Letting Job Postings Talk: Recent Trends in Digitalization*

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Abstract

We construct a novel dataset of Canadian online job postings, classified by occupation. The data, provided by Indeed, an online job board, represents vacancies advertised by employers across Canada. We have classified these job postings into standard occupations using text analytics. This dataset has been used to study changes in the demand for jobs linked to digitalization over the COVID-19 pandemic. To this end, we leverage time-series and cross-sectional variations in COVID-19 containment policies, examining their impact on jobs broadly related to digitalization. Our findings reveal that vacancies in digital production jobs increased more substantially than in traditional jobs during the reopening phases. However, no substantial differences were observed when considering different types of vacancies according to the use of digital technologies (i.e., occupations at low risk of automation or those that allow remote work). Overall, our results do not support the popular idea that the COVID-19 pandemic marked a significant turning point in digitalization trends, but rather document a modest shift in this direction.

JEL codes: J23, J24, O14

Keywords: job postings, labor demand, digitalization

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1 Introduction

Historically, the empirical labor market research has focused on data derived from labor force surveys, population censuses, and various consumer and firm surveys. The data is typically low-frequency, subject to publication lags, and often relatively aggregated. Such characteristics hinder the analysis of labor market developments in real time and the identification of trends within disaggregated market segments. As was particularly evident during the COVID-19 pandemic, these limitations represent substantial challenges for both policymakers and academics.

This paper leverages comprehensive data on job postings from a leading job board, Indeed, to offer insights into the Canadian labor market during the COVID-19 pandemic with a particular focus on digitalization. Job posting data have recently shown to be useful in a variety of contexts. For example, Hensvik et al. (2021); Marinescu et al. (2021); Bernstein et al. (2023) analyze the evolution of job vacancies, search behavior, and the resulting labor market tightness at different stages of the pandemic using several job boards. Forsythe et al. (2020) documented a substantial drop in job postings in the U.S. at the onset of the pandemic using data from Burning Glass Technologies. Jones et al. (2023) use Burning Glass Technologies data for Canada to complement traditional data sources and to understand the magnitude of the flows in the labor market at the onset of the pandemic.

Our main contribution lies in constructing a new dataset of online job postings, classified by standard occupations using text analytics. We enhanced an algorithm originally developed by Turrell et al. (2022), adapting it to the data provided by Indeed and to the bilingual setting of the Canadian labor market. This adaptation has allowed us to achieve an acceptable level of accuracy at the 4-digit level of the Canadian National Occupation Classification (NOC), the most granular level of our analysis.

We then demonstrate the economic usefulness of our new dataset by employing it to examine trends in digitalization during the pandemic. To achieve this, we group job titles based on their role in digital production (such as software development, hardware production, information technology support), and in digital adoption (namely, occupations that offer the possibility for remote work, or have low risk of automation).

In our application to the COVID-19 context, we leverage the variation in the containment measures across Canadian provinces to estimate the effects of the pandemic on digitalization. To mitigate biases arising from the correlation between the disease spread and other local shocks, we adopt a differences-in-differences approach and an event-study approach. These methods allow us to exploit variations in the timing of lockdowns and reopenings across provinces.

Our findings indicate that less stringent containment measures lead to stronger recovery in openings for jobs involved in the production of digital technology than for other jobs. Postings for jobs that can be done remotely and that are not at high risk of automation, also increase slightly more during reopenings; however, the difference compared to other types of job postings is not significant. Similarly, no significant differences are observed during lockdowns. These findings complement and contrast with those by Soh et al. (2022) with the same data for the U.S.; whereas they document changes favoring digital workers relative to non-digital ones, these changes are driven by a relatively small decline in the demand for digital workers compared to others. In contrast, we find that demand for digital production occupations increases more than for other occupations during reopenings. We also offer suggestive evidence that, during the pandemic, firms posted fewer low-wage and female-oriented vacancies in occupations not linked to the digital economy, as opposed to those in the digital economy where this phenomenon was not observed.

Our paper contributes to a growing body of literature using online job postings data to analyze labor market outcomes. While the use of these data has become particularly prolific during the pandemic, there are notable precedents. Turrell et al. (2022) used the online vacancies from the job site Reed to examine labor mismatch in relation to the productivity puzzle in the U.K. They found that regional mismatches played a more prominent role than occupational mismatches in explaining productivity statistics. Using data from CareerBuilder, Marinescu and Wolthoff (2020) document that job titles explain over 90% of the wage variance. The Indeed data featured in our study has also been previously used in labor market research. For instance, Gimbel and Sinclair (2020) analyzed mismatches between job seekers and employers in the U.S., and Adrjan and Lydon (2019) showed that labor market tightness, as measured by job postings and clicks, correlates with posted wages. Our paper combines text analytics with occupation descriptors to systematically structure job posting data into occupations within the Canadian context.

The application to digitalization during the COVID-19 pandemic aligns with the literature of acceleration of technological change with recessions. Hershbein and Kahn (2018) showed that firms in areas severely impacted by the 2008 crisis persistently increase both their skill requirements and capital investments.[1] Consistent with these findings, Jaimovich

[1]Corroborating this, Yagan (2019) identifies a persistent employment loss in hard-hit areas, attributed to workers dropping out from the labor force.

and Siu (2020) report that job losses in routine occupations are concentrated in recessions, without corresponding employment gains in these occupations during recoveries. Foote and Ryan (2014) also observe that middle-skill workers, predominantly in routine occupations, are concentrated in cycle-sensitive industries (like manufacturing and construction), leading to cyclical fluctuations in their employment levels. The COVID-19 crisis not only reduced the opportunity costs of technological change typically associated with economic crises, but also made disease-control measures more conducive to the adoption of digital technologies. Our paper focuses on job postings related to the production of digital technologies, extending beyond the concept of automation risk that has been predominant in this literature.[2]

Although there has been much discussion about the acceleration of technology adoption during the pandemic, the evidence is still limited. Alexopoulos and Lyons (2021) analyzed various unstructured data sources to assess trends in the adoption of digital technologies in Canada, both before and after the pandemic. These technologies include artificial intelligence, data science, and robotics. While some indicators suggest technological sectors have been outpacing others during the pandemic, others point to a slowdown in technology adoption during the recessionary periods. Barrero et al. (2021) document a substantial increase in new U.S. patent applications related to remote work technologies since the onset of the pandemic. Our results complement these studies. While we do not find conclusive evidence of accelerated technology adoption during the pandemic, our analysis reveals that firms notably increased their demand for jobs in digital production as restrictions were eased.

The remainder of the paper is organized as follows. Section 2 presents the data on job postings and discusses its usefulness for labor market research. Section 3 explains the algorithm we built to classify the data into occupations. We then turn to the application to digitalization during the pandemic. Section 4.1 presents how we group the data using the classifications relevant to analyze digitalization, and Section 4.2 shows the recent trends in these groups. We present the event study that leverages province-level variation in lockdowns and reopenings in Section 4.3. Section 5 concludes.

[2] Atalay et al. (2021) and Hershbein and Kahn (2018) also classify job postings according to their relation to technology. However, their classification exercise is more demanding in terms of information than ours, as they use the job posting text, something we do not have.

2 Online Job Postings Data

We use job postings collected by Indeed, the largest job site in Canada.[3] Indeed advertises job postings by employers directly on its website, as well as postings collected from employers' websites, which are treated to avoid duplication. The data include the job title, the first and last day visible, and the city and province, and they are available from 2018 on.

Figure 1 shows the annual growth rate of the smoothed number of new job postings (7-day moving average) published each day in Canada. Growth rates for 2021 and 2022 refer to 2019 to avoid base-year effects caused by large drops at the beginning of the pandemic. The volume of online job postings in Indeed closely follows the trend in online job board vacancies from the Job Vacancy and Wage Survey (JVWS, dots in Figure 1), and with total employment from the Labour Force Survey (LFS) (Figure 2). These are both collected by Statistics Canada, which is the official statistics office. Reassuringly, the data on job postings show a distribution across provinces that is similar to that of employment in the LFS in Canada (Figure 3).

Overall, the data on online job postings provided by Indeed appears representative and hence useful for labor market research on online vacancies. The data are unstructured, containing over four million unique job titles. Figure 4 shows a word cloud of the text in the job postings. We next explain how we classify the data into occupations in the Canadian context.

3 Classifying Job Postings into Occupations

We construct a text analytics algorithm to classify job titles into relevant occupation classifications. The Indeed data lack occupational variables that can be directly mapped into the standard occupation categories. Instead, we utilize the job title and company name in the job postings to classify them into Canada's four-digit National Occupation Classification (NOC), version 2016.3. This version was the most recent and offered the highest level of disaggregation of the NOCs at the time of our analysis.

We build upon an algorithm developed by Turrell et al. (2022). Unlike the approach of Turrell et al. (2022), our job ads data do not include job descriptions; instead, we only have access to the job title and company name for each posting. Our adaptation of the algorithm

[3]After entering the Canadian market in 2015, Indeed was considered the top source for job hires in the country by 2017 (see e.g., "Indeed goes to work in Canada" in *Strategy*, October 7, 2015, and "Indeed helps more people get hired than any other job site" in the Indeed Blog).

