Did the Pandemic and Current Labour Shortages Change the Quality of Jobs?

Final Report to Future Skills Foundation*

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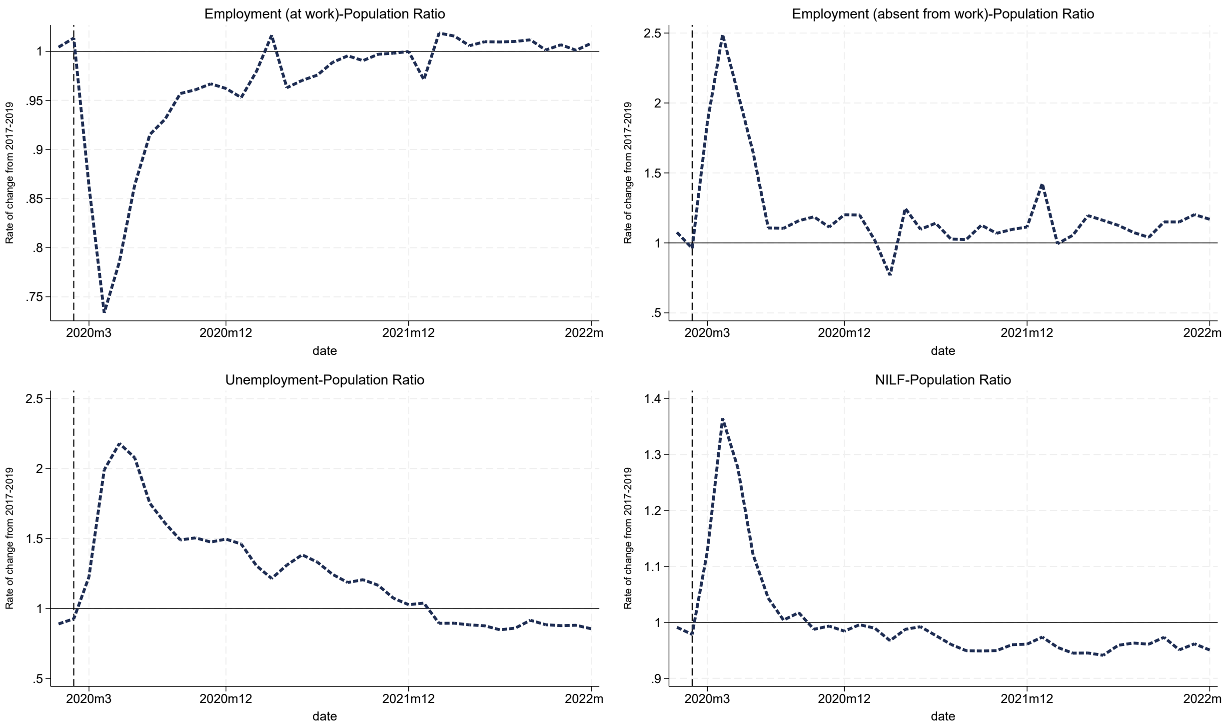
1 Introduction

With the onset of the Covid-19 pandemic, the Canadian labour market was thrown into turmoil (Lemieux et al. (2020), Jones et al. (2021)). In the months following the outbreak, unemployment more than doubled and among those that retained their employment, large numbers were absent from work. As did other labour markets around the world,[1] and as can be seen in figure 1, the Canadian labour market seized up in the late spring and early summer of 2020.

Figure 1: Employment, Unemployment, and NILF



Notes: The figure plots the changes in the employment (at work), employment (absent from work), unemployment, and NILF (Not in the Labour Force) rates, as a rate of change from monthly averages of the 2017-19 reference period. The source of the statistics are authors' calculations using the Canadian Labour Force Survey.

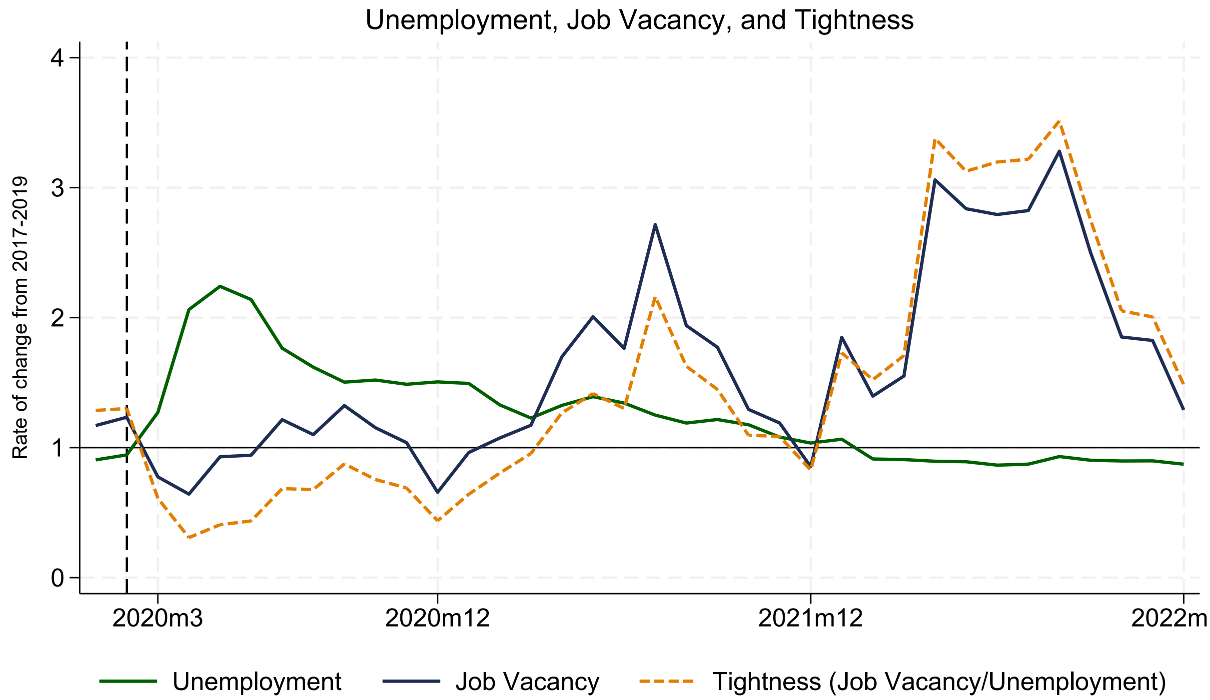
Surprisingly however, in the following months labour demand as proxied by the number of job postings recovered rapidly (see figure 2). And, by the end of the summer of 2020, unemployment started receding rapidly and many of those initially laid off or absent from work returned to work (even if this was often remote work).[2] By August 2020, labour

[1]See for example Kahn et al. (2020) for a description of how the US labour market fared in the first few months of the Covid pandemic.

[2]In the US, Gallant et al. (2020) were among the first to predict this turnaround in employment based

demand had begun an impressive recovery, and since then increases in job postings and rehiring of temporary unemployed severely reduced the number of individuals available for filling new positions in the labour market (Jones et al., 2021). During much of 2021 and 2022, labour demand (proxied by job postings) was much stronger than prior to the pandemic and talk turned perceived labour shortages. Since early 2022, employment as a share of the population exceeds and unemployment is much below the rates observed during 2017-2019 (see figure 1). By any historical measure, the labour market in 2022 was very tight.

