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What COVID-19 May Leave Behind: Technology-Related Job Postings in Canada

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Abstract

We use data from online job postings listed on a job board to study how the demand for jobs linked to new technologies during the COVID-19 crisis responded to pandemic mitigation policies. We classify job postings into a standard occupation classification, using text analytics, and we group occupations according to their involvement in the production and use of digital technologies. We leverage the variation in the stringency of containment policies over time and across provinces. We find that when policies become more stringent, job postings in occupations that are related to digital infrastructure that allow for remote work fare relatively better than postings in more traditional occupations. Job postings for positions in occupations with low risk of automation recover faster during reopenings than postings for more traditional occupations. Occupations typically populated by disadvantaged groups (e.g., women and low-wage workers) post relatively few job postings if they are not linked to new technologies. We also find that cities with scarce pre-pandemic job postings related to digital technologies post fewer job ads overall when policies become more stringent.

Topics: Coronavirus disease (COVID-19), Econometric and statistical methods, Labour markets
JEL codes: J23, J24, O14

1 Introduction

Previous research documents that technological change accelerates during recessions (see, e.g., Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). The opportunity cost of resource reallocation decreases in downturns and firms let go—or decrease their recruiting of—employees with low complementarity to new technologies. These costs increase during recoveries, reducing the speed of reallocation and favoring investment in physical capital. This feature is among the main suspects behind the jobless recoveries that took place during the most recent recessions in the US.

The COVID-19 pandemic and the mitigating policies in response to it present a unique opportunity to understand how firms adjust to an extreme shock via technological change. First, the magnitude of the economic shock induced by the pandemic is the largest since the Second World War. Second, the massive job losses during the lockdowns, followed by the huge job gains in the reopenings may imply a substantial labor reallocation (see, e.g., Barrero et al., 2020). Third, the role of digital technologies during the pandemic is rather special. Digital technologies have been instrumental to the continuity of economic activity during the pandemic while also respecting the epidemiological requirement of physical distancing. These observations call for a deeper understanding of the long-term effects of the pandemic regarding technology adoption. As a starting point, this paper documents how firms' recruitment needs that are linked to the *production and use of digital technologies* evolved compared to traditional occupations. We examine the evolution of job postings vis-à-vis changes in the pace of the pandemic and in the containment measures.

We use high-frequency data on new online job postings in Canada provided by Indeed.[1] We first classify job postings according to a standard occupation classification, the Canadian National Occupation Classification (NOC), using text analytics. Our classifications are based on the algorithm developed by Turrell et al. (2019) and feature an acceptable level of accuracy at the 4-digit level. Then we group job titles according to their role in the production of digital technologies (i.e., software development, hardware production, information technology support) and the use of technology (i.e., occupations with possibilities for remote work or

[1]High-frequency job posting data have been extensively used to analyze the impacts of the COVID-19 crisis on the labor market. For example, Hensvik et al. (2021); Marinescu et al. (2020); Bernstein et al. (2020) use several job boards to analyze the evolution of job vacancies and search behavior and the resulting labor market tightness at different stages of the pandemic. Forsythe et al. (2020) document a large drop in job postings in the US at the onset of the pandemic, using data from Burning Glass Technologies. Jones et al. (2021) use these 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. We contribute by focusing on technology-related job postings.

with high risk of automation). To do this, we use several classifications that were developed in the literature on the measurement of the digital economy (see, e.g., STATCAN, 2019) and on occupational risks due to COVID-19 (Chernoff and Warman, 2020; Baylis et al., 2020; Dingel and Neiman, 2020). Most of these classifications require matching occupations to their descriptors in the O*NET database, for which we employ a crosswalk between the Standard Occupation Classification (SOC) on O*NET and the NOC developed by the Brookfield Institute (Vu, 2019).

We leverage the variation in the disease spread and the containment measures across provinces and cities in Canada to estimate the effects of COVID-19 on technology-related previously defined categories of occupations. We exclude jobs in the health care sector due to their special evolution linked to the pandemic. Since the spread of COVID-19 across the country is potentially related to other local shocks, we use an event-study approach in which we exploit the differences in the timing of the lockdowns and the reopenings across provinces.