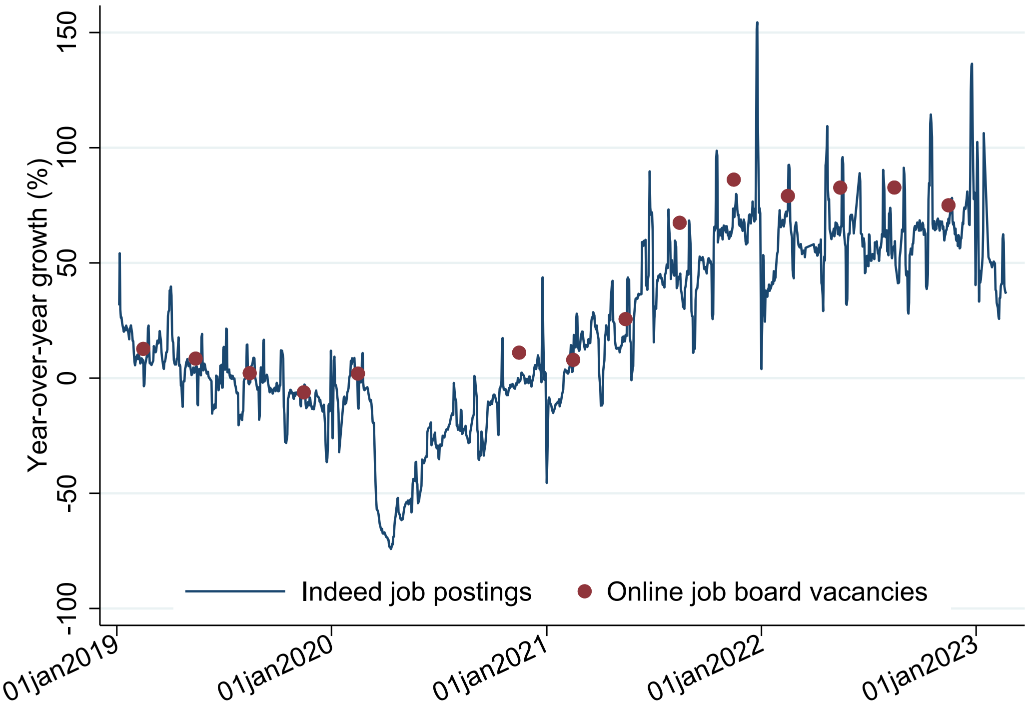


Figure 1: Year-over-year growth of online job postings on Indeed and online job board vacancies collected by Statistics Canada

Note: Job postings are daily data, smoothed with a 7-day moving average. Vacancy data are collected on a quarterly basis. To avoid base-year effects associated with the COVID-19 pandemic, the year-over-year growth rate calculations use 2019 values for 2021 and 2022.

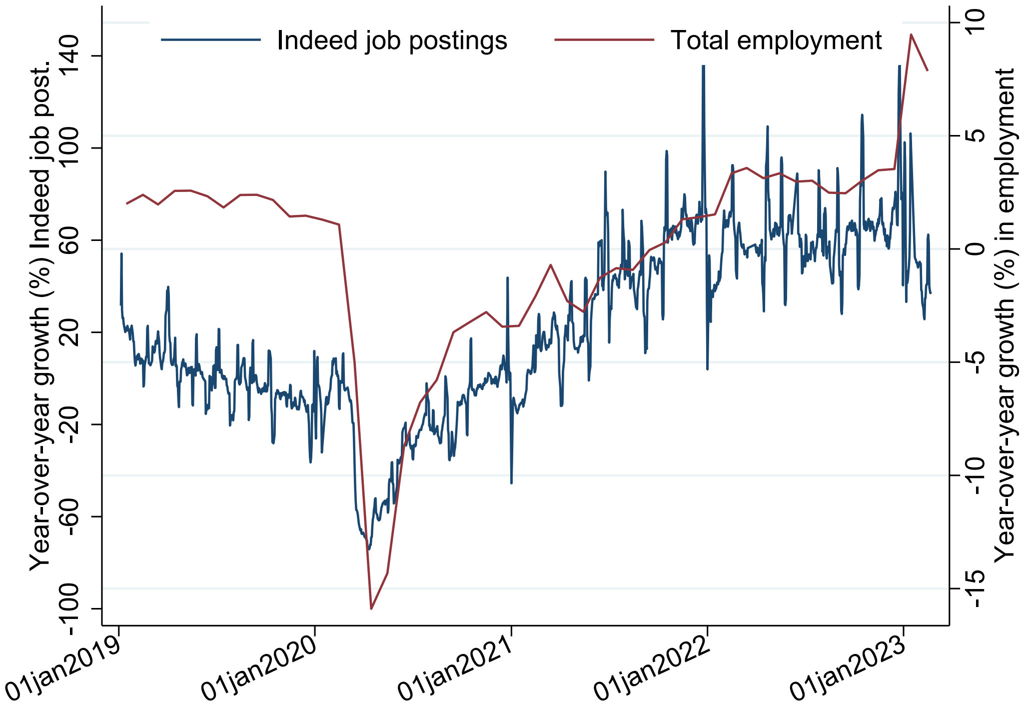


Figure 2: Year-over-year growth in online job postings on Indeed and total employment

Note: Job postings are daily data, smoothed with a 7-day moving average. Employment data are collected monthly. To avoid base-year effects associated with the COVID-19 pandemic, the year-over-year growth rate calculations use 2019 values for 2021 and 2022.

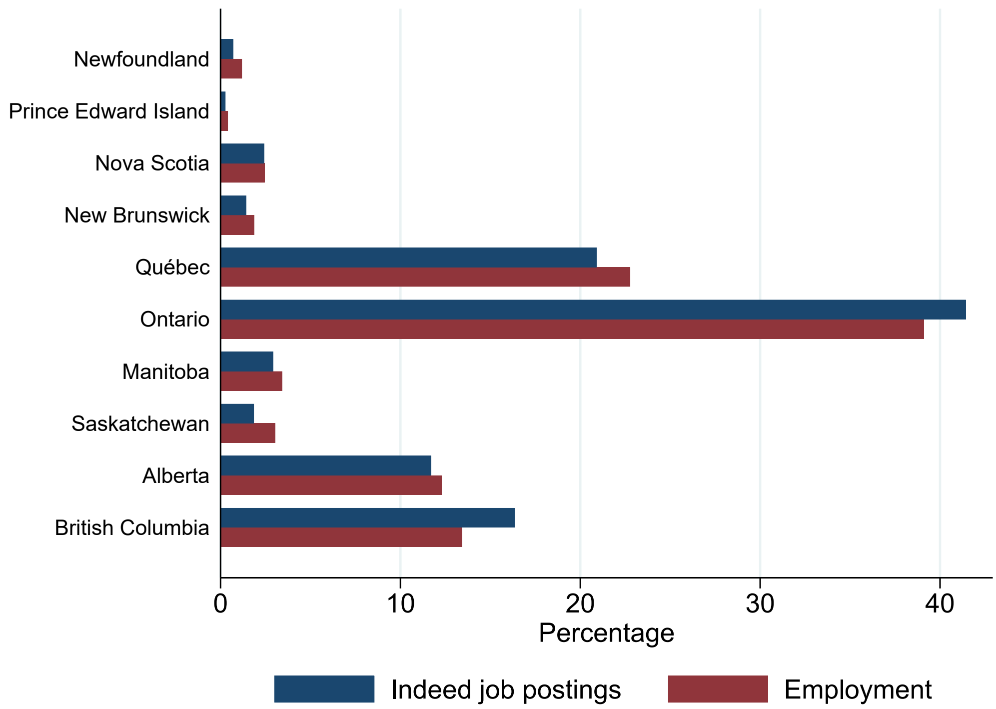


Figure 3: Percentage of online job postings and employment by Canadian provinces in 2019

Note: Job postings data are collected daily. Employment data are collected monthly.

Figure 4: Word cloud of online job postings since March 2020

performs adequately, achieving accuracy at the high end of comparable classifications. The main modifications we made to the algorithm by Turrell et al. (2022) include (i) mapping jobs to the Canadian NOC, for which we create dictionaries in English and in French, (ii) expanding the list of abbreviations, and (iii) using company names, which we believe offer some insight about the sector of each vacancy.

We first clean the text in job postings following standard text analytic techniques.[4] Abbreviations in the job postings are expanded using an adaptation of Turrell et al. (2022)'s dictionary that adds abbreviations from human resources websites.

To perform the matches, we compile two types of dictionaries by scraping text data from the Government of Canada website[5]: the job title dictionary and the broader text dictionary. The job title dictionary contains sample job titles for each of the 500 NOC titles. The broader text dictionary has information on descriptions and main tasks for each job title. Dictionaries are constructed in English, French, and bilingual (appending the previous two). Due to efficiency considerations, job postings in English are classified using the English-

[4] Trailing white spaces are deleted, numbers and punctuation signs are removed, and words are made lowercase. All plural words are turned singular using the lemmatizer from Python's Natural Language Toolkit (NLTK). We also drop job postings with an empty job title, as this is the primary data used for our classification.

[5] See `https://noc.esdc.gc.ca/Structure/Hierarchy?objectid=%2Fd0IGA6qD8JPRfoj5UCjpg%3D%3D#wb-cont`.

only dictionary. Job postings either from Quebec (Canada's main francophone province) or those using francophone special characters, such as accents or cedilla, are classified using the bilingual dictionary. This is because some job postings in Quebec are in English.

There are two stages in the matching algorithm. First, it looks for an exact match between the title in the job posting and the title from the NOC. If found, the relevant four-digit NOC is returned. If no exact match is found, the algorithm proceeds to a second stage, the so-called fuzzy match, comparing both the job title and the company name to the broader NOC dictionaries. Our algorithm uses the term frequency-inverse document frequency (*tf-idf*) technique. It calculates the cosine similarity between the job-posting text and the NOC category. It then returns the job posting that has the smallest cosine distance, ensuring that no job postings remain unmatched. More details are in Appendix A.