Figure 2: The Changes in Unemployment, Job Postings, and Tightness



Notes: The figure plots the changes in the number of unemployed individuals, number of job postings, and labour market tightness, as a rate of change from monthly averages of the 2017-19 reference period. The source of the statistics are authors' calculations using the Canadian Labour Force Survey and data from Lightcast (formerly Burning Glass Technologies).

How then has this tight labour market affected the terms of employment offered to job seekers in the labour market? Have the terms of employment regarding both compensation and non-financial benefits changed? We would expect that employers would raise both compensation and offer better non-wage attributes to attract applicants to open po-

on a standard matching model, the composition of unemployment between recall and search unemployment, and the robust job vacancy statistics reported in the summer of 2020.

sitions. We would also expect them to become less selective and lower the requirements for employment.[3] In this report, we document how the quality of jobs offerings changed during these tumultuous few years in the Canadian labour market focusing specifically on skill, education, and experience requirements as well as job benefits.

Benefits attached to jobs can come in a variety of forms. Some are traditional, or financial such as health insurance and retirement plans. Other benefits can relate to flexible work arrangements, whether individuals are allowed (or required) to work remotely, to training, and the ability to acquire skills on the job. As part of our report, we analyze how frequently these diverse types of benefits are mentioned in job postings and document their prevalence in the labour market.

Little is known about how workers value different job amenities and even less is known about how these valuations evolved during the Covid-19 pandemic. Mas and Pallais (2020), in a discrete choice experiment, measured workers' willingness to pay for job alternatives. They found working from home, pre-pandemic, to be the most valued job alternative: employees would take an 8 percent wage cut to work from home. This particular benefit gained even more significance during Covid-19, which entailed a significant increase in the prevalence of working from home (Mehdi and Morissette, 2021).[4] Our analysis can not speak to the value workers attach to job flexibility, however, we demonstrate that compared to before the pandemic, employers have become twice as likely to promote job flexibility as an attribute of employment when posting jobs.

We use online job posting data (Lightcast) to study to what extent the Covid-19 pandemic altered the quality of the jobs in Canada. However, our analysis is limited to English language postings, and in the remainder of the paper, when we refer to job postings, we refer to only those posted in the English language. Compared to looking at the distribution of employment, the analysis of job postings has the advantage of being

[3]See Hershbein and Kahn (2018) and Modestino et al. (2020) who use data from job postings similar to ours but for the US to study the changes in requirements that occurred during the Great Recession. Consistent with our expectations, these authors find that the share of jobs demanding experience, education, cognitive skills, and computer skills increased during the Great recession when labour markets were loose.

[4]Barrero et al. (2021) predict this shift to telework to be persistent and Messacar et al. (2020) report that for about 40 percent of jobs, telework is feasible, but that this share varies substantially across industries and occupations. Moreover, Mas and Pallais find in their experiment that a majority of workers do not value scheduling flexibility—specifically, the ability to set their own days, work times, or number of hours worked. Workers are inelastic in response to changes in the price of scheduling flexibility.

forward-looking – employers are posting jobs that correspond to their needs in the future, not those in the past. The Lightcast data allows us to measure such employer needs and offers in great depth including skill requirements of jobs such as experience, education, cognitive skills, social skills, and computer skills, and job benefits such as insurance, flexibility, and rewards. This makes it easier to identify emergent trends than relying exclusively on data about the existing distribution of job quality. We also employ data from the Labour Force Survey (LFS) to rank occupations and industries by their mean wages and study to what extent the Covid-19 pandemic differentially altered the job skill requirements and job benefits across the wage distribution.

2 Measuring Job Characteristics Using Data on Online Job Posting

We analyze approximately 6.5 million online job postings in Canada spanning from January 2017 to December 2022. These online job postings are collected and compiled by Lightcast (formerly known as Burning Glass Technologies), an employment analytic and labour market information firm. Lightcast collects online job postings from online job boards and company websites, aggregates and parses the postings, removes duplicates, and lastly, compiles the data in a systematic fashion amenable to analysis. The result is a data-set intended to encompass the universe of jobs posted online (in English) in Canada.

The data-set includes around 2.5 million observations from pre-pandemic periods and approximately 4 million observations from periods during and after the pandemic. Having access to essentially the population of job postings allows us to describe across-industry, and across-geography overall changes in characteristics of jobs posted in Canada before, during, and after the pandemic.

Our analysis of skill requirements and compensation will rely on skill descriptors of jobs data made available by Lightcast. In addition to the skill descriptors, Lightcast provides us with information on industry, occupation, and location of the job and the range of compensation associated with the job. However, Lightcast does not collate information on the benefits associated with posted jobs. To describe how benefits among posted jobs evolved turn to the raw text of the job postings. We purchased this raw text data from Lightcast and using Natural Language Processing (NLP) techniques, compile a dataset of benefits attached to job postings. This procedure is described in more detail below.

For the skill requirements, we will consider experience, education, as well as specific skills demanded in the posting. Skill requirement data includes information on the detailed description of the skills required by each vacant job. We perform a keyword analysis to construct our skill measures. For instance, we label a job as requiring cognitive skill if at least one of the keywords in problem-solving, research, analytical, critical thinking, math, and statistics is involved in the list of required skills. We present the keywords used to construct skill measures in table A1. A similar strategy is followed by a range of studies in the literature. We closely follow Hershbein and Kahn (2018) and Deming and Kahn (2018) and construct our skill measures using the keywords listed in table A1.

To generate the data on benefits, we use a technique called Named Entity Recognition (NER), which is an NLP technique that involves analyzing text and identifying spans of words that correspond to named entities. From the raw text data, we randomly sampled 1,000 job postings. Using an entity tagging software, a research assistant was charged with labeling job benefits or amenities within these 1,000 job postings according to a pre-defined list of benefits created to capture the relevant benefits offered by employers. The list of benefits that the analyst associates with the text is shown in table A2 and an example of the tagging process is shown in figure A1.

From the 1,000 randomly sampled job postings, only 565 job postings contained any information on benefits. We use the 565 tagged job postings to train a large language model to automatically detect and categorize job benefits in job postings. To train the large language model for the NER task we use the pipelines offered by the popular open-source NLP library, SpaCy (Honnibal and Montani, 2017). The advantage of using pipelines is that they encapsulate the majority of complicated code within the library, streamlining the code to perform a variety of NLP tasks, like NER. The language model that we use is known as RoBERTa: a transformers model pre-trained on a large corpus of English data.[5] We choose this model due to it's state-of-the-art performance on virtually every NLP task,

[5]See Liu et al. (2019) for more information on the training process for RoBERTa. RoBERTa is trained on a combination of Bookcorpus (Zhu et al., 2015), and the English wikipedia which totals 16GB of text.

and it's ability to understand language in context.[6] Once the RoBERTa is model trained, we use it to label benefits in the remaining raw data. This process is computationally intensive and we therefore limited ourselves to a one-in-ten sample stratified by industry and occupation code of the original data, sufficient to describe the distribution of benefits in a granular manner.

