47 (4.35)	-4.54 (5.995)	-1.65 (6.41)	-0.11 (8.072)
Metis	2.05 (3.673)	-2.16 (5.39)	0.39 (6.23)	0.67 (6.33)	0.96 (7.952)
Inuk and others	-2.03 (10.43)	-1.69 (11.87)	0.58 (15.00)	1.42 (16.18)	-5.05 (18.84)
Visible minority	**-2.97***** (0.864)	**-3.05***** (0.998)	**-3.32*** (1.651)	**-3.08*** (1.318)	-2.33 (1.82)
Immigration	**-3.28***** (0.718)	0.136 (0.889)	**-2.67*** (1.06)	**-3.77**** (1.247)	**-4.42*** (1.759)
BA or above	**9.97***** (0.596)	**7.25***** (0.657)	**9.71***** (0.935)	**10.13***** (0.956)	**11.06***** (1.38)
Region control	Yes	Yes	Yes	Yes	Yes
Year control	Yes	NA	NA	NA	NA
N	528,300				

*OLS regression on hourly wage paid to workers (real 2001 Dollars). ***:p<0.001; **:p<0.01; *:p<0.05*

Table 3—Manufacturing 2 SLS Unconstrained

	Second-stage regressions			First-stage regressions		
	2006	2011	2016	2006	2011	2016
Intercept	-0.279 (0.329)	0.194 (0.345)	0.212 (0.337)	0.045 (1.79)	1.58 (1.27)	-0.611 (1.37)
Effective Wage Premium	0.019 (0.015)	-0.008 (0.024)	**-0.039*** (0.021)			
Share of male	-0.364 (0.429)	0.360 (0.352)	0.112 (0.341)	-2.17 (2.31)	-1.79 (1.28)	1.32 (1.37)
Share married	0.143 (0.136)	**-0.259*** (0.134)	0.056 (0.121)	-0.368 (0.731)	**-1.54***** (0.506)	**1.58***** (0.527)
Share visible minority	**-3.49***** (1.21)	0.028 (0.159)	0.086 (0.114)	0.123 (6.91)	**1.53***** (0.591)	-0.161 (0.489)
Share Age 30-40	**1.003**** (0.486)	0.188 (0.637)	-0.597 (0.622)	-0.994 (3.03)	**-9.90***** (2.67)	2.75 (2.30)
Share Age 40-50	-0.689 (0.621)	0.597 (0.579)	-0.478 (0.631)	**-6.60**** (3.26)	2.94 (2.09)	**-9.59***** (2.48)
Share Age 50+	0.581 (0.440)	-0.551 (0.384)	0.036 (0.421)	0.763 (2.37)	**-2.92**** (1.37)	**4.97***** (1.64)
Share Wage in 2nd decile	0.448 (0.628)	-0.765 (0.545)	-0.166 (0.612)	-4.26 (3.33)	**3.85*** (1.97)	-3.48 (2.40)
Share Wage in 3rd decile	0.462 (0.381)	-0.409 (0.337)	-0.175 (0.360)	**5.74***** (1.97)	1.34 (1.22)	-0.988 (1.44)
ITshare2001				**3.41***** (1.38)	0.866 (0.961)	1.42 (1.30)
ITshareIV0106				**5.86***** (1.56)	0.569 (1.13)	**-3.2***** (1.26)