Accuracy of the classification algorithm: We evaluated the performance of the algorithm by manually verifying the classification produced by the algorithm in 100 random job titles. Accuracy according to this procedure (percentage of correct matches) is 70% for job postings in English. By incorporating the company name into the algorithm, we gain a 3-percentage-point increase in accuracy compared to using only the job title. For our French sample with the bilingual dictionary, the accuracy is 66%. And when we manually delete the English job postings in our French sample and use only the French dictionary, we obtain an accuracy of 74.5%.

The accuracy values we obtain are adequate for a 4-digit automatic classification according to Turrell et al. (2022), particularly when job ad text is missing, as in our case.[6] Also, using the NOC for classifying job postings in Canada seems to be a good choice. In a classification exercise using Turrell et al. (2022)'s algorithm to classify our job postings into the 3-digit UK Standard Occupation Classification, as they do in their paper, we achieved a decreased accuracy level (64%) in our English sample.

Figure 5 provides reassuring insights into the distribution of Indeed job postings across broad occupational groups (NOC 1 digit) in comparison to employment levels in these groups, as indicated by the LFS data. The distributions look fairly similar. Certain groups, like managers, are overrepresented in the Indeed job postings, while others, such as operators, appear to be underrepresented. This seems in line with the presence of a larger proportion of high-skilled vacancies in online job postings than in vacancies in general.

[6] Turrell et al. (2022) obtained 76% accuracy using job description and sector, information we do not have. Algorithms that use only job titles tend to have much lower accuracy rates, as noted by Belloni et al. (2014).

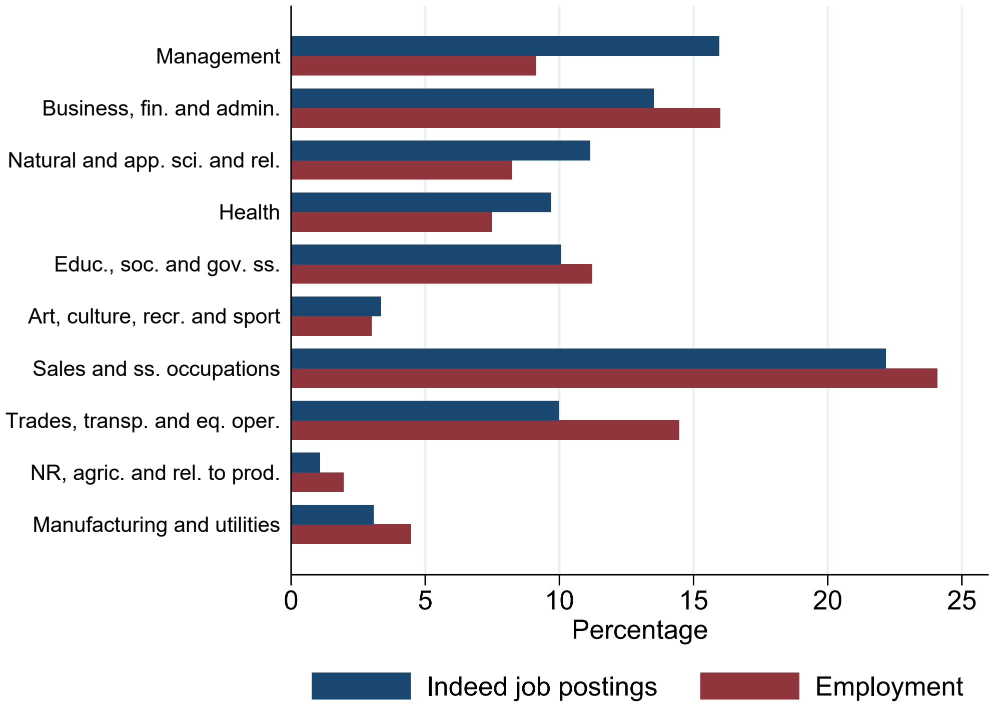


Figure 5: Percentage of job postings and employment by occupation groups in Canada in 2019

4 Application: Did Digitalization Accelerate During the COVID-19 Pandemic?

The first confirmed case of COVID-19 in Canada was reported on January 27, 2020. On March 11, 2020, the World Health Organization declared COVID-19 a global pandemic, leading to the implementation of travel bans and local movement restrictions in several countries, including Canada. Provincial governments in Canada were in charge of implementing containment measures to slow the virus' spread. Following the initial state of emergency declared in March 2020, Canada experienced several rounds of lockdowns and subsequent gradual reopenings over the next two years. The timing of these restrictions varied across provinces, corresponding to changes in COVID-19 case numbers, hospitalizations, deaths, and vaccination rates. These measures had substantial economic impacts: GDP plummeted in April 2020, and had not yet returned to pre-pandemic levels by the end of 2021. By that time, more than three quarters of the population had received full immunization, thanks to the rapid development of vaccines.

Classifying job posting data into occupations reveals significant differences in how various job types responded to the pandemic. Such heterogeneity is especially noteworthy during

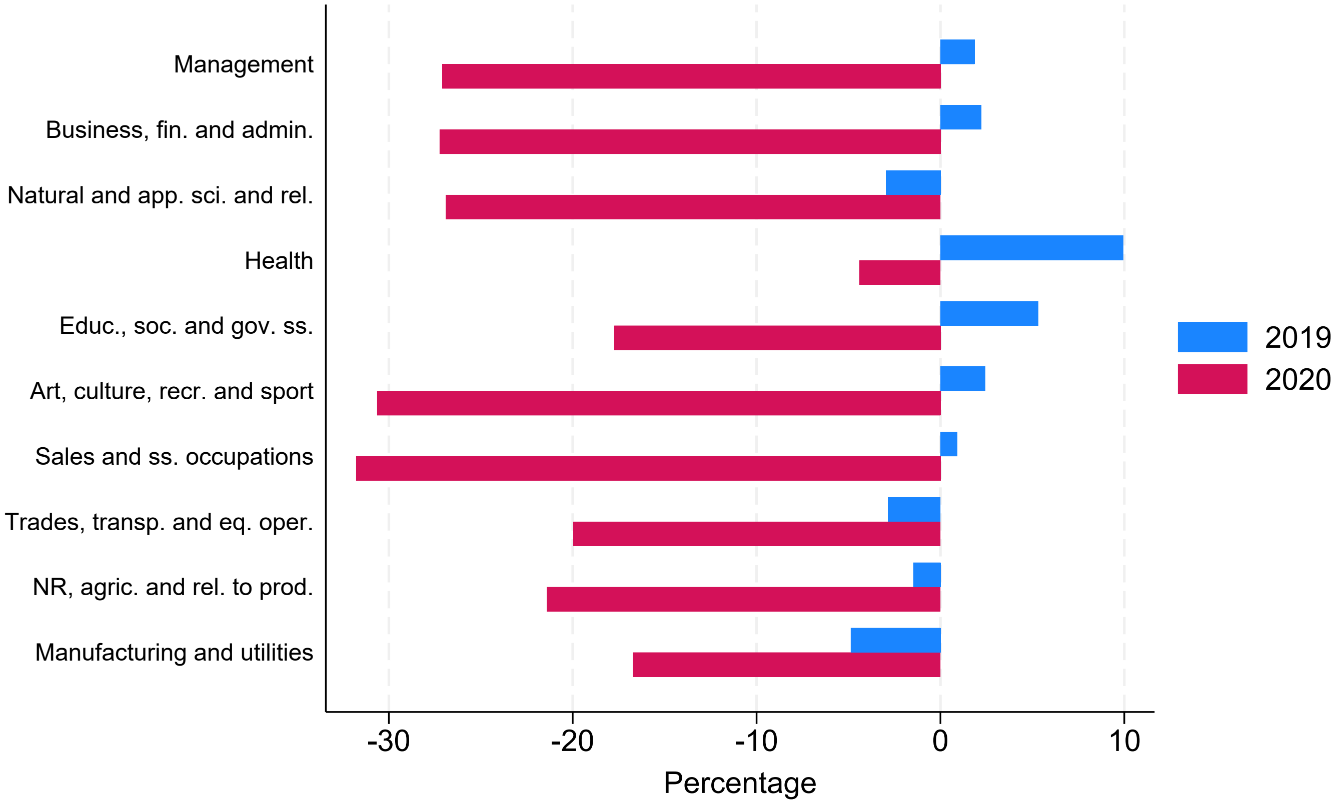


Figure 6: Annual changes in job postings by occupation groups in Canada in 2019 and 2020

a disruptive event like the COVID-19 pandemic, when shifts in occupational demand are expected. Figure 6 shows that while there was a widespread decline in vacancies in 2020 compared to 2019, some occupation groups were disproportionally affected. For instance, art, culture, recreation and sports, as well as sales and services, experienced a drop of more than 30% in 2020, despite growing positively in 2019. The least affected group was health occupations, which saw a modest decline of less than 5%. This was followed by manufacturing occupations, which declined by 17% (having already dropped in the previous year), and education, social and government services, which decreased by 18% after experiencing growth the year before.

Given the observed heterogeneity in the responses of vacancies during the COVID-19 pandemic, it is reasonable to speculate that some occupations, particularly those linked to digital technologies, may have experienced changes at a different pace. The pace of change in occupations linked to digital technologies, compared to other sectors, forms the focus of our subsequent analysis.

4.1 Occupations Related to Digitalization

We classify occupations according to their relation to digitalization, either via production or adoption. The production side is comprised of occupations involved in the development of digital technologies. Regarding digital adoption, we characterize occupations according to their possibility of remote work and their automation risk. Jobs that allow people to work from home, and at low risk of automation, are complementary to digital technologies. In all these classifications, we exclude jobs related to health care; this is group 3 in the NOC and some other titles (Managers in health care, and Health information management occupations). The reason for this exclusion is that these jobs may have responded differently due to the specific demands of the pandemic.