3 Changes in experience, education, and skill requirements

Using the measures provided by Lightcast, we explore education, experience, and skill requirements, as well as wage offers of job postings varied over the 2017-2022 period.

We use two alternative experience measures: (i) whether a posting demanded any experience at all and (ii) how many years of experience job ads required. Panel A in table 1 summarizes the variation in these experience measures over the study period. On average, 39 percent of jobs listed any experience requirement during the three years prior to the pandemic (2017-2019). This share stayed roughly stable during the first two years of the pandemic, but in 2022 the share of postings with an experience requirement rose to 46.1 percent. At the same time, conditional on listing an experience requirement, minimum experience requirements declined by about a third of a year in 2022.

Panel B in table 1 shows how education requirements developed. As for experience, we find little variation prior to 2022, while the share of jobs listing an education requirement increased from 2021 to 2022 from 31.6 to 36 percent. And, we again observe that conditional on posting a requirement, these requirements became less demanding in 2022. In 2022, the fraction of jobs that require higher levels of education declined markedly. For instance, the share requiring a bachelor degree or more fluctuated between 60.2 and 62.5 percent until 2021 and then declines by 12 percentage points in 2022. At the same time, the fraction of jobs requiring at least a high school degree increased by approximately 13 percentage points in 2022.

[6] We use the en_core_web_trf pipeline offered by SpaCy. This pipeline reported the highest performance on the NER task reporting a 90% accuracy rate, a 5% increase from the next best pipeline.

These findings are difficult to interpret: the increase in the share of jobs listing experience or education requirements suggests that employers became more demanding but average education or experience requirements became less demanding, conditional on listing an education requirement. The two patterns observed in 2022 do not allow for easy conclusions about how the demand for labour evolves along the experience or education dimension.

Next, we consider the stated demand for skills such as cognitive, computer, software, management, and social skills. Panel C in table 1 indicates that 92.1 percent of job postings in 2017-2019 require any skills. By 2022, the share of job postings listing any skill requirement had increased by an additional 3 percentage points. Out of 11 requirements, only "Finance' and "Writing" decreased while the decrease in "Writing" was minimal. More pronounced increases are only observed "Soft Skills" and in "Technical Support". The share of jobs requiring cognitive skills increased by 1.1 percentage points from 31.9 to 33 percent of postings. At the same time, the number of job postings with a social skill requirement increased by 4 percentage points, character skills by 4.2 percentage points, and the share requiring creativity by 0.7 percentage points—a sizeable increase of a small base of 6.7 percent in 2017/2019. Thus, in 2022 we observe that job postings shifted requiring soft skills exemplified by key-words such as communication, teamwork, collaboration, negotiation, time management, and detail-oriented.

We also consider the number of skills required by each job as a proxy for the complexity of the jobs. The results indicate a rise in the number of skills needed for jobs post-pandemic suggesting maybe that jobs became mre complex inducing employers to require a greater array of skills. However, this shift is substantially accounted for by soft skills such as character and interpersonal abilities.

A final aspect of job requirements extracted by Lightcast relates to the fraction of jobs that require working from home. Panel D in table 1 shows that the fraction of jobs requiring work-from-home flexibility has increased considerably after the pandemic. This is of course consistent with the well-known phenomenon that an increasing share of the workforce has shifted to work from home during the pandemic. We see that the share of job postings requiring working from home rose from less than 1 percent to 5.4 percent by 2021 and has stabilized in the data since.

	2017-2019	2020	2021	2022
Characteristics of Job Postings				
Panel A: Experience Requirements				
Any	0.390	0.393	0.379	0.461
Conditional on any:				
0-2	0.412	0.435	0.421	0.487
3-5	0.459	0.450	0.456	0.414
6 +	0.129	0.115	0.124	0.099
Years of Experience	3.61	3.47	3.54	3.22
Panel B: Education Requirements				
Any	0.327	0.311	0.316	0.360
Conditional on any:				
HS	0.343	0.346	0.319	0.446
BA	0.528	0.513	0.555	0.435
MA/MS +	0.074	0.074	0.070	0.068
BA +	0.602	0.587	0.625	0.504
Years of Education	14.72	14.70	14.81	14.30
Panel C: Skill Requirements				
Any	0.921	0.919	0.910	0.953
Conditional on any:				
Cognitive	0.319	0.304	0.325	0.330
Basic Computer	0.254	0.242	0.246	0.258
Specialized Software	0.324	0.308	0.328	0.326
Technical Support	0.174	0.197	0.189	0.196
Data Analysis	0.047	0.045	0.050	0.050
Management	0.196	0.186	0.189	0.202
Finance	0.177	0.156	0.158	0.162
Social	0.553	0.553	0.567	0.592
Character	0.411	0.421	0.432	0.453
Creativity	0.067	0.068	0.075	0.074
Writing	0.149	0.151	0.150	0.145
Number of Skills	9.78	9.643	10.115	10.292
Panel D: Work From Home				
Work From Home	0.006	0.024	0.054	0.050
# Ads	2,529,747	804,622	1,213,811	1,854,967

Table 1: Overall Changes: Skill Requirements

Note: This table summarizes the mean of skill requirements. The source of data is Lightcast 2017-2022.

4 Compensation and Benefits

Both compensation (wages) and non-compensation-related benefits are valued by employees. Lightcast contains hourly wages for job postings that lists such information. Over time, the proportion of jobs with explicit wage offers increased.[7] However, while more job postings list information related to wages, Panel A in Table 2 shows no distinct trend in average wages among job postings that include such wage information.

For non-wage benefits, our variables are constructed using the NLP procedure described in Section 2. Nevertheless, Lightcast does provide information on one aspect of job postings that can be described as a benefit: the ability or requirement to work from home. This allows us to determine how our measure compares with that generated by Lightcast. The first row of Panel D in table 1 shows that using the Lightcast measure the fraction of jobs requiring work-from-home (Remote Work) flexibility has increased considerably after the pandemic, from 0.6 percent in 2017-2019 to 5.0 percent in 2022. In addition to the work-from-home measure collected by Lightcast, using the NER model, we also provide information on the frequency with which job postings mention remote work (or similar phrases). Reassuringly, our measure (first row of Panel B in table 2) tracks the increase in the Lightcast measure (1.7 percent to 5.8 percent), even if we overall find that a larger fraction of job postings mentioned remote work compared to the Lightcast measure.

Our NLP methodology yields estimates of the number of job postings that mention other aspects related to work flexibility. We find that the fraction of jobs providing flexible working hours and work-life balance (Job Flexibility) almost doubled after the pandemic. Specifically, the proportion of jobs offering flexibility in physical hours worked increased from around 11 percent in 2017/2019 reference period to 14.9 percent in 2020, 17.2 percent in 2021, and 20.8 percent in 2022. We observe a similar rise in the fraction of jobs offering paid time off, sick leave, and maternity/paternity leave ("Time off") during and after the pandemic. There is thus a clear trend towards more flexible work arrangements visible in this data that goes beyond simply allowing for (or requiring) remote work. The job

[7] It was around 28 percent in the 2017/2019, 37 percent in 2020, 41 percent in 2021, and 43 percent in 2022. Hourly wages are inflation-adjusted using the 2021 Consumer Price Index (CPI).

posting data strongly suggests that work arrangements are becoming significantly more flexible.