Table 4—Manufacturing 2 SLS Constrained

	Second stage regressions			First stage regressions		
	2006	2011	2016	2006	2011	2016
Intercept	0.037 (0.623)	0.037 (0.623)	0.037 (0.623)	0.045 (1.073)	1.58 (1.10)	-0.611 (1.37)
Effective Wage Premium	-0.003 (0.035)	-0.003 (0.035)	-0.003 (0.035)			
Share of male	-0.670 (1.18)	0.468 (0.926)	0.156 (0.999)	-2.17 (1.39)	-1.79 (1.11)	1.32 (1.14)
Share married	0.131 (0.436)	-0.238 (0.403)	-0.007 (0.380)	-0.368 (0.440)	**-1.54***** (0.436)	**1.58***** (0.438)
Share visible minority	-3.45 (3.86)	0.013 (0.490)	0.096 (0.373)	0.123 (4.15)	**1.53***** (0.510)	-0.161 (0.407)
Share Age 30-40	0.781 (1.32)	0.411 (1.61)	-0.488 (1.62)	-0.994 (1.82)	**-9.90***** (2.30)	2.75 (2.48)
Share Age 40-50	-0.910 (1.96)	0.640 (1.77)	-0.091 (1.96)	**-6.60***** (1.96)	**2.94*** (1.80)	**-9.59***** (2.06)
Share Age 50+	0.430 (1.29)	-0.456 (1.09)	0.019 (1.13)	0.763 (1.43)	**-2.92***** (1.18)	**4.97***** (1.36)
Share Wage in 2nd decile	0.213 (1.97)	-0.723 (1.66)	0.039 (1.97)	**-4.26**** (2.004)	**3.85*** (1.70)	**-3.48*** (2.00)
Share Wage in 3rd decile	0.600 (1.20)	-0.418 (1.05)	-0.132 (1.17)	**5.74***** (1.187)	1.34 (1.05)	-0.988 (1.20)
ITshare2001				**3.41***** (0.830)	0.866 (0.829)	1.42 (1.08)
ITshareIV0106				**5.86***** (0.941)	0.569 (0.975)	**-3.2***** (1.05)

Table 5—Service 2 SLS Unconstrained

	Second stage regressions			First stage regressions		
	2006	2011	2016	2006	2011	2016
Intercept	**-0.305**** (0.129)	-0.128 (0.135)	0.059 (0.133)	-0.326 (0.292)	**-0.890**** (0.367)	-0.289 (0.387)
Effective Wage Premium	**-0.232***** (0.029)	**-0.183***** (0.029)	**-0.110***** (0.026)			
Share of male	**0.351**** (0.160)	**-0.335**** (0.137)	-0.074 (0.136)	**1.31***** (0.353)	**-1.035***** (0.367)	**1.10***** (0.371)
Share married	-0.040 (0.050)	**-0.126***** (0.048)	0.014 (0.045)	0.171 (0.114)	-0.213 (0.139)	-0.083 (0.143)
Share visible minority	-0.486 (0.320)	**0.128**** (0.054)	-0.007 (0.044)	-0.680 (0.507)	-0.107 (0.150)	-0.191 (0.130)
Share Age 30-40	**0.476***** (0.187)	**0.899***** (0.233)	0.033 (0.234)	**1.64***** (0.481)	**4.30***** (0.673)	**-1.53**** (0.794)
Share Age 40-50	**-0.416*** (0.227)	0.263 (0.225)	**-0.511**** (0.244)	**-1.75***** (0.485)	**1.55***** (0.594)	**-1.34**** (0.692)
Share Age 50+	**0.734***** (0.167)	0.125 (0.159)	0.062 (0.159)	0.416 (0.371)	**1.97***** (0.400)	-0.026 (0.458)
Share Wage in 2nd decile	-0.076 (0.191)	0.120 (0.163)	-0.061 (0.160)	0.545 (0.422)	0.048 (0.445)	-0.137 (0.448)
Share Wage in 3rd decile	-0.123 (0.133)	0.095 (0.097)	0.092 (0.102)	-0.308 (0.241)	-0.302 (0.270)	0.036 (0.29)
ITshare2001				**-0.923***** (0.203)	-0.257 (0.259)	0.513 (0.331)
ITshareIV0106				**2.24***** (0.264)	**-0.843***** (0.337)	0.186 (0.363)