We find that tighter containment measures result in stronger declines in openings for jobs that cannot be done remotely and do not produce digital technologies, compared to the remaining types of jobs. The gap is more pronounced and persistent during periods of lockdown. In terms of changes in policy stringency, no differences are observed across jobs with different risks of automation. However, vacancies for non-automatable jobs pick up strongly during recoveries.

Using information about occupations and their demographic compositions, pre-pandemic, from the LFS, we observe that more stringent policies particularly affect vacancies in occupations with a high prevalence of women and at high risk of automation. On the contrary, there does not seem to be less demand for jobs in female-oriented occupations that are at low risk of automation. Also, vacancies for low-wage occupations fall more with increased stringency when they are not linked to the production of digital technologies or they cannot be done from home. Otherwise, they do relatively well in terms of job postings as stringency increases. We interpret this as a *digital advantage for typically disadvantaged groups.*

We also use a subset of cities for which we have consistent information on job postings and COVID-19 cases. We find that the reductions in new job postings that accompany periods of high stringency in containment policies are larger in cities that had a high proportion of non-digital vacancies prior to the pandemic. We read this as a sign of *city-level inertia.*

Our main contribution lies in the literature on the acceleration of technological change during recessions. Hershbein and Kahn (2018) show that firms persistently increased both their skill requirements and capital investments in areas that were hit hard by the 2008 crisis.[2] In line with these results, Jaimovich and Siu (2020) show that employment losses in routine occupations are concentrated during recessions, whereas there are no employment gains in those occupations during recoveries. Foote and Ryan (2014) further note that middle skill workers, mainly those holding routine occupations, are concentrated in industries with strong cyclicality (e.g., manufacturing and construction) and that this yields cyclical fluctuations in the employment of such workers. The COVID-19 crisis did not only imply a reduction in the opportunity costs for technological change typically associated with economic crises but disease-control measures have also favored the use of digital technologies. Our paper focuses on job postings that are broadly linked to digital technologies, going beyond the concept of automation-enabling technologies.

Despite a prolific literature on the effects of COVID-19 on the labor market, only a few papers have addressed jobs related to digital technologies and technological change. To date, most studies have calculated the potential effects of the crisis on automation and other ways of adopting new technologies. For instance, some papers identify which occupations have the most risk, given the trends in automation and the risk of viral transmission; for example Chernoff and Warman (2020) for the US and 25 other countries and Baylis et al. (2020) for Canada. They find that women and low-educated workers have a higher risk of job destruction as they are more prevalent in occupations with the highest automation and highest risk of viral transmission. In addition, Baylis et al. (2020) show that, given their lower chances for remote work, low-educated workers have a higher likelihood of job loss than high-educated ones, despite having similar virus transmission risk. Dingel and Neiman (2020) classify occupations according to the feasibility of working from home. The possibility of using new technologies and working remotely has been of recurrent interest throughout the pandemic. We draw on all of these papers and others to produce classifications of technology-related occupations. Unlike these papers, we examine the evolution of job postings. To the best of our knowledge, very few papers have empirically examined technology-related jobs, mainly due to the lack of timely data. Ding and Saenz Molina (2020) is an exception. Using the Current Population Survey for the US, they show a disproportionate displacement of workers in occupations at high risk of automation at the beginning of the pandemic. For Canada, Gallacher and Hossain (2020) find a similar result for occupations with a low

[2] Reassuringly, Yagan (2019) shows a persistent employment loss in hard-hit areas resulting from workers dropping out of the labor force—the so-called hysteresis.

potential for remote work.[3]

Although much has been said about the acceleration of technology adoption during the pandemic, the evidence remains scarce and mixed. Alexopoulos and Lyons (2021) analyze a variety of unstructured data to assess the pre- and post-pandemic trends in the adoption of digital technologies in Canada, defined as AI, data science and robotics. Some indicators suggest that technological sectors have been outpacing other sectors during the pandemic and others imply a slowdown in technology adoption, especially at the onset of the pandemic. Bloom et al. (2021) document a strong increase in new patent applications in the US related to technologies that have been supporting remote work since the beginning of the pandemic. We complement these studies by showing that occupations that use and produce digital technologies have had more job postings than more traditional occupations during the pandemic.