One other important aspect of the jobs is the coverage of insurances offered. The detailed description of jobs in the Lightcast data allows us to measure whether a job offers health, dental, and vision insurance as well as life and disability insurance. Our results suggest that the fraction of jobs offering at least one of health, dental, and vision insurance ("Insurance Coverage") rose from 9.8 percent in the reference period to 14.6 percent in 2020, 18.1 percent in 2021, and 24.3 percent in 2022. Likewise, the proportion of jobs offering life and/or disability insurance ("Protection") more than doubled subsequent to the pandemic.

	2017-2019	2020	2021	2022
Characteristics of Job Postings				
Panel A: Wages				
Real Log Hourly Wage	3.068	3.095	3.069	3.044
# Ads	699,097	300,849	492,970	792,873
Panel B: Benefits				
Remote Work (RoBERTa)	0.017	0.043	0.064	0.058
Job Flexibility	0.112	0.149	0.172	0.208
Time off	0.059	0.088	0.111	0.148
Insurance Coverage	0.098	0.146	0.181	0.243
Protection	0.031	0.058	0.074	0.098
Retirement Benefits	0.068	0.083	0.112	0.157
Ownership & Rewards	0.120	0.127	0.163	0.191
Fringe Benefits	0.116	0.170	0.216	0.282
Growth	0.205	0.208	0.224	0.283
Equality	0.364	0.387	0.420	0.508
# Ads (10 Percent Random Sample)	252,766	82,335	110,001	185,175

Table 2: Overall Changes: Job Benefits

Note: This table summarizes the mean of wage and non-wage benefits. The source of data is Lightcast 2017-2022. The 10 percent random sample of the dataset is stratified by year, 2-digit sectors, 3-digit occupations, and provinces.

Employers also offer a range of non-wage benefits such as retirement benefits and contributions ("Retirement Benefits"), stock options, equity, bonuses and profit sharing ("Ownership & Rewards"), as well as employee discounts, gym/fitness center access, post-secondary scholarship, relocation assistance, commuter benefits, free lunch ("Fringe Benefits"). The fraction of job postings offering any of these benefits increased substantially. Specifically, the proportion of jobs offering Retirement Benefits increased from 6.8 percent in 2017-2019 to 15.7 percent in 2022. The fraction of jobs offering Ownership & Rewards increased from 12 percent to 19.1 percent. Likewise, the share of jobs offering Fringe Benefits more than doubled to 28.3 percent in 2022.

Employers also provide education assistance, on-the-job training and professional development opportunities to enhance the productivity of their workers. 20.5 percent of jobs offered such productivity-enhancing opportunities in 2017-2019. By 2022, the share of job postings advertising such opportunities rose to 28.3 percent. Last, we look at Equity, Diversity, and Inclusion initiatives. Our results show that the proportion of jobs listing such initiatives increased from 36.4 percent prior to the pandemic to 50.8 percent by 2022.

Across the board, we observe that from 2017 and 2022, an increasing number of jobs are advertising a wide range of non-wage benefits, while average offered wages did not rise. This observation is consistent with firms advertising benefits much more than financial compensation to attract new employees.

In the next section, we examine heterogeneity in changes in job benefits across occupations and industries to assess the role played by differential shifts in demand and supply factors across occupations and industries.

5 Changes in Job Requirements and Benefits across the Occupation-Industry Wage Distribution

As Forsythe, Kahn, Lange and Wiczer (2022) point out for the US, labour shortages have increased more in some industries than in others, and we might expect this process to continue as the economy adapts to the disparate effects of the pandemic on the structure of demand and the nature of work. During the Great Recession, occupations, industries, or regions most affected by economic shocks experienced the greatest changes in the nature of work (Hershbein and Kahn, 2018; Modestino et al., 2020). For instance, Hershbein and Kahn (2018) find that skill requirements in job postings increased more in regions that were hit harder by the Great Recession. Moreover, routine-cognitive occupations experienced the most pronounced increases in demand for skills. Modestino et al. (2020) find that upskilling was larger in states and occupations that experienced greater increases in the supply of available workers. In this section, we study to what extent a shift like the restructuring of production toward routine-biased technologies and more-skilled workers, observed during the Great Recession in the US, took place in the Canadian economy during the Covid-19 pandemic.

We start by examining the employment and vacancies across 665 detailed occupation-industry pairs encompassing all of Canadian employment.[8] We are particularly interested in whether occupation-industry pairs towards the bottom or the top of the wage distribution increased by more. In figure 3, we show the change in the share of each occupation-industry cell in employment (blue) or job postings (red) between 2017-2019 and 2022. Occupation-industry pairs are sorted by average wages within each specific pairing in 2017-2019, and changes between 2017-19 and 2022 are smoothed using a locally weighted regression.[9]

The y-axis of the figure corresponds to the change in employment (or vacancies) in the percentile of each occupation-industry cell as a share of total Canadian employment. A value of 0.01 implies that the share of an occupation-industry pair in employment (or job postings) increased by 0.01 between 2017-2019 and 2022.[10]

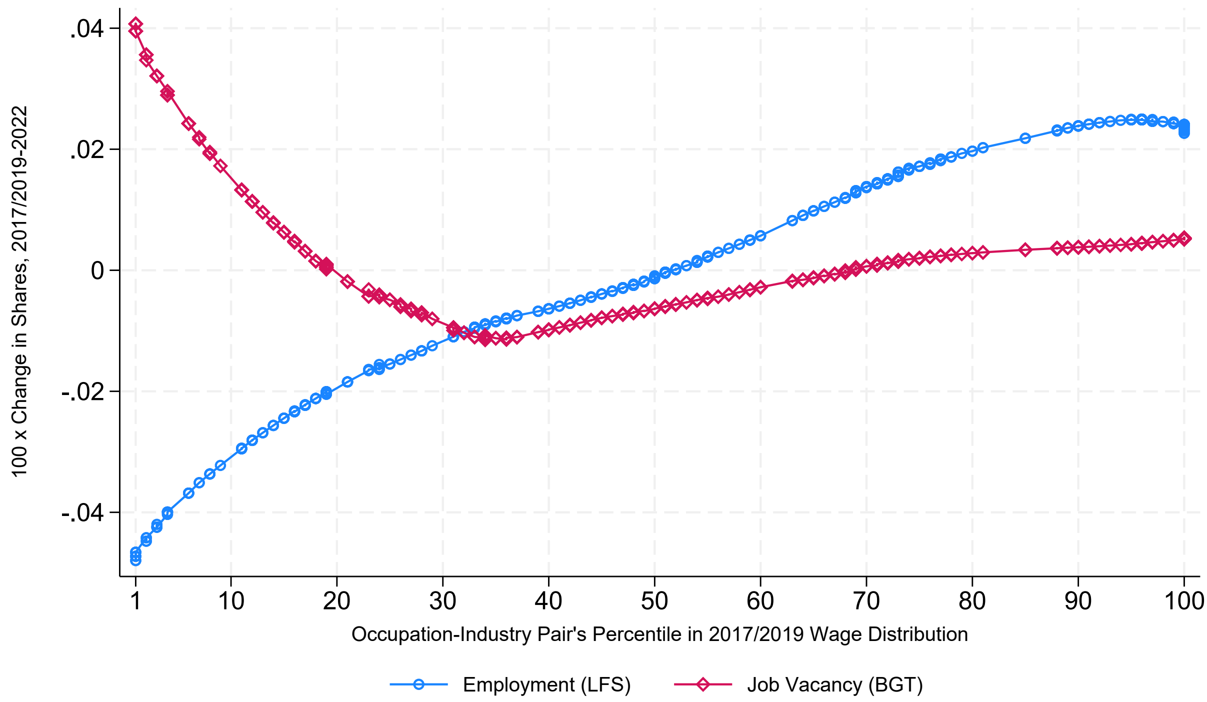
The figure suggests that following the outbreak of the pandemic, employment growth grew more rapidly among occupation-industry pairs in the upper wage percentiles. Employment shifted toward the upper end of the wage distribution. At the same time, we