Table 6—Service 2 SLS Constrained

	Second stage regressions			First stage regressions		
	2006	2011	2016	2006	2011	2016
Intercept	-0.125 (0.174)	-0.125 (0.174)	-0.125 (0.174)	-0.326 (0.293)	**-0.890**** (0.295)	-0.289 (0.305)
Effective Wage Premium	**-0.174***** (0.037)	**-0.173***** (0.037)	**-0.173***** (0.037)			
Share of male	0.111 (0.297)	-0.320 (0.245)	0.119 (0.259)	**1.31***** (0.355)	**-1.035***** (0.296)	**1.10***** (0.293)
Share married	-0.037 (0.119)	-0.123 (0.105)	0.012 (0.102)	0.171 (0.115)	-0.213 (0.112)	-0.083 (0.113)
Share visible minority	-0.456 (0.749)	0.129 (0.119)	-0.024 (0.044)	-0.680 (0.509)	-0.107 (0.121)	-0.191 (0.103)
Share Age 30-40	0.371 (0.353)	**0.866**** (0.389)	0.166 (0.429)	**1.64***** (0.483)	**4.30***** (0.542)	**-1.53***** (0.625)
Share Age 40-50	-0.324 (0.523)	0.248 (0.475)	-0.393 (0.532)	**-1.75***** (0.487)	**1.55***** (0.479)	**-1.34***** (0.545)
Share Age 50+	**0.603*** (0.355)	0.109 (0.301)	0.189 (0.296)	0.416 (0.373)	**1.97***** (0.323)	-0.026 (0.361)
Share Wage in 2nd decile	-0.160 (0.444)	0.121 (0.355)	-0.098 (0.361)	0.545 (0.424)	0.048 (0.359)	-0.137 (0.353)
Share Wage in 3rd decile	-0.136 (0.314)	0.099 (0.212)	0.048 (0.227)	-0.308 (0.242)	-0.302 (0.218)	0.036 (0.228)
ITshare2001				**-0.923***** (0.204)	-0.257 (0.209)	**0.513**** (0.260)
ITshareIV0106				**2.24***** (0.265)	**-0.843***** (0.271)	0.186 (0.285)

Table 7—Manufacturing 3 SLS

	Unconstrained			Constrained		
	2006	2011	2016	2006	2011	2016
Intercept	-0.273 (0.327)	0.226 (0.342)	0.213 (0.335)	0.063 (0.184)	0.063 (0.184)	0.063 (0.184)
Effective Wage Premium	0.020 (0.015)	-0.006 (0.023)	**-0.037*** (0.020)	-0.002 (0.011)	-0.002 (0.011)	-0.002 (0.011)
Share of male	-0.376 (0.427)	0.350 (0.349)	0.171 (0.339)	**-0.703**** (0.367)	0.458 (0.289)	0.204 (0.305)
Share married	0.133 (0.136)	**-0.263**** (0.133)	0.042 (0.121)	0.121 (0.138)	**-0.244**** (0.128)	-0.019 (0.117)
Share visible minority	**-3.00***** (1.12)	0.038 (0.158)	0.067 (0.113)	**-3.00***** (1.21)	0.031 (0.155)	0.074 (0.115)
Share Age 30-40	**0.993**** (0.484)	0.181 (0.63)	-0.634 (0.614)	0.750** (0.409)	0.382 (0.500)	-0.545 (0.490)
Share Age 40-50	-0.553 (0.614)	0.542 (0.572)	-0.273 (0.624)	-0.793 (0.613)	0.614 (0.557)	0.076 (0.594)
Share Age 50+	0.553 (0.437)	-0.519 (0.381)	-0.030 (0.418)	0.397 (0.403)	-0.433 (0.342)	-0.06 (0.346)
Share Wage in 2nd decile	0.434 (0.623)	-0.855 (0.538)	-0.214 (0.603)	0.205 (0.618)	-0.810 (0.525)	-0.017 (0.604)
Share Wage in 3rd decile	0.388 (0.378)	-0.407 (0.334)	-0.266 (0.357)	0.526 (0.375)	-0.401 (0.333)	-0.225 (0.359)
N	528,300					