Finally, our paper contributes to a growing body of literature that uses online job postings data to analyze labor market outcomes. Turrell et al. (2019) used online vacancies from the job site Reed to study the labor mismatch related to the productivity puzzle in the UK. They find that the regional rather than the occupational mismatch play a bigger role in explaining the productivity statistics. Using data from CareerBuilder.com, Marinescu and Wolthoff (2020) find that job titles explain over 90% of the wage variance. The Indeed data, featured in our paper, have been used in labor market research. Some examples include Gimbel and Sinclair (2020), which studies the mismatch between job seekers and employers in the US, and Adrjan and Lydon (2019), which shows that the tightness in the labor market, as measured by the number of job postings and clicks on these postings, is related to the posted wages. Our paper leverages a mixture of text analytics and occupation descriptors to analyze the evolution of job postings in technology-related occupations.[4]

Overall, our findings suggest that the firms' demand since the onset of the pandemic has gravitated toward technology-related jobs more so than in normal times. We interpret this as an indication of the acceleration of technology adoption, which may affect present or future productivity.

[3]The literature on the economic impacts of COVID-19 has been prolific and includes a variety of topics, such as employment changes due to business dynamics (Kurmann et al., 2021; Crane et al., 2020), entrepreneurship (Haltiwanger, 2021), economic activity (Bartik et al., 2021; Diebold, 2020), the turnover of workers (Brochu et al., 2020; Jones et al., 2021) and inequality (Adams-Prassi et al., 2020; Cortes and Forsythe, 2020; Lemieux et al., 2020), among others. Similar to this work, many of these papers use non-traditional data and emphasize the need for high-frequency data for analyzing the turbulent pandemic times.

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

The reminder of the paper is organized as follows. Section 2 describes Canadian policies during the pandemic, Section 3 presents the data on job postings and Section 4 examines the classifications we use. In Section 5, we show the correlations between the growth in the number of job postings and the containment policies by category. In Section 6, we present the event study that leverages province-level variation in lockdowns and reopenings and, in Section 7, we discuss whether trends in the digitalization of vacancies might affect our results. Section 8 concludes.

2 Background: The COVID-19 Pandemic in Canada

The first COVID-19 case in Canada was confirmed on January 27, 2020. On January 30, the World Health Organization (WHO) declared a "public health emergency of international concern." Several countries immediately reacted with travel bans to China, where the virus appeared to have originated, but this did not prevent its fast international spread.

Although the first Canadian cases were linked to travel from the affected regions of China, less than two months later, community spread was underway. On March 11, 2020, the WHO declared COVID-19 a pandemic. By the third week of March, most provinces in Canada had declared a state of emergency and foreign nationals were not permitted to enter the country. Since then, several rounds of lockdowns followed by gradual reopenings have taken place. The provincial governments are in charge of determining the timing of their restrictions, which they gauge according to the evolution of the number of cases, hospitalizations, deaths and rates of vaccination.

The Government of Canada has responded with generous stimulus packages and economic support policies since the very beginning of the pandemic. These have been rather effective in mitigating pandemic-induced increases in income inequality.

There have been five waves of case-count increases, and the mortality rate due to the disease has dropped from wave to wave, partly due to the record release and roll-out of vaccinations during 2021. After Pfizer/BioNTec received the first emergency approval by the WHO and Health Canada, in December 2020, approvals for many other vaccine producers followed. Canada's massive vaccination campaign began on December 14, 2020. Despite temporary supply disruptions, more than 75% of the population had received two or more doses by the end of 2021.