Digital Production: We group those occupations related to the production of hardware, software and supporting services.[7] A detailed list of NOC codes we included in this category is in the Appendix B. All remaining sectors are included in the so-called non-digital category.

Digital Adoption: We use the definitions of categories related to feasibility of working from home (Dingel and Neiman, 2020) and the automation risk (Chernoff and Warman, 2023). Their definitions are based on the O*NET descriptor data that characterizes occupations along several dimensions. We mapped the 4-digit NOC categories to the O*NET categories, based on the U.S. Standard Occupation Classification, using a crosswalk designed by the Brookfield Institute (Vu, 2019).[8] Whenever we have more than one category in the O*NET classification that maps to one category in the NOC, we average the measures of feasibility of working from home and of automation risk across O*NET categories.

The criteria for assessing whether an occupation can be done from home, as proposed by Dingel and Neiman (2020), are based on 17 questions from the O*NET version 24.2, specifically from the work context and generalized work activities questionnaires. Their measure is 0 for an occupation that cannot be done remotely and 1 if the job can be performed remotely. We use the 0.5 cutoff for cases in which several O*NET categories are associated with one NOC category. Occupations are considered feasible to be done from home if the average is 0.5 or above, and they cannot be done from home if the average is below 0.5.

To determine the automation risk based on Chernoff and Warman (2023), we standardize

[7]The definitions are based on work by STATCAN (2019) to estimate the digital economy, which are in line with international standards used by Organisation for Economic Cooperation and Development countries. They classify products of the Canadian Supply and Use Tables within the national accounts in order to get a measure of output and jobs associated with these activities.

[8]For more details, see the related GitHub website and the blog post. Their work leverages the existing crosswalks between the NOC and the International Standard Classification of Occupations (ISCO), and between ISCO and O*NET, adjusting manually the matching such that there are not NOC codes unmatched.

and aggregate a series of O*NET descriptors into the following variables: routine cognitive, routine manual, non-routine analytical, non-routine interpersonal, and non-routine manual. These variables are combined into the index of routine task-intensity (RTI), normalized to be between 0 and 1. After averaging the RTI index for NOC categories that have multiple associated O*NET categories, we classify occupations as being at low automation risk if the index is below 0.5, and at high risk if it is 0.5 or higher.

It is worth mentioning that the occupation classifications, especially those related to the feasibility of working from home, correspond to the period when the O*NET survey was conducted. However, many occupations have changed their nature and transformed in response to the pandemic. We discuss this matter, and further details about the construction of the measure of the possibility to work from home and automation risk, in Appendix B. We highlight some changes between the O*NET version 24.2 used in Dingel and Neiman (2020) corresponding to February 2020, and the version 25.2 that corresponds to May 2021. We observe changes in the descriptors of many occupations that confirm shifts favoring work from home. As we may be underestimating the effect of the pandemic on the possibility of working from home, our results are on the conservative side in this respect.

4.2 Descriptive Analysis

Job postings related to digital production represent 8% of total non-health-related job postings, which broadly aligns with the 5.9% of workers in digital industries estimated by STATCAN (2023) for 2020. The proportion of vacancies for jobs that could be done remotely is 52%, aligning with estimates by Statistics Canada researchers (38.9% of employment could be done at home in 2019, according to Deng et al., 2020), and for the U.S. (37% as per Dingel and Neiman, 2020). Additionally, half of job postings are identified as having low automation risk. This is compared to 40% of workers facing high and moderate automation risk (a probability of 50% or more) in 2016, as reported by Frenette and Frank (2020).

The categorization of job postings into each of these classifications is not mutually exclusive. In fact, there is notable correlation between them, as detailed in Table 7 in the Appendix. While potential for remote work and automation risk are evenly distributed among job postings not related to digital production, those with remote work potential constitute 82% of postings related to digital production, and those with low automation risk account for 64% of this category. Furthermore, over two-thirds of job postings with remote work potential have low risk of automation, and a similar proportion of postings without

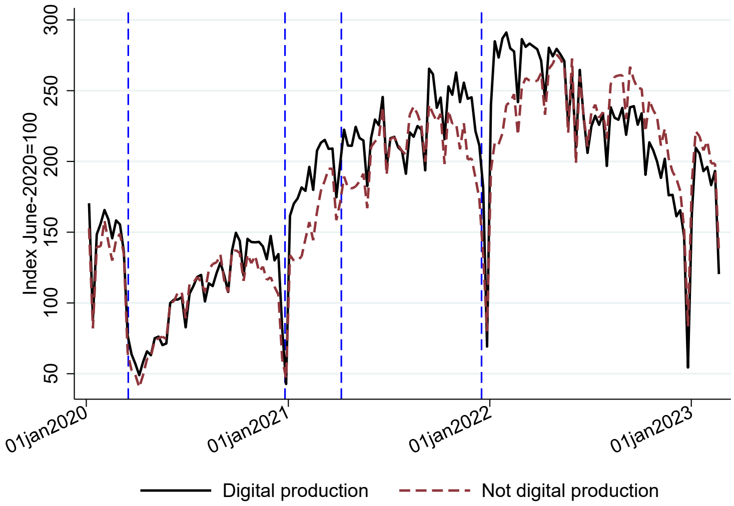


Figure 7: Online job postings related to digital production and the rest

Note: Online job postings in health-related occupations are excluded. Weekly data indexed to June 1, 2020=100. The vertical lines correspond to the beginning of the lockdowns between the first and the fourth waves, using Ontario as a reference.

remote work potential are at high risk of automation.

Figures 7-9 show the evolution of new job postings in occupations related to digitalization. All figures show the 7-day moving average of job postings, indexed to June 1, 2020, after the first lockdown. The vertical lines indicate the lockdowns based on the dates they were implemented in Ontario. Although the trends of the various occupation groups are closely aligned, reflecting inherent fluctuations of new job postings, those in digital production outpaced job postings in other occupations from the onset of COVID-19 until mid-2022. Since then, the trend reverted with new job postings in occupations not in digital production growing more rapidly. This resonates with the easing labor demand in the big technological companies that was present in the news headlines. Job postings in occupations that can be done from home and at low risk of automation display smaller differences with others; they experienced slightly more growth since the onset of the pandemic, with a brief interruption in the second half of 2022.

A pertinent question regarding digital-related online job postings is whether the pandemic has altered the proportion of vacancies advertised online across different occupation groups. To address this, we analyze data from the JVWS. The JVWS provides quarterly data on recruitment strategies for vacancies at the 4-digit NOC level. Unfortunately, data for the second and third quarter of 2020 are missing. We use the third quarter of 2021 as last data point. We specifically examine trends in the proportion of vacancies advertised on online job

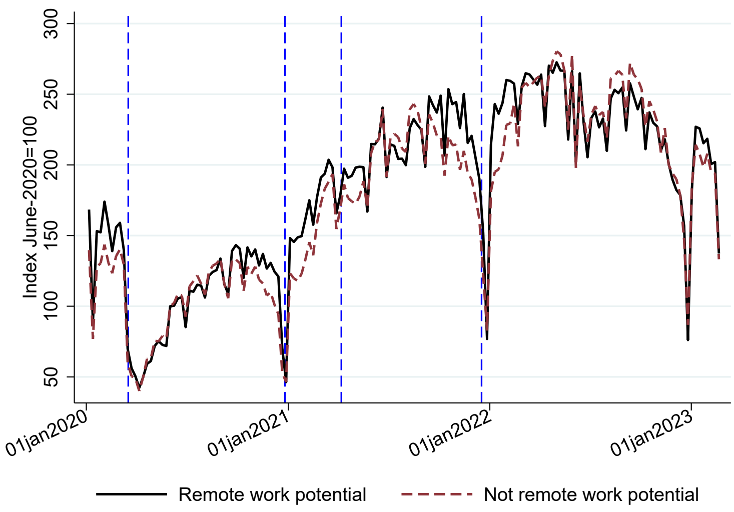


Figure 8: Online job postings in occupations suitable for remote work vs. other occupations

Note: Online job postings in health-related occupations are excluded. Weekly data indexed to June 1, 2020=100. The vertical lines correspond to the beginning of the lockdowns between the first and the fourth waves, using Ontario as a reference.

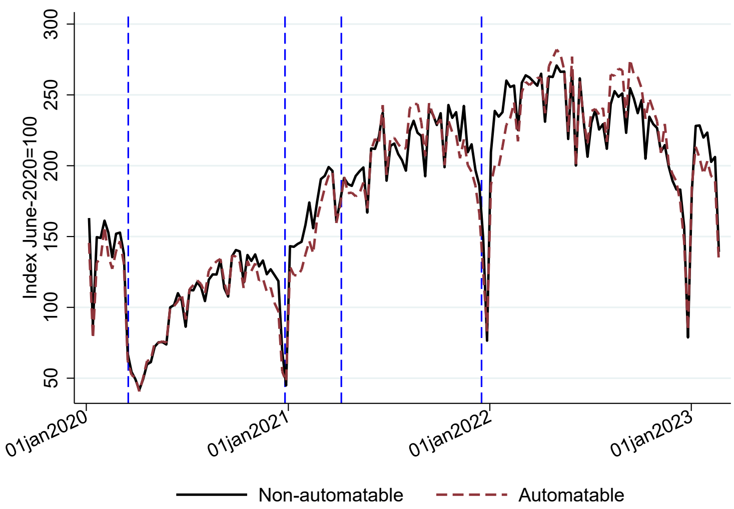


Figure 9: Job postings in occupations with low risk of automation vs. the rest

Note: Online job postings in health-related occupations are excluded. Weekly data indexed to June 1, 2020=100. The vertical lines correspond to the beginning of the lockdowns between the first and the fourth waves, using Ontario as a reference.