Table 8—Service 3 SLS

	Unconstrained			Constrained		
	2006	2011	2016	2006	2011	2016
Intercept	**-0.300**** (0.129)	-0.116 (0.134)	0.102 (0.133)	-0.110 (0.073)	-0.110 (0.073)	-0.110 (0.073)
Effective Wage Premium	**-0.233***** (0.029)	**-0.174***** (0.028)	**-0.112***** (0.027)	**-0.173***** (0.017)	**-0.173***** (0.017)	**-0.173***** (0.017)
Share of male	**0.362**** (0.159)	**-0.340***** (0.136)	-0.076 (0.135)	0.112 (0.127)	**-0.348***** (0.109)	0.132 0.114
Share married	-0.046 (0.050)	**-0.125***** (0.048)	0.007 (0.045)	-0.041 (0.051)	**-0.126***** (0.047)	0.006 (0.046)
Share visible minority	-0.433 (0.318)	**0.129***** (0.054)	-0.012 (0.044)	-0.418 (0.321)	**0.132***** (0.054)	-0.029 (0.045)
Share Age 30-40	**0.477***** (0.186)	**0.871***** (0.231)	-0.029 (0.232)	**0.360**** (0.151)	**0.852***** (0.171)	0.145 (0.191)
Share Age 40-50	**-0.409*** (0.226)	0.235 (0.223)	**-0.474**** (0.242)	-0.326 (0.225)	0.248 (0.214)	-0.347 0.238
Share Age 50+	**0.734***** (0.167)	0.124 (0.158)	0.020 (0.158)	**0.597***** (0.152)	0.111 (0.134)	0.171 (0.132)
Share Wage in 2nd decile	-0.108 (0.19)	0.118 (0.162)	-0.121 (0.159)	-0.196 (0.190)	0.127 (0.160)	-0.154 (0.162)
Share Wage in 3rd decile	-0.132 (0.132)	0.104 (0.097)	0.076 (0.101)	-0.142 (0.135)	0.105 (0.096)	0.0282 (0.102)
N	528,300					

Endnotes

1 The long-form Canadian census (or the National Household Survey-NHS in 2011) is collected at the same time as the Canadian census. The main difference between the Canadian census and the long-form census is that the questions tend to be much more detailed (asking for example detailed information about a respondent's occupation), and while the Canadian census is asked to almost all those who live in Canada, the long-form Canadian census randomly samples 25 percent (or in the NHS's case, 33 percent) of the population.

2 For the 2018 vintage, the question asked for internet use within the past three months, not past twelve months like in previous vintages.

3 Middle skill in this strand of research was often considered to be those in the middle of the wage distribution, who are neither considered low or high skilled—and involved a range of occupations.

4 While in the 2021 Census, Statistics Canada added a gender variable separate from sex, to capture those who are non-binary and transgender, in the previous waves of the census, only the sex of a particular respondent (separate from gender) was captured.

5 It's important to note that the methodology for the 2011 National Household Survey (NHS) differs substantially from the other long-form census waves,due to a legal change impacting its mandatory nature. This includes substantially higher sampling rates to account for sample non-response rate. Butfor brevity, we will refer to the 2011 NHS as a "census wave".

6 Census Sub-division is a geographical classification used by Statistics Canada to denote geographies that generally corresponds to municipalities (and counties).

7 While in recent years, Statistics Canada has started measuring gender separately from sex (in particular for the 2021 census), due to its recency, and the use of data as far back as 2001, we are only able to incorporate sex-based differences, as opposed to gender-based differences in this report.

8 In Canada, the three main indigenous identities include First nations, Inuit, and Metis and we specifically distinguish between these three identities.

9 In 2019, those who worked in professional occupations in natural and applied sciences, the two-digit NOC that corresponds with tech occupations, worked on average 39 hours per week.

10 We thank David Green and Benjamin Sand for their willingness to share their replication code which allowed us to closely recreate the analysis to ensure comparability with their original results.

11 Due to O*NET not being available before 2003, the 2001 digital intensity measure is the exact same as that in 2006, which means that the digital intensity percentile for both years comprise of the exact same occupations.

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