The economic impacts of COVID-19 have been massive. The largest annual GDP drop corresponds to April 2020; by the end of 2021, GDP had not yet recovered to pre-pandemic levels. Employment, unemployment and hours worked had returned to pre-pandemic levels by November 2021. However, these aggregate numbers mask large sector-wise disparities in employment. Unevenness has changed along the duration of the pandemic, with certain sectors and demographic groups being hard hit at different times.

3 Data

Our main data source is Indeed, the world's largest job site,from which we obtain our job postings data.This site has approximately 250 million unique visitors each month.[5] This company was established in Canada, in 2015, and by 2017 it was considered the top source for job hires in the country.[6] The job postings data they collect comprise advertisements either posted by employers directly on the Indeed website or collected by Indeed from separate websites and treated to avoid duplication. They are recorded on the date they were first visible.

The data have been available since 2018 on a daily frequency and are updated weekly with one-week lags. We use the data up to October 31, 2021. Across all the analysis, we use the data on the Canadian provinces and exclude the territories, given the sparsity of information on these regions.

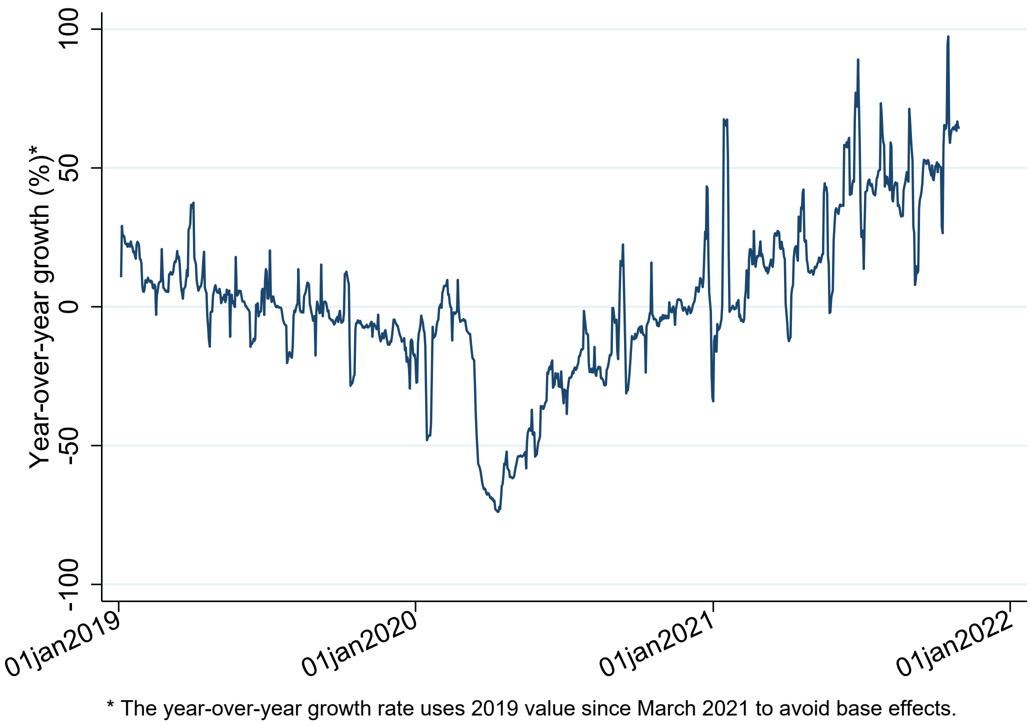
Figure 1 shows the annual growth rate of the smoothed counts (seven-day moving averages) of the new job postings published each day in Canada. The growth rates since March 2021 refer to 2019 to avoid the base-year effects caused by large drops at the beginning of the pandemic. Not surprisingly, the year-over-year growth in job postings hit a trough in April 2020, during the first wave of the COVID-19 pandemic. Setbacks during further waves and consequent lockdowns were small compared to the initial drop. By the end of 2021, annual growth rates of new job postings were considerably above pre-pandemic levels.