[8]Our data includes all non-institutionalized workers who are aged 15 to 64, employed full-time, and working for pay (i.e., excludes unpaid family workers and self-employed workers).

[9]To this end, we first calculate the employment share of an occupation-industry pair in total employment using the formula: $Share_{os,t} = \frac{Employment_{os,t}}{\sum_{os=1}^{os=665} Employment_{os,t}}$ where os is the occupation-industry pair and t is year. Next, we calculate the changes in the employment share of the occupation-industry pairs after the pandemic using the formula: $\Delta Share_{os} = \left(Share_{os,2022} - Share_{os,2017/2019}\right)$. We follow the same strategy to construct vacancy shares of occupations and the changes in vacancy shares. Specifically, we replace $Employment_{os}$ by $Vacancy_{os}$. Next, we multiply $\Delta Share_{os}$ by 100.

[10]By construction, the sum of the shares must equal one each year, and thus the sum of the changes in these shares must be zero. Yet, due to smoothing, the sum of the changes may not precisely equal zero.

Figure 3: Changes in Employment and Job Postings by Occupation



Notes: The data sources are the monthly Labour Force Survey (LFS) and Lightcast. Each line plots 100 times the change in vacancy share (red) or employment share (blue) between 2017/2019 and 2022. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles are measured as the employment-weighted percentile rank of an occupation-industry pair's mean log wage in the LFS 2017/2019.

observe that the job postings shifted towards less well-compensation occupation-industry combinations. If we take job postings as a proxy of demand, then this indicates a shift in demand favoring less well-paid occupations and industries while employment shifted toward more highly-paid occupations and industries. These findings are consistent with an overall strong labour market and upgrading along the job ladder combined with significant demand to replace individuals lower down the job ladder. This would suggest that firms have to compete to attract workers into historically lower-paying sectors of the economy, potentially by raising compensation or improving benefits. Therefore, we now turn to study to what degree these heterogeneous changes in employment and job vacancy coincide with changes in the quality of the job defined by skill requirements and job benefits.

We first measure the share of job postings in a given occupation-industry *os* in a year that requires a skill (or offers a benefit). Subsequently, we analyze the change (in percentage points) in this share between 2017-2019 and 2022. These changes are then examined across the wage distribution and smoothed using a non-parametric regression.

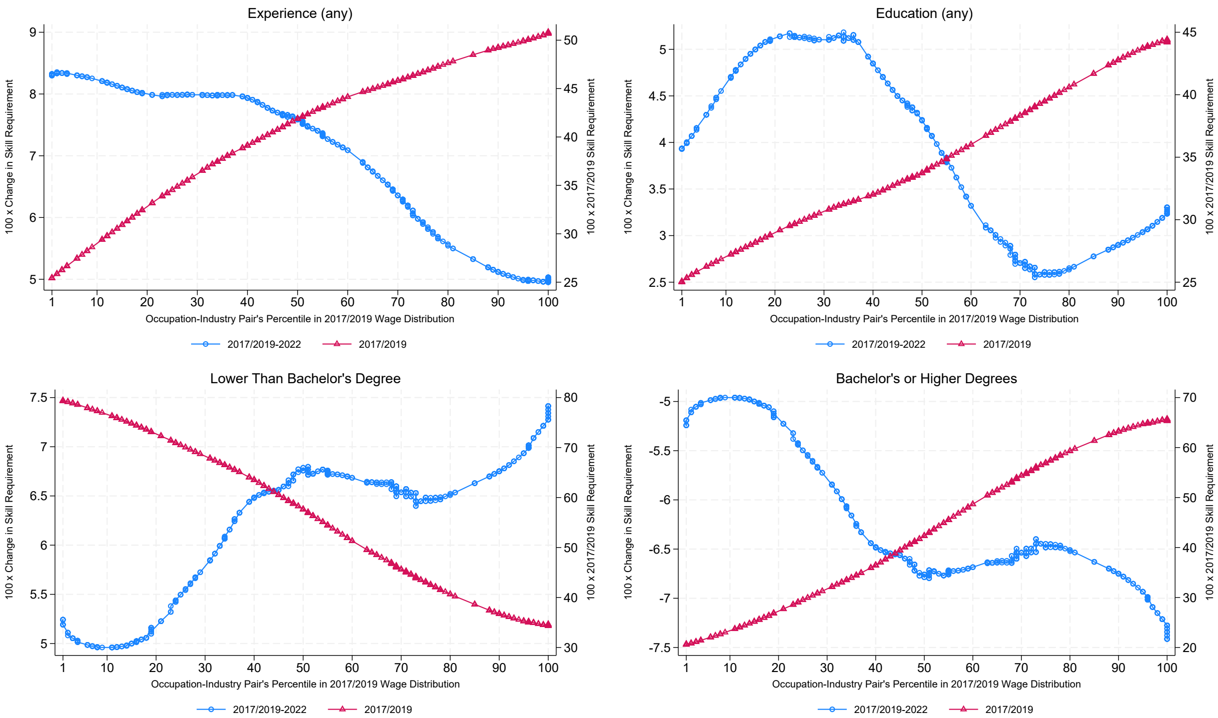
In Figure 4, we consider the changes in the share jobs with different education and experience requirements. The red line, measured on the right y-axis, shows the percent of jobs listing different requirements in 2017-2019.

Both the fraction of jobs requiring experience and education increase along the earnings distribution. Specifically, the upper-left panel of Figure 4 shows that the share of jobs requiring experience was approximately 25 percent at the bottom of earnings distribution while it was around 50 percent at the top. Notably, jobs within occupation-industry pairs at the bottom of the wage distribution have experienced slightly greater increases in the experience requirement compared to the rest of the distribution. Specifically, the fraction of jobs requiring experience rose around 8.5 percentage points at the bottom, indicating an approximate 35 percent increase, while it increased about 5 percentage points at the top, corresponding to roughly a 10 percent increase.