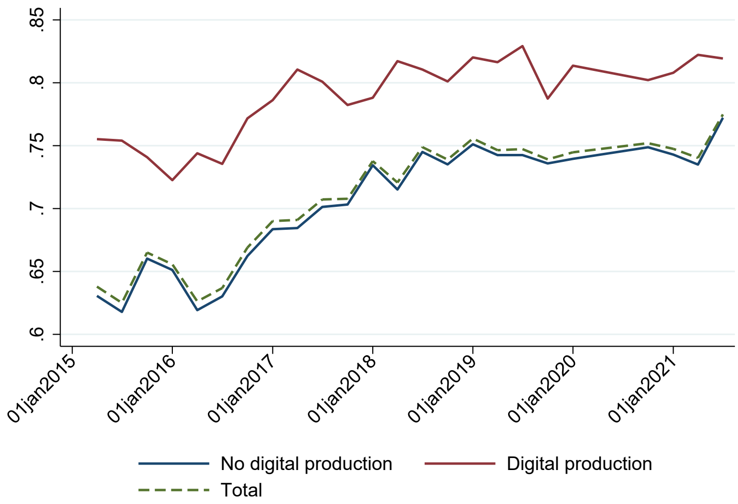


Figure 10: Proportion of online job board vacancies for jobs in digital production and the rest

boards to assess whether there was a shift toward digital posting in the occupation groups under study.

Figures 10-12 show the proportion of job postings of each type that are listed online. Although the proportion of digital-related job postings (in digital production, with remote work potential, and at low risk of automation) that are listed online is larger than for those not digital-related, these proportions remained largely stable throughout the pandemic. The gaps in the proportion of online vacancies before and after the pandemic year of 2020 are broadly similar. Overall, the pandemic does not appear to have substantially disrupted the trend in the proportion of online vacancies for any of the key groups analyzed in this study.

4.3 The Effect of Containment Policies on Digital-Related Job Postings

In this section, we take advantage of differences in the timing of the policies across provinces to estimate the effect they have on job postings related to digital technology. This exercise allows us to analyze whether demand for digital-related jobs changed with containment measures. We perform two exercises. First, we use a differences-in-differences approach, and second, we use an event study to observe how changes in job postings evolve in time.

Differences-in-Differences

We analyze the evolution of job postings in each group defined by their relation to digital technologies, comparing periods before and after each lockdown and reopening. The post-

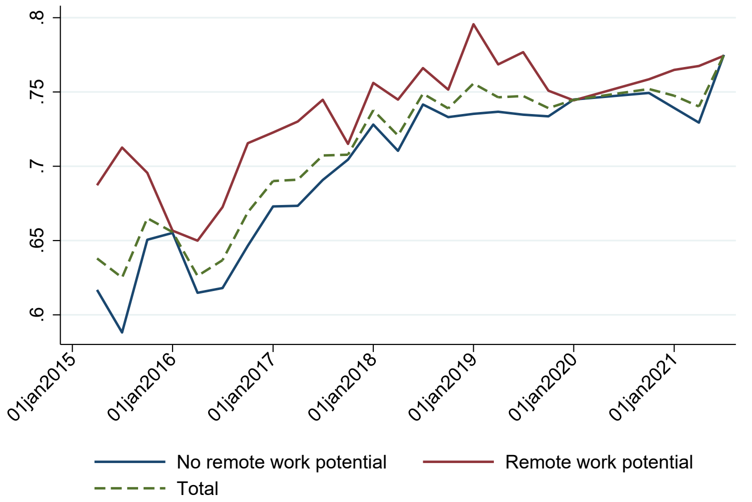


Figure 11: Proportion of online job board vacancies for occupations with remote work potential and the rest

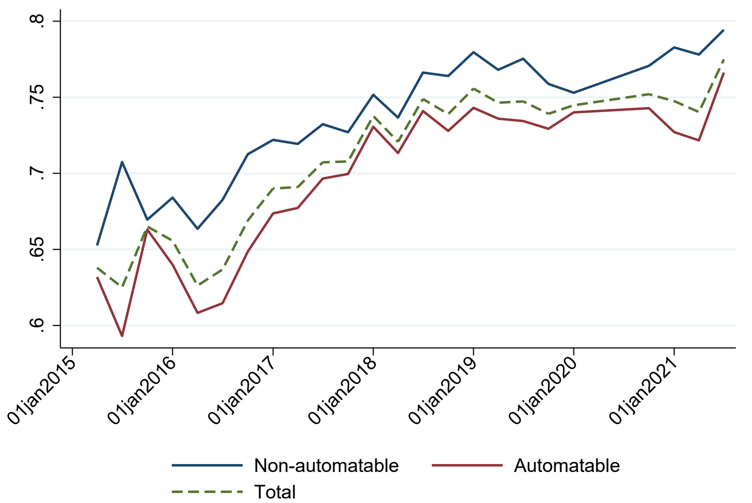


Figure 12: Proportion of online job board vacancies for occupations with low and high automation risk

lockdown period extends until the commencement of the first reopening, while the post-reopening period lasts until the onset of the second lockdown, and so forth. Our analysis focuses on the first and second lockdowns and reopenings, as these periods had more clearly defined dates compared to later policies. The analysis concludes on mid-May, 2021, a decision informed by the Canadian's government approval of vaccionations for all adults since then. We estimate the following equation:

$$JP^{j}_{pt} = \delta Event^{k}_{pt} + \lambda_{pw} + \phi_{py} + \epsilon_{pt} \qquad (1)$$

where p is the province, t is the week, w is the week number in the year, and y is the year. JP^j is the year-over-year growth of the smoothed (three-week moving average) job postings in occupation group j (i.e., digital production, possible to work from home, low automation risk, etc.). $Event^k$, with $k \in \{Lockdown, Reopening\}$, is an indicator that equals one if the week t is during the 1^{st} or 2^{nd} lockdown or reopening periods respectively. We include trends for province-by-week (λ_{pw}) to absorb seasonal patterns and for province-by-year (ϕ_{py}) to absorb macroeconomic fluctuations. For each of the occupational groupings, we conducted a test of the difference between the coefficients for lockdowns and reopenings.[9] The results of these tests are in Table 8 in the Appendix and serve to complement the findings discussed below.

The results of the analysis are presented in Tables 1-3 for each of the groupings respectively. The first panel of each table shows the estimates regarding the first and second lockdowns, and the second panel those of the first and second reopenings. The third panel is a placebo exercise. We take the same weeks as for the first and second lockdowns but one year before, i.e., in 2019 and beginning of 2020. We cannot do the same exercise for the reopenings, as the weeks of the second reopening, one year prior, overlap with the first lockdown.

Our analysis confirms that job postings related to digital technologies (digital production, with possibility of remote work, or at low risk of automation) were less negatively impacted during lockdowns (showing smaller declines) and exhibited a greater increase during reopenings. However, the differences in estimates are relatively modest, averaging 3 percentage points for lockdowns and 4 for reopenings. The only statistically significant difference ob-

[9]To conduct the test, we stacked the data from both categories in each grouping (e.g., digital production and non-digital production), and fully interacted all variables with an indicator taking the value one for the data on digital production. The essence of the test involves evaluating whether the coefficient on the indicator, when interacted with the variable $Event^k$, is statistically different from zero.

served was an almost 8 percentage point larger increase in digital production job postings compared to other categories during the reopening phase. The magnitude is particularly noteworthy, considering it is compared to the overall average growth of 19% for all job postings during the observation period. Placebo tests consistently indicate that there were no unique features associated with the lockdown weeks; in fact, in the corresponding period of the previous year, job postings not related to digitalization were increasing at a faster rate than the others.

Table 1: Dependent variable: growth of job postings in digital production and others, with respect to 2019–JP^j

	Lockdown		*Reopening*		*Placebo Lockdown*	
VARIABLES	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.
Lockdown	-21.31***	-24.57***				
	(3.488)	(2.443)				
Reopening			15.15***	7.37***		
			(3.675)	(2.311)		
Lockdown weeks, 1 year before					2.02	8.51***
					(4.156)	(2.831)
Observations	1,230	1,230	1,230	1,230	1,230	1,230
Adjusted R^2	0.08	0.29	0.06	0.18	0.04	0.19

Note: 3-week moving average of job postings. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the lockdown weeks in 2019, the growth is with respect to 2018.

Table 2: Dependent variable:growth of job postings according to the possibility of remote work, with respect to 2019–JP^j

	Lockdown		*Reopening*		*Placebo Lockdown*	
VARIABLES	Remote	No Remote	Remote	No Remote	Remote	No Remote
Lockdown	-23.21***	-25.46***				
	(2.610)	(2.416)				
Reopening			7.92***	7.58***		
			(2.396)	(2.369)		
Lockdown weeks, 1 year before					6.91**	9.54***
					(2.989)	(2.838)
Observations	1,230	1,230	1,230	1,230	1,230	1,230
Adjusted R^2	0.26	0.30	0.17	0.20	0.16	0.20

Note: 3-week moving average of job postings. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the lockdown weeks in 2019, the growth is with respect to 2018.