Online job postings collected by Indeed co-move with online job board vacancies as reported by the Job Vacancy and Wage Survey (Figure 2) and with figures for total employment according to the Labour Force Survey (LFS) (Figure 3). These data are collected by Statistics Canada, the country's official statistics office. Reassuringly, the data on job postings follow a similar distribution, across provinces, to the employment data in the LFS in Canada

[5]This is according to Comscore Total Visits (March 2020) and Google Analytics, Unique Visitors (February 2020).

[6]See the articles "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: Indeed job postings, year-over-year changes of the seven-day moving averages



(Figure 4).[7]

Overall, the data on online job postings provided by Indeed appear representative and hence useful for labor market research on online vacancies. The data are unstructured, containing over two million unique job titles (see a word cloud of the text in the job postings since March 2020 in Figure 5). Classification is explained in the next section.

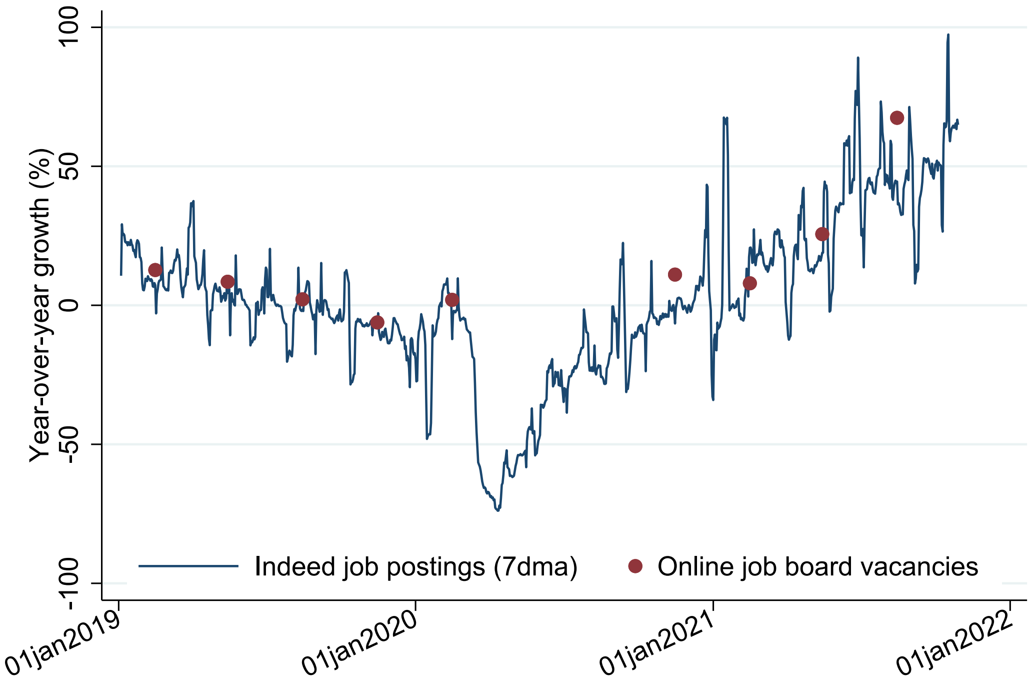
We also use data on daily new COVID-19 deaths per province, obtained from the John Hopkins University database. For our city-level analysis, we leverage data published by various municipalities regarding new COVID-19 cases. We use the Public Use Micro-Data File of the LFS to characterize occupations according to their pre-pandemic gender, education and wage-level compositions.

4 Classifications

In this section, we explain how we classify the unique job titles in the job posting data into standard occupation classifications, using text analytics. Then we describe how we group occupations into categories in relation to firms' use and production of technology.