Likewise, the red line in the upper-right panel shows that the fraction of jobs requiring education was around 25 percent at the bottom of the earnings distribution and 45 percent at the top before the Covid-19 pandemic. Compared to the pre-pandemic periods, the fraction of jobs requiring any education experienced an overall increase; however, the increase has been slightly greater at the bottom percentiles of the earnings distribution. Yet, when we look at the share of jobs requiring a bachelor's and higher degrees, we observe a decline after the pandemic with slightly lower decreases at the bottom percentiles of the wage distribution (see lower-right panel). Conversely, the opposite is true for jobs requiring a lower than a bachelor's degree (see lower-left panel). In conjunction with the overall increases in demand for lower-than-bachelor's degrees, this suggests that the increases in the demand for education are largely driven by the rises in demand for lower-than-bachelor's degrees.

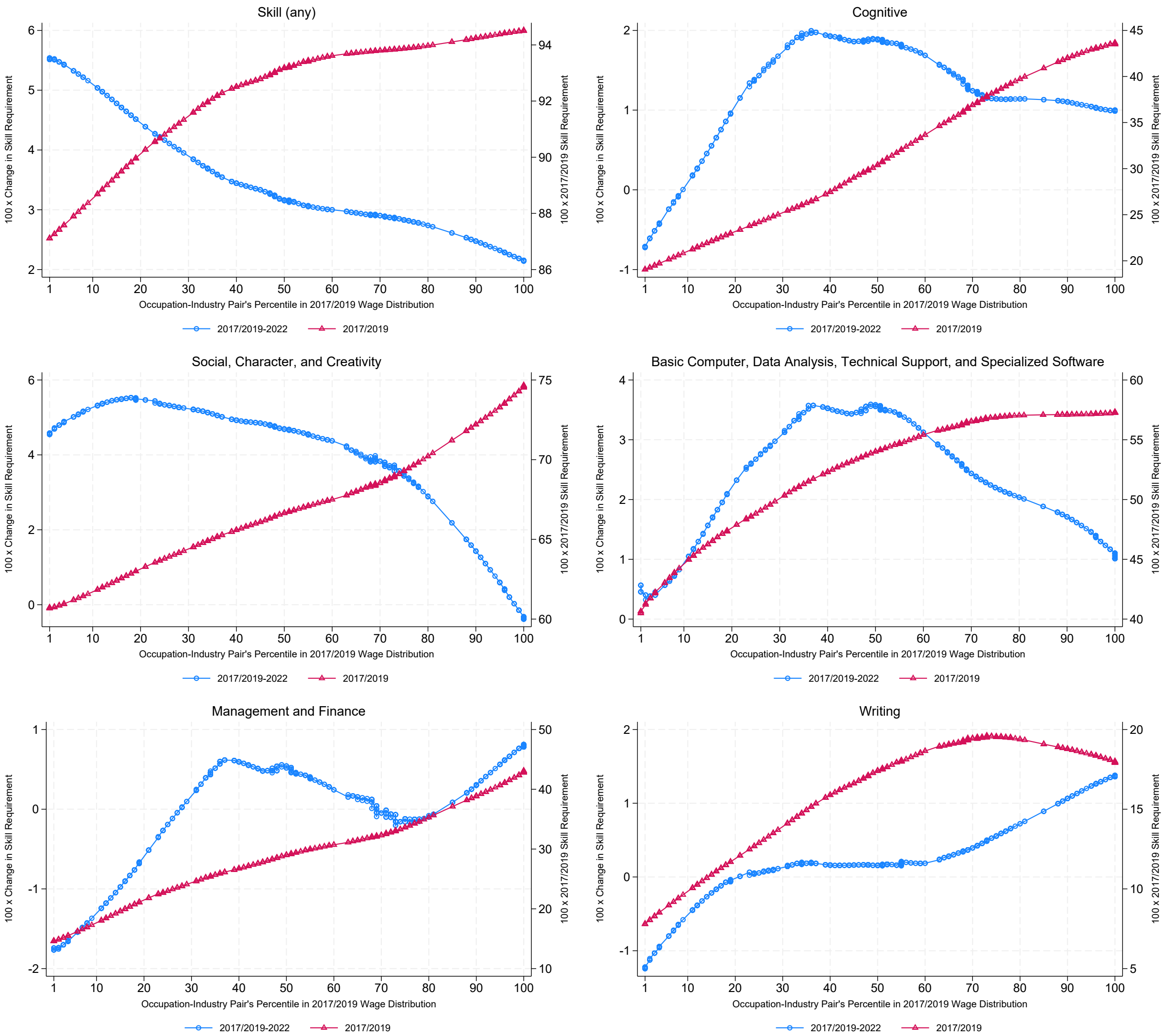
Figure 5 examines changes in skill requirements listed. As observed previously (indicated by the red line), higher-paid jobs tend to be more prone to post skill requirements. However, for certain skills, lower paid occupation-industries became more likely to post requirements (notably for social skills). Conversely, for others (writing, management and finance, cognitive), occupation-industries toward the top of the distribution became more selective.

Figure 4: Smoothed Changes in the Skill Requirements



Notes: The data sources are the monthly Labour Force Survey (LFS) and Lightcast (BGT). Pre-pandemic distribution of job skills is given on the right y-axis of each figure while changes in job skills between the 2017/2019 and 2022 periods are given on the left y-axis of each figure. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles are measured as the employment-weighted percentile rank of occupation-industry pairs' mean log wage in the LFS 2017-2019.