In summary, our analysis does not support the widely-held hypothesis that the pandemic significantly accelerated digitalization. While we observe a notable increase in vacancies related to digital production, particularly during reopenings, we did not identify significant effects in terms of digital adoption. It is important to consider that this finding may

Table 3: Dependent variable: growth of job postings according to automation risk, with respect to 2019–JP^j

VARIABLES	*Lockdown* Non-Atom.	*Lockdown* Autom.	*Reopening* Non-Atom.	*Reopening* Autom.	*Placebo Lockdown* Non-Atom.	*Placebo Lockdown* Autom.
Lockdown	-22.51***	-25.96***				
	(2.735)	(2.383)				
Reopening			9.25***	6.02**		
			(2.510)	(2.360)		
Lockdown weeks, 1 year before					6.99**	9.00***
					(3.081)	(2.857)
Observations	1,230	1,230	1,230	1,230	1,230	1,230
Adjusted R^2	0.18	0.35	0.11	0.23	0.10	0.24

Note: 3-week moving average of job postings. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. For the lockdown weeks in 2019, the growth is with respect to 2018.

partly result from the static nature of our definitions, which might not fully capture the dynamic aspects of remote work arrangements and automation. Some discussion about this is included in the Appendix B, regarding the changes in the work-from-home profile of occupations. Overall, our analysis suggests a temporary boost in digital production rather than a permanent shift.

Event Study

To complement our previous analysis, we perform an event study. This method is useful for examining the persistence of changes over time and verifying that the growth trajectories of both categories within each grouping were aligned prior to the pandemic. Diverging from our previous analysis, this exercise focuses exclusively on the first lockdown and subsequent reopening, as these events were adequately spaced apart. Additionally, we restrict our comparison to the 10 weeks before and the 10 weeks after each event. The model we estimate is as follows:

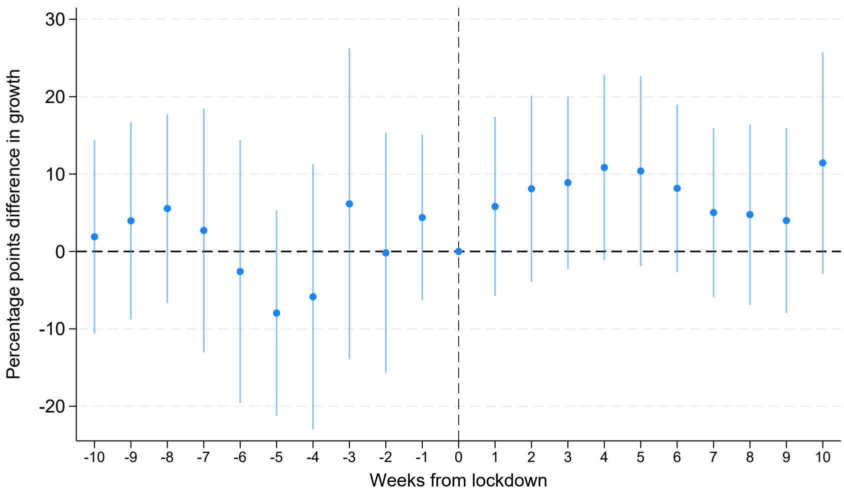
$$\Delta JP^d_{pt} = \sum_{\tau=-10}^{10} \delta_\tau \mathbb{1}(Week_\tau)_t + \phi_{py} + \epsilon_{pt} \tag{2}$$

where p is the province, t is the week, and y is the year. The dependent variable is ΔJP^d, that is, the difference between year-over-year growth of job postings–3-week moving average—in *digital-oriented* occupation groups d (i.e., digital production, potential for remote work, low automation risk), minus those in non-digital-oriented occupations (i.e., the complements). Unlike our previous exercise, we do not include province-by-week fixed effects in this analysis, as doing so would absorb a substantial proportion of the variability, making it impossible to estimate the weekly coefficients accurately. The interpretation of the estimates as effects of the lockdown and reopening rely on the parallel trends assumption. In the absence of the event, job postings in different types of occupations should be growing at the same rate, i.e., the difference in growth should be close to zero. We verify this for the weeks before each event.

Figure 13 presents the event study coefficients for the difference in growth rates between job postings in digital production and others during the first lockdown. Figure 14 provides the analogous estimates for the first reopening. Each coefficient represents the difference in growth rates relative to the start of the lockdown or reopening. Notably, coefficients for the weeks leading up to the lockdown or reopening are not significantly different from zero, confirming the parallel trends assumption.

In alignment with our previous findings, this analysis also indicates a higher growth rate for digital production job postings compared to other categories. Regarding the lockdown, the growth rate difference peaks at just over 10 percentage points, 4-5 weeks following the lockdown, and is significant at the 90 percent confidence level. Although this difference declines over time, it remains positive.

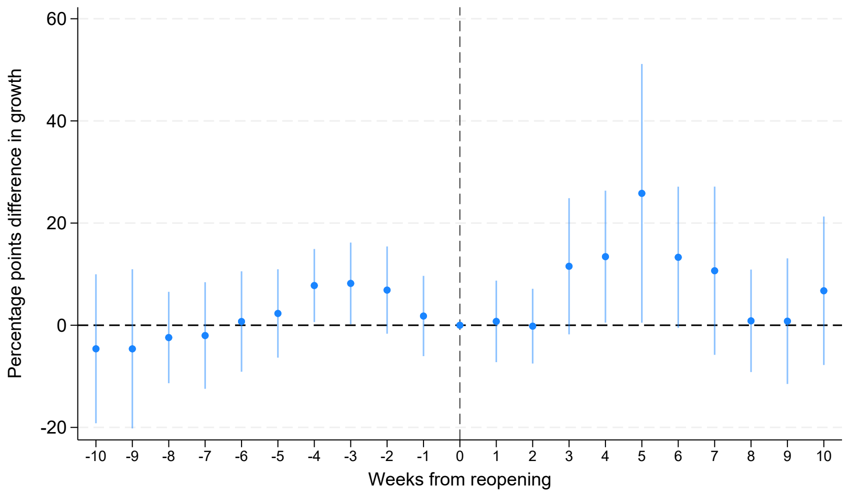
The post-reopening period shows even larger differences. These are statistically significant for weeks 3-6 following the reopening, peaking near 26 percentage points in week 5, before decreasing to near zero by weeks 8 and 9.



Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.

Figure 13: Dependent variable: difference in growth of job postings in digital production and the rest–ΔJP^d. First lockdown

For completeness, we have also included figures corresponding to the differences in growth rates of job postings according to their potential for remote work and automation risk (Figures 15-18). These figures reveal much smaller differences, which are not statistically signif-



Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.

Figure 14: Dependent variable: difference in growth of job postings in digital production and the rest–ΔJP^d. First reopening

icant, echoing the findings of our previous exercise.

Overall, this analysis suggests a temporary yet substantial increase in firms' vacancy posting for digital production roles, especially during periods when restrictions were relaxed. However, we find no evidence of any notable changes in firms' posting behavior for jobs associated with technology adoption, such as those allowing for remote work or those at low risk of automation.

4.4 Is Digitalization a Hedge for Low-Wage and Female Workers?

During the pandemic, there has been widespread interest in whether low-wage or female workers were disproportionally affected by the economic downturn induced by restrictions. One example from the literature supporting this view is the study by Chernoff and Warman (2023), which showed that low-wage women are often employed in jobs at the highest risk of automation, a process supposed to have accelerated with the pandemic. Additionally, Alon et al. (2021) observed that, unlike in previous recessions, the employment loss during the pandemic recession was particularly concentrated among women. In our analysis using job posting data, we explore a related but distinct question: Are occupations predominantly occupied by low-wage workers and women less affected when they are engaged in digital production?

In this section, we estimate Equation 1 to analyze job postings categorized as $j \in \{occupation\ group \times characteristic\ of\ occupation\}$. Here *occupation group* corresponds to digital production and non-digital production jobs, while *characteristics of occupation* refers to distinctions between low-wage vs. high-wage, and female-oriented vs. male-oriented. Within both digital and non-digital production groups, we further divide occupations based on wage levels and gender orientation.

For defining these categories within the digital production groups, we use data from the Labour Force Survey (LFS) for 2018 and 2019, Public Use Micro-data File (PUMF). Occupations are classified as low-wage if the proportion of workers in the lowest two quintiles of the hourly wage distribution exceeds the provincial average. Similarly, female-oriented occupations are those with a proportion of female workers above the provincial average. It is worth noting that the LFS-PUMF occupation classification roughly aligns with the 2-digit NOC. For reference, Table 9 in Appendix C lists the two occupations with the highest number of postings in each subgroup.

Table 4: Dependent variable: growth of job postings in digital production and others, by wage level, with respect to 2019–JP^j

	Lockdown				*Reopening*			
	Low-Wage		High-Wage		Low-Wage		High-Wage	
VARIABLES	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.
Lockdown	-3.55	-23.39***	-21.88***	-26.17***				
	(16.904)	(2.386)	(3.469)	(2.681)				
Reopening					18.84	0.97	15.68***	12.80***
					(12.492)	(2.336)	(3.732)	(2.566)
Observations	1,136	1,230	1,230	1,230	1,230	1,230	1,230	1,230
Adjusted R^2	0.22	0.34	0.05	0.20	0.23	0.23	0.03	0.12

Note: 3-week moving average of job postings. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the lockdown weeks in 2019, the growth is with respect to 2018. The group of low-wage-digital-production, has fewer observations due to sparsity.

Table 4 shows the regression results concerning low- and high- wage occupations. Notably, job postings in digital production occupations fall less during lockdowns and increase more during reopenings than other occupations. The differences for low-wage occupations are substantial (20 percentage points during the lockdowns, and 18 during reopenings). However, due to the noise in the data, these differences are not statistically significant (refer to Table 10 in the Appendix for the statistical significance test of the difference).