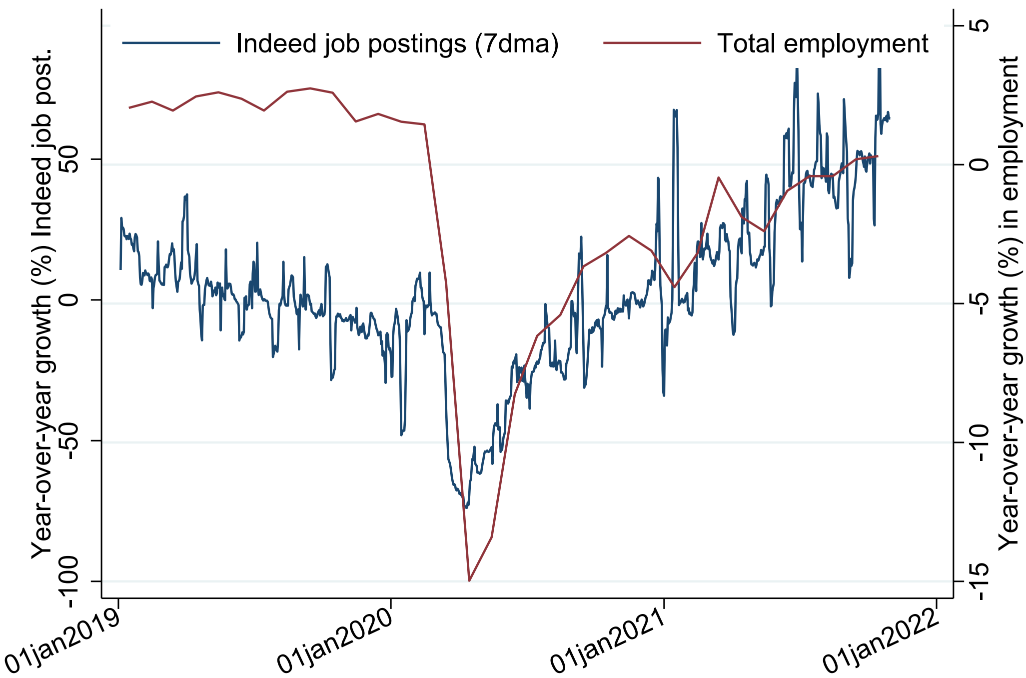
[7]We do not have information on salaries, but Adrjan and Lydon (2019) show that Indeed job postings follow a similar distribution for salaries as do the conventional data in Ireland.

Figure 2: Indeed job postings (seven-day moving averages) versus online job board vacancies, year-over-year change



The year-over-year growth rate uses 2019 value since March 2021 to avoid base effects.

Figure 3: Indeed job postings (seven-day moving averages) versus total employment, year-over-year change



The year-over-year growth rate uses 2019 value since March 2021 to avoid base effects.

Figure 4: Percentage of job postings and employment across Canadian provinces, 2019