Figure 5: Smoothed Changes in the Skill Requirements



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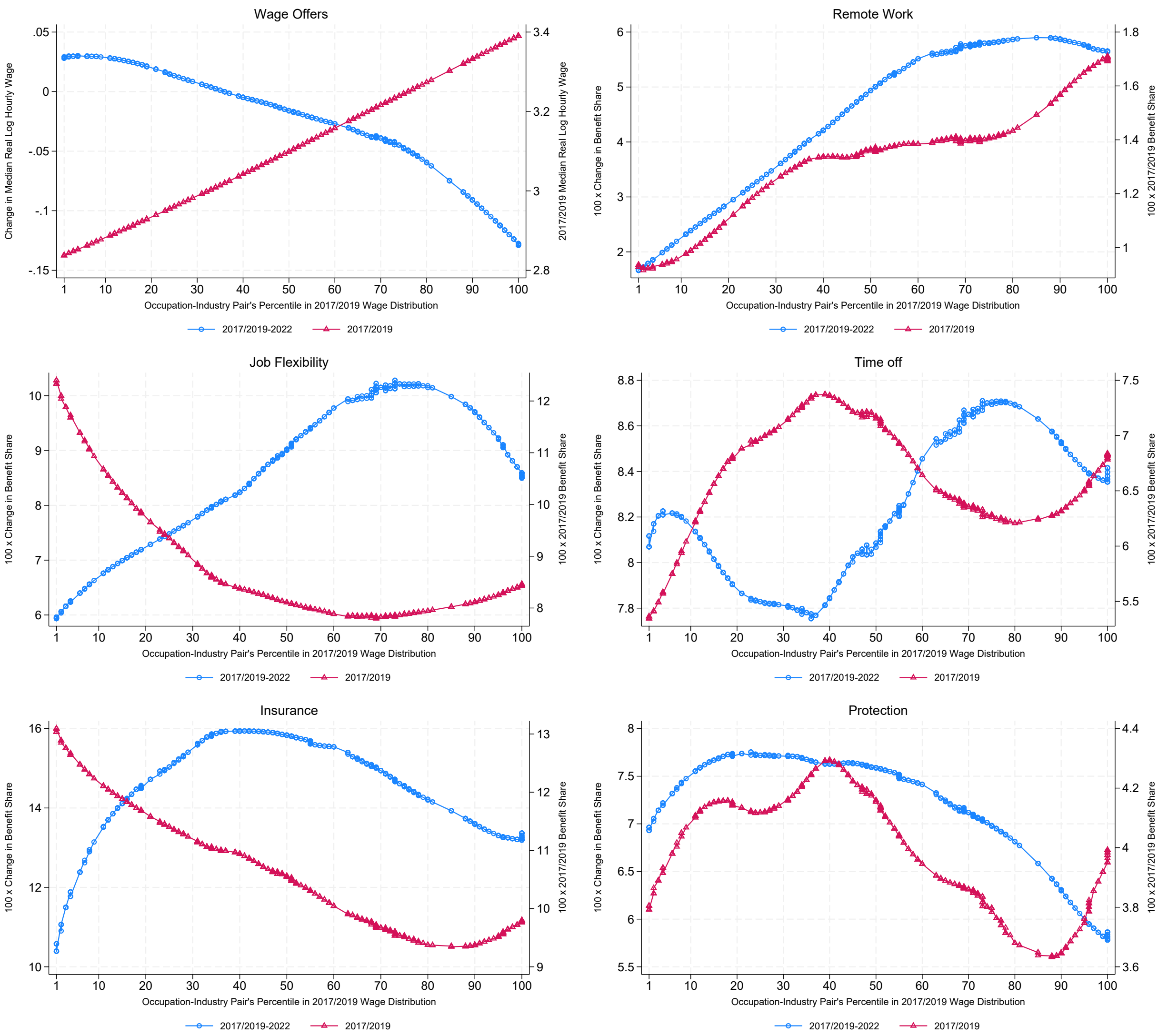
Finally, when we consider job benefits, we observe a similar divergence in the trend to offer benefits across the wage distribution in Figures 6 and 7. Wage offers and analogous compensation benefits such as Ownership & Rewards and Retirement Benefits become disproportionately more common toward the bottom of the wage distribution. On the other hand,it has become relatively more common to list benefits such as job flexibility, time off, remote work, and growth.

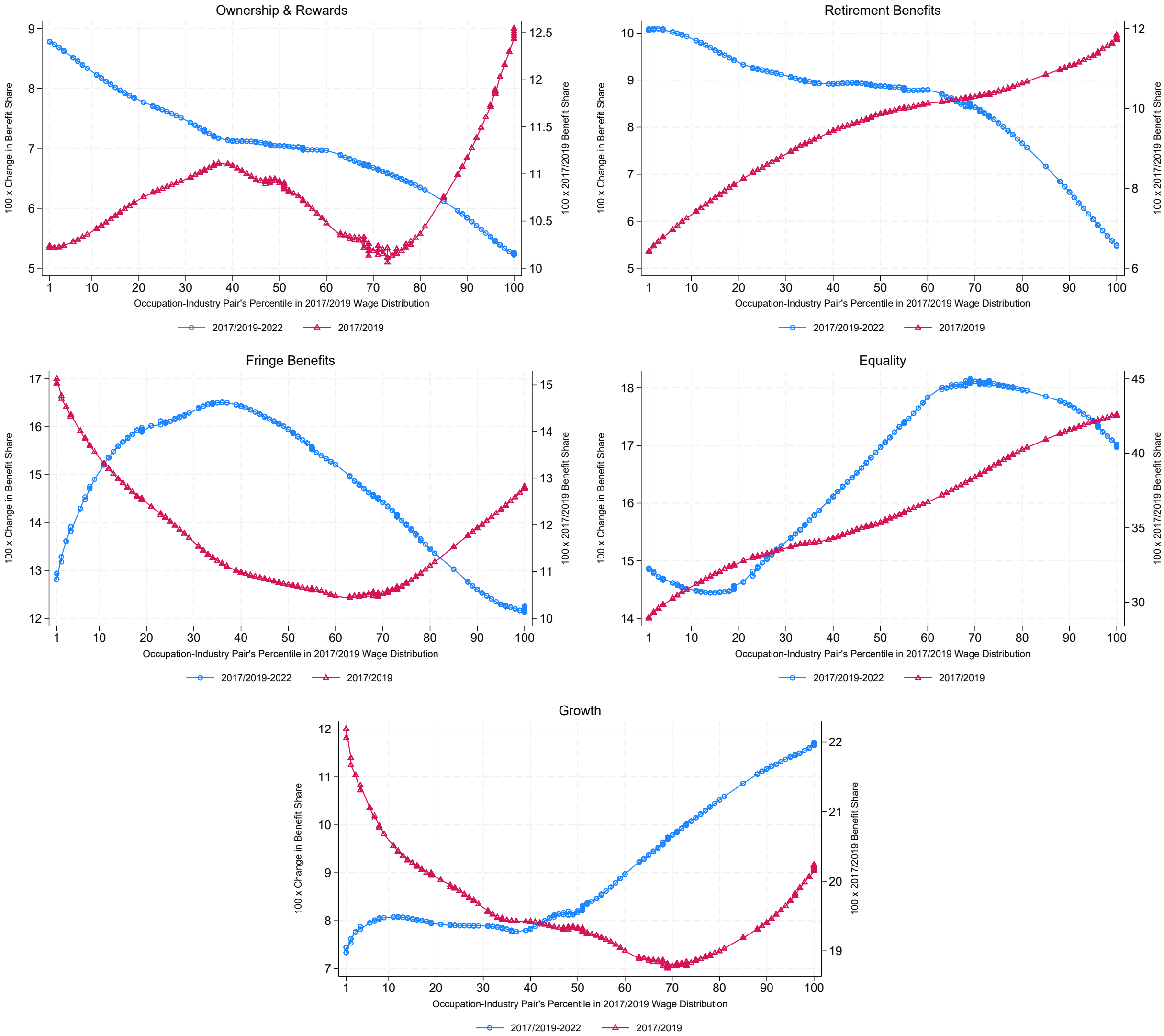
Figure 6: Smoothed Changes in the Job Benefits



Notes: The data sources are the monthly Labour Force Survey (LFS) and Lightcast (BGT). Pre-pandemic distribution of job benefits is given on the right y-axis of each figure while changes in job benefits between the 2017/2019 and 2022 periods are given on the left y-axis of each figure. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles are measured as the employment-weighted percentile rank of an occupation-industry pair's mean log wage in the LFS 2017-2019.

In summary, the analysis across occupations and industries does not allow for an easy

Figure 7: Smoothed Changes in the Job Benefits



Notes: The data sources are the monthly Labour Force Survey (LFS) and Lightcast (BGT). Pre-pandemic distribution of job benefits is given on the right y-axis of each figure while changes in job benefits between the 2017/2019 and 2022 periods are given on the left y-axis of each figure. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles are measured as the employment-weighted percentile rank of an occupation-industry pair's mean log wage in the LFS 2017-2019.

interpretation of how requirements and benefits have changed across occupation-industry pairs ranked by compensation. Demand, as measured by job postings has increased by more among traditionally less well-paid jobs, and for these, compensation-linked benefits seem to have become more common. However, these jobs are also becoming more likely to list education and experience requirements as well as some skill requirements. Benefits associated with job flexibility and time off—benefits that might be associated with work-life balance—are become more commonly advertised among the highly compensated occupation-industry pairs.