Results regarding female-oriented and male-oriented occupations are presented in Table 5. The interpretation is more complex: job postings for female-oriented occupations in digital production increased more (38 percentage points) compared to those not in digital production during reopenings, but less during lockdowns. Furthermore, digital production

Table 5: Dependent variable: growth of job postings in digital production and others, by gender presence, with respect to 2019–JP^j

	Lockdown				Reopening			
	Female-Oriented		Male-Oriented		Female-Oriented		Male-Oriented	
VARIABLES	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.
Lockdown	-29.99**	-21.81***	-22.10***	-29.63***				
	(13.758)	(2.619)	(3.549)	(2.542)				
Reopening					45.70***	7.29***	16.72***	10.16***
					(14.422)	(2.415)	(3.985)	(2.561)
Observations	1,208	1,230	1,230	1,230	1,230	1,230	1,230	1,230
Adjusted R^2	0.14	0.47	0.01	0.35	0.15	0.42	-0.00	0.23

Note: 3-week moving average of job postings. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the lockdown weeks in 2019, the growth is with respect to 2018. The group of female-oriented-digital-production, has fewer observations due to sparsity.

occupations that are male-oriented experienced a significantly smaller decline compared to non-digital production occupations.

Overall, this evidence suggests that having a role in digital production offers some (but limited) protection for typically disadvantaged workers (low-wage and female) against the fluctuations during the pandemic's lockdowns and reopenings. Specifically, for female-oriented occupations, this protected effect is observed only during reopening phases.

5 Conclusion

In this paper we use data on Canadian online job postings provided by Indeed. As the data is unstructured and we lack detailed job posting texts, we successfully classify these postings into standard occupations using text analytics, with an acceptable level of accuracy.

Our study makes use of the data to study digitalization trends during the COVID-19 pandemic, a period marked by intense debate over the potential acceleration of technological change. Unlike previous recessions when this has happened, the COVID-19 recession is unique because digital technologies have played a crucial role in maintaining economic activities while adhering to social distancing requirements.

We examine the evolution of job postings related to digitalization throughout the pandemic. By categorizing occupations based on their role in digital production and adoption, including the potential for remote work and automation risk, and by leveraging the variation in COVID-19 policy responses across Canadian provinces over time, our study fails to support the prevalent belief that technological change accelerated during the pandemic.

While we observe a temporary and notable spike in the demand for digital production jobs, particularly during the easing of restrictions, this trend does not appear to be persistent in time. Additionally, our analysis reveals no significant difference in job postings for roles complementary to digital technology, specifically those suitable for remote work and those with a low risk of automation.

When examining specific types of occupations within digital production and others, we find that jobs commonly held by low-wage workers or women show relatively large gains in postings compared to others when they are involved in digital production. This observation leads to the hypothesis that participation in digital production may serve as a protective factor for typically disadvantaged workers.

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Appendix

A Turrell et al. (2022)'s Classification Algorithm

We adapt Turrell et al. (2022)'s algorithm, which classifies British job postings to the U.K. Standard Occupation Classification (UK SOC). They use the job title, description, and sector in job postings from the recruitment website Reed.com. They also build dictionaries using the information published by the Office for National Statistics (ONS), for the four-digit UK SOC job titles and job descriptions. These are the steps involved in the original algorithm:

1. Cleaning the job postings text data using standard techniques.

2. Creating a vector space for the dictionaries using term frequency-inverse document frequency (*tf-idf*). The *tf-idf* matrix includes the number of times a group of up to three (1-3-grams) salient words appears in the text for each occupational code (*tf*), and the inverse of the frequency in which the group of words appears across a set of occupational codes (*idf*).[10]

3. Searching for exact matches between job titles in job postings and the occupations' list.

4. Combining the job posting title, the description, and the sector into one string and expressing this string as a vector in the *tf-idf* matrix.

5. For jobs that were not matched exactly, calculating the cosine similarity between the string obtained in the previous step, and the information in dictionaries, and selecting the five categories in the occupations' list with the highest cosine similarity.

6. If the job posting title is empty, it returns the job posting with the highest cosine similarity. Instead, if there is text in the job posting title, the *fuzzywuzzy* Python package is used to identify the best fuzzy match out of the top five ONS categories, following Levenshtein distance calculations.

Turrell et al. (2022) chose to classify jobs to the three-digit UK SOC. Their algorithm has an accuracy of 76%.

[10] Salient words are those defined as having a useful meaning regarding job vacancies; these are defined in the original algorithm for UK.

B Occupation Groupings

B.1 Digital Production

The NOC categories we classify as related to digital production are listed in Table 6.

Table 6: NOC categories related to digital production

NOC Code	NOC Title
131	Telecommunication carriers managers
213	Computer and information systems managers
1254	Statistical officers and related research support occupations
1422	Data entry clerks
1454	Survey interviewers and statistical clerks
2133	Electrical and electronics engineers
2147	Computer engineers (except software engineers and designers)
2161	Mathematicians, statisticians and actuaries
2171	Information systems analysts and consultants
2172	Database analysts and data administrators
2173	Software engineers and designers
2174	Computer programmers and interactive media developers
2175	Web designers and developers
2241	Electrical and electronics engineering technologists and technicians
2242	Electronic service technicians (household and business equipment)
2281	Computer network technicians
2282	User support technicians
2283	Information systems testing technicians
7202	Contractors and supervisors, electrical trades and telecommunications occupations
7241	Electricians (except industrial and power system)
7242	Industrial electricians
7243	Power system electricians
7244	Electrical power line and cable workers
7245	Telecommunications line and cable workers
7246	Telecommunications installation and repair workers
7247	Cable television service and maintenance technicians
7333	Electrical mechanics
9222	Supervisors, electronics manufacturing
9223	Supervisors, electrical products manufacturing
9523	Electronics assemblers, fabricators, inspectors and testers
9524	Assemblers and inspectors, electrical appliance, apparatus and equipment manufacturing
9525	Assemblers, fabricators and inspectors, industrial electrical motors and transformers

B.2 Work from Home

The classification proposed by Dingel and Neiman (2020) is based on two questionnaires of the O*NET, version 24.2 (February 2020). If the response to any of the questions is *True*, the occupation is coded as one that cannot be done remotely.

Work Context Questionnaire:

- Average respondent says they use e-mail less than once per month.

- Average respondent says they deal with violent people at least once a week.
- Majority of respondents say they work outdoors every day.
- Average respondent says they are exposed to diseases or infection at least once a week.
- Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week.
- Average respondent says they spent majority of time walking or running.
- Average respondent says they spent majority of time wearing common or specialized protective or safety equipment.

Generalized Work Activities Questionnaires

- Performing general physical activities is very important.
- Handling and moving objects is very important.
- Controlling machines and processes—not computers nor vehicles—is very important.
- Operating vehicles, mechanized devices, or equipment is very important.
- Performing for or working directly with the public is very important.
- Repairing and maintaining mechanical equipment is very important.
- Repairing and maintaining electronic equipment is very important.
- Inspecting equipment, structures, or materials is very important.

B.3 Automation Risk

The automation risk classification provided by Chernoff and Warman (2023) is derived from three questionnaires in O*NET, version 24.3 (May 2020): the abilities questionnaire, generalized work activities questionnaire, and work context questionnaire. By adding a set of standardized descriptors ($Standardized\ descriptor = \frac{descriptor - Mean(descriptor)}{Standard\ Deviation(descriptor)}$) they create variables that categorize occupations into routine and non-routine. The following is a list of variables and their corresponding descriptors:

- **Routine Cognitive (RC):** importance of repeating the same tasks; importance of being exact or accurate; (reverse of) structured versus unstructured work.
- **Routine Manual (RM):** pace determined by speed of equipment; controlling machines and processes; spending time making repetitive motions.
- **Non-Routine Analytical (NRA):** analyzing data or information; thinking creatively; interpreting the meaning of information for others.
- **Non-Routine Cognitive (NRC):** establishing and maintaining interpersonal relationships; guiding, directing and motivating subordinates; coaching and developing others.
- **Non-Routine Manual (NRM):** operating vehicles, mechanized devices, or equipment; spending time using hands to handle, control or feel objects, tools or controls; manual dexterity and spatial orientation.

After constructing these five variables, they are combined to create the Routine Task-Intensity (RTI) index for each occupation: $RTI = RC + RM - NRA - NRI - NRM$. The index is then normalized between 0 and 1 using the formula $\frac{RTI-Min(RTI)}{Max(RTI)-Min(RTI)}$. This normalized index is what we ultimately use to categorize occupations. After averaging those with multiple O*NET categories per one NOC category, we classify an occupation as having a high automation risk when the averaged normalized RTI is 0.5 or higher, and as having low automation risk when it is below 0.5.

B.4 Changes in the Work-from-Home Profile of Occupations

As discussed in the text, the classification of occupations used in this paper is static and reflects the characterizations of occupations at the beginning of the pandemic. This is particularly important concerning the potential for working from home. We have observed how numerous occupations have adapted to meet the requirements of social distancing. For instance, many physical instructors have transitioned to online teaching using conferencing applications.

We use Dingel and Neiman (2020)'s definition of work from home. Our analysis focuses on assessing changes in the mean rating of the questions employed by the authors to construct their work-from-home measure. We compare data from the original paper, which used O*NET version 24.2 from February 2020, to the updated version 25.3 from May 2021. This comparison aims to identify shifts in the occupational profiles that may not be adequately captured by our chosen work-from-home measure. Specifically, we consider a rating increase of more than 10% as indicative of increased importance for a particular descriptor within an occupation. Conversely, a decline of more than 10% suggests a decrease in importance.