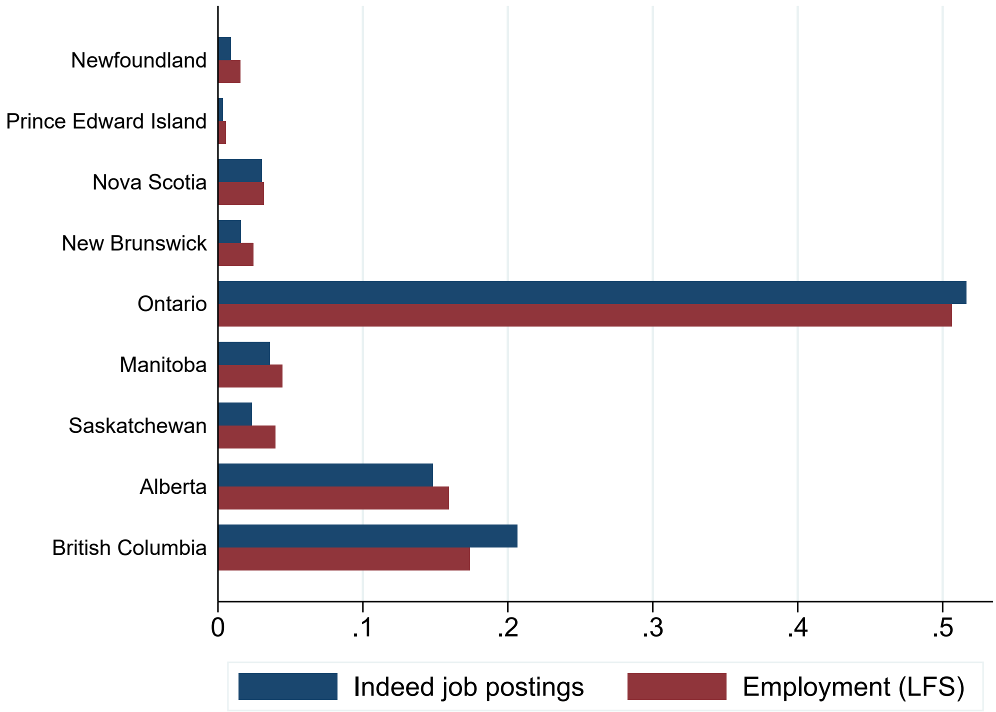


Figure 5: Word cloud of Indeed job postings since March 2020

4.1 Canadian National Occupation Classification

We construct a text analytics algorithm to classify job titles into relevant occupation classifications. The Indeed data do not have any occupational variables that can be directly mapped into standard occupation categories. Instead, we use the text in the job postings to classify occupations into Canada's four-digit National Occupation Classification (NOC), version 2016.3, which provided the most recent and highest disaggregation of the NOCs at the time of our analysis.

We build on an algorithm developed by Turrell et al. (2019), about which we include further details in Appendix A. Unlike these authors, our job ads data include information only on job titles and we do not have job descriptions. However, our algorithm performs adequately, as our accuracy is at the high end of comparable classifications. Our main adaptations to the algorithm of Turrell et al. (2019) is that we (i) map jobs to the Canadian NOC, for which we create dictionaries; (ii) we expand the list of abbreviations; and (iii) we use company names on top of job titles to perform each match.

In our algorithm, we clean the text on job postings, following standard techniques in the text analytics literature.[8] Abbreviations in the job postings are expanded using an adaptation that adds abbreviations from human resources websites to the dictionary developed by Turrell et al. (2019). To perform the matches, we compile two types of dictionaries by scraping text data from the Government of Canada website[9], where we find 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 the descriptions and main tasks for each job title.

The dictionaries are constructed in English, French, and there is a bilingual one (by appending the previous two). Job postings in English are classified using the English-only dictionary. Job postings that either belong to Quebec (Canada's main francophone province) or include francophone special characters, such as accents or cedillas, are classified using the bilingual dictionary. This is because some job postings in Quebec are in English.

Our algorithm creates a term frequency-inverse document frequency (*tf-idf*) matrix, based on the broader text dictionary. This matrix consists of scores that allocate the rele-

[8] Trailing whitespaces are deleted, numbers and punctuation signs are removed, and words are lowercased. All plural words become singular, using the lemmatiser from Python's Natural Language Toolkit (NTLK). We also drop job postings with empty job titles, as the job title is the primary data used for our classification.

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

vance of the words used for the matching of the Indeed job titles to the NOC categories.[10]

The algorithm has two ways of mapping the job postings to the NOC codes. It first searches to see whether there is an exact match between the title in the job posting and an NOC title. If found, the relevant four-digit NOC is returned. If no exact match is found, then the algorithm proceeds to a second match, which is referred to as a fuzzy match. The fuzzy match uses job posting text data beyond the job titles (including the company name, which may include words related to the sector) and NOC data beyond the title. The algorithm then calculates the cosine similarity between the job-posting texts and the NOC categories, keeps the five with the highest similarities, and returns the job postings with the lowest distance.[11] No job postings remain unmatched.

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. This procedure informs that the algorithm achieves 70% accuracy for job postings in English. We verify a three-percentage-point gain in accuracy by adding the company name to the algorithm. For our French sample using the bilingual dictionary, we obtain a 66% accuracy rate. This is below the accuracy we obtain when manually deleting the English job postings from our French sample and using only the French dictionary (74.5%).