6 Concluding Remarks

To conclude, we have developed a NLP-based method that allows us to document changes in the frequency of job postings listing various types of benefits. Our findings reveal a significant increase in the propensity of job postings in 2022 advertising various benefits such as work-life balance, compensation analogous benefits like retirement benefits or ownership benefits, as well as other rewards.

Simultaneously, we analyze whether job postings are becoming increasingly likely to post skill requirements or formal qualifications (experience and education) and indeed they are.

The picture that emerges is thus muddled. On one hand, a tight labour market is evident, particularly among the lower end of the wage distribution. Contrary to expectations, we do not observe a decline in skill requirements as one would expected if employers are competing for workers. Moreover, the number of benefits offered are increasing, this increase is not necessarily concentrated within occupations and industries experiencing heightened labour market tightness.

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A Appendix

Job Skill Definitions

Job Skills	Keywords and Phrases
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Basic Computer	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Specialized Software	Programming language or specialized software (e.g., Java, SQL, Python) [Created by BGT]
Data Analysis	Data analysis, data understanding, data analytics, data engineering, data modeling, data visualization, data science, data collection, data cleaning, predictive analytics, predictive model, tableau, spreadsheet
Technical Support	Computer installation, repair, maintenance, troubleshooting, web development, site design, software installation, help desk support
Management	Project management, supervisory, leadership, management (not project), mentoring, staff
Finance	Budgeting, accounting, finance, cost
Social	Communication, teamwork, collaboration, negotiation, presentation
Character	Organized, detail-oriented, multitasking, time management, meeting deadlines, energetic
Creativity	Creativity
Writing	Writing, editing, preparing a report, preparing proposal

Table A1: Description of Job Skills

Job Benefit Entities

Entity	Job Benefit
Insurance Coverage	Health, dental, and vision insurance
Retirement benefits	Retirement benefits, including retirement contributions
Time off	Paid time off, sick leave, and maternity/paternity leave
Job Flexibility	Flexible working hours, work-life balance
Remote Work	Work from home options
Fringe Benefit	Employee discounts, gym/fitness center access, post-secondary scholarship, Relocation Assistance, Commuter Benefits, Free Lunch
Growth	Education assistance, On-the-job training, and professional development opportunities
Ownership & Rewards	Stock options, equity, Bonuses and profit sharing
Equality	Diversity and inclusion initiatives
Protection	Life and disability insurance

Table A2: Job Benefit Entities

NER Tagging Software

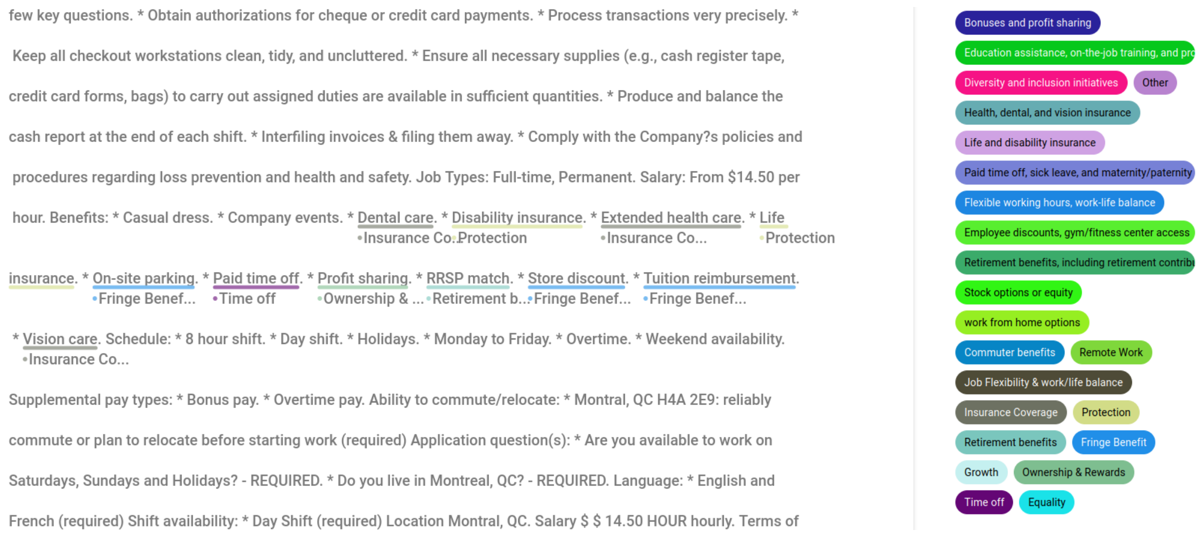

Figure A1: NER Labeling software

Notes: To obtain tags, we use a powerful open-source annotation tool to assist with our NER task. The figure is a screenshot of the tagging process using the Doccano software (Nakayama et al., 2018).

NER Model Output

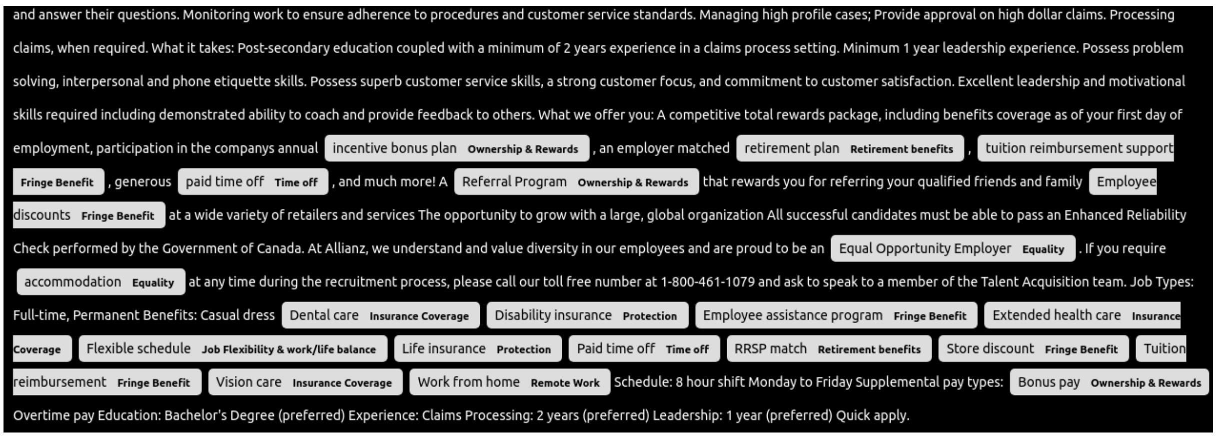

Figure A2: NER Model Output

Notes: The figure is a screenshot that demonstrates the application of our trained RoBERTa Model to the dataset containing job postings from Lightcast. In this context, our trained model objective is to process the context of the job posting to identify and label specific entities within the text from the Job Benefit Entities list.