In general, within the work context, we observe a decrease in importance of dealing with physically aggressive people and exposure to disease or infections. These changes are indicative of an increased inclination toward work-from-home arrangements. Additionally, more occupations now receive higher ratings for tasks such as checking email, outdoor activities, and spending time walking and running.

When it comes to work activities, we have observed that more occupations are receiving increased ratings for tasks such as controlling machines and processes, handling and moving objects, operating vehicles, mechanized devices, or equipment, performing general physical activities, and repairing and maintaining electronic and mechanical equipment.

An example that aligns with our expectations is *Physical education specialists*, for whom both the disease and infection exposure rating, as well as the rating for repairing and maintaining electronic and mechanical equipment, has decreased. This suggests that this occupation has become more amenable to remote work.

C Additional Tables

Table 7: Cross-tabulation between occupation groups related to digital technologies

	Remote Work	*No Remote Work*
Digital Prod.	82%	18%
No Digital Prod.	50%	50%
	No Automatable	*Automatable*
Digital Prod.	64%	36%
No Digital Prod.	49%	51%
	No Automatable	*Automatable*
Remote Work	68%	32%
No Remote Work	31%	69%

Note: Column totals.

Table 8: Test for difference between coefficients within each grouping: digital production, possibility of remote work, and automation risk

Variable	Digital Production		Remote Work		Automation Risk	
	Lockdowns	Reopenings	Lockdowns	Reopenings	Lockdowns	Reopenings
Difference	3.27	7.78*	2.26	0.34	3.44	3.23
	(4.259)	(4.341)	(3.556)	(3.369)	(3.627)	(3.445)

Note: Differences refer to the category related to digital technologies (i.e., digital production, remote work, and low automation risk) compared to the rest.

Table 9: Occupations in digital production groups with predominantly low-wage workers and women

DIGITAL PRODUCTION		NO DIGITAL PRODUCTION	
Low-wage	**High-wage**	**Low-wage**	**High-wage**
Data entry clerks	Information systems analysts and consultants	Other customer and information services representatives	Corporate sales managers
Assemblers and inspectors, electr. appl., apparatus and equip. manuf.	User support technicians	Retail salespersons	Retail and wholesale trade managers
Female-oriented	**Male-oriented**	**Female-oriented**	**Male-oriented**
Computer and information systems managers	Information systems analysts and consultants	Other customer and information services representatives	Corporate sales managers
Statistical officers and related research support occupations	User support technicians	Cooks	Retail and wholesale trade managers

Note: These are the top two occupations in terms of numbers of job postings, by each group.

Table 10: Test for difference between coefficients within each grouping - characteristics: digital production categorized by wage level (high vs. low) and gender prevalence (female-oriented vs. male-oriented)

Variable	Lockdowns		Reopenings		Lockdowns		Reopenings	
	Low-wage	High-wage	Low-wage	High-wage	Female-oriented	Male-oriented	Female-oriented	Male-oriented
Difference	19.84	4.29	17.87	2.88	-8.18	7.53*	38.41***	6.56
	(16.960)	(4.384)	(12.628)	(4.529)	(13.966)	(4.365)	(14.582)	(4.737)

Note: Differences refer to digital production compared to the rest.

D Additional Figures

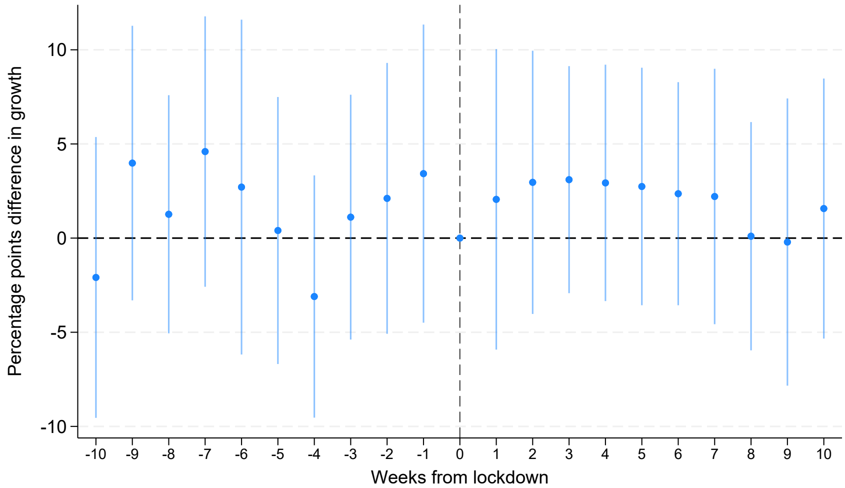

Figure 15: Dependent variable: difference in growth rates, job postings with remote work possibility vs. others–ΔJP^d. First lockdown

Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.

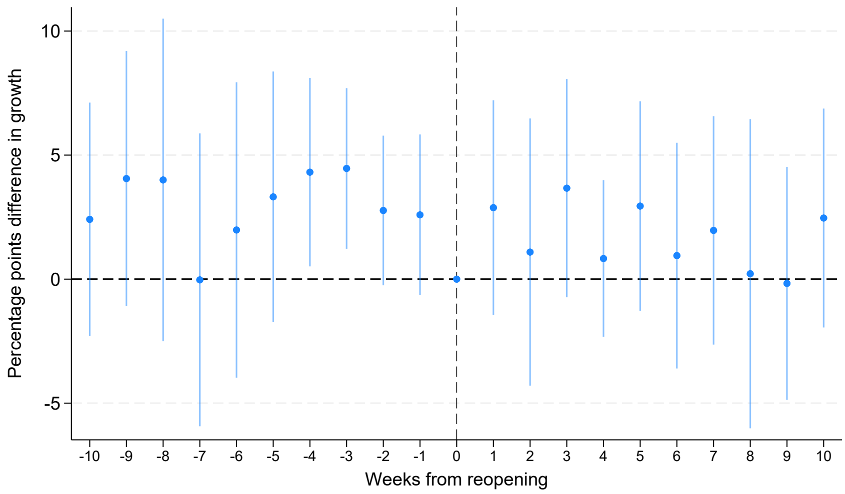

Figure 16: Dependent variable: difference in growth rates, job postings with remote work possibility vs. others–ΔJP^d. First reopening

Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.

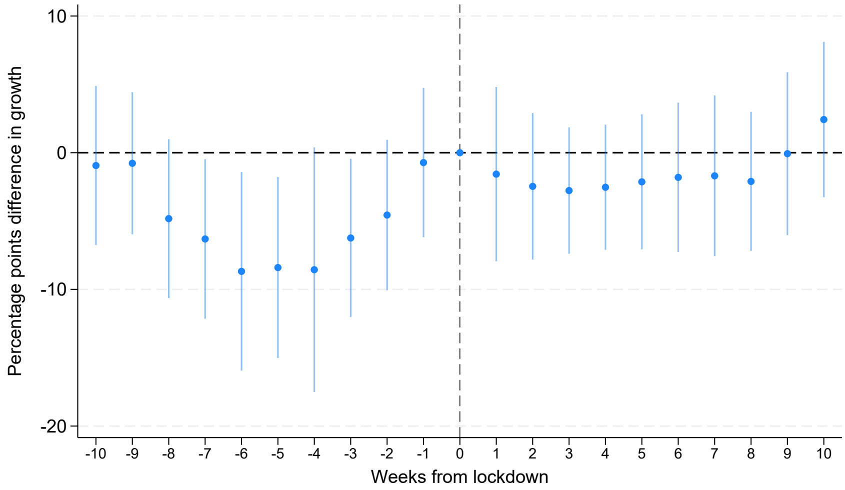

Figure 17: Dependent variable: difference in growth rates: job postings in occupations with low automation risk vs. others–ΔJP^d. First lockdown

Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.

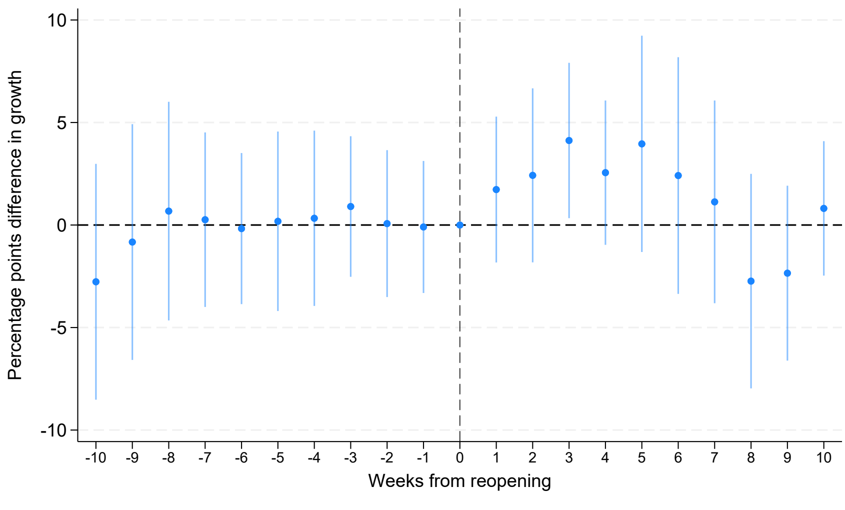

Figure 18: Dependent variable: difference in growth rates: job postings with low automation risk vs. others–ΔJP^d. First reopening

Note: 3-week moving average of job postings. Growth rates with respect to same week in 2019. Robust standard errors.