The accuracy values we obtain are acceptable for a 4-digit automatic classification according to Turrell et al. (2019), particularly when the job ad text is missing, as in our case.[12] Also, using the NOC for classifying job postings in Canada seems to be a good choice. In a classification exercise where we used the algorithm of Turrell et al. (2019) to classify our job postings according to the 3-digit UK Standard Occupation Classification, as they do in their paper, we achieved a decreased accuracy rate of 64% in our English sample.

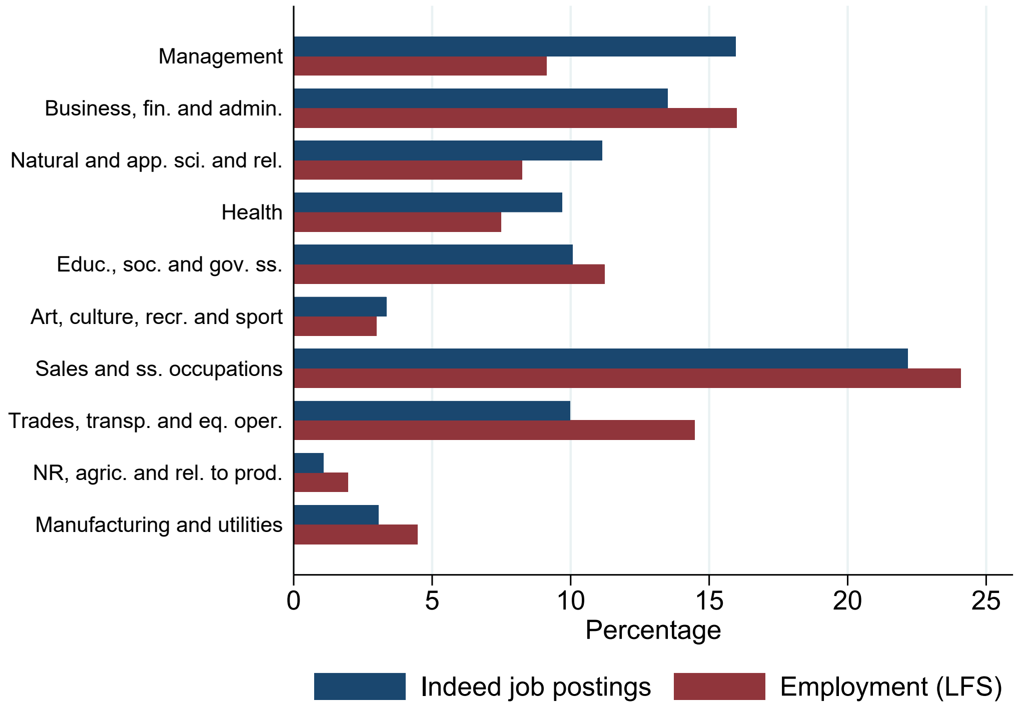
Reassuringly, Figure 6 shows the distribution of the Indeed job postings for broad occupational groups (NOC 1 digit) compared to the employment levels for these groups, according to the LFS. The distributions look fairly similar. Some groups, such as managers, are overrepresented in the Indeed job postings. Some other groups, such as operators, are underrepresented. This seems in line with the high-skill bias typical of online job postings.

[10] A *tf-idf* matrix includes the number of times a word appears (*tf*) and the inverse of the frequency at which a word appears across a set of documents (*idf*). The *idf* weighs down the *tf* when a word appears across many different documents. Each NOC category can be represented as a vector of the *tf-idf* scores, normalized using the Euclidean norm.

[11] This step uses the *fuzzywuzzy* Python package, following Levenshtein distance calculations.

[12] Turrell et al. (2019) obtained a 76% accuracy rate using the job description and sector, information we do not have. Algorithms that use job titles tend to have much lower accuracy rates (see, e.g., Belloni et al., 2014).

Figure 6: Percentage of job postings and employment by occupation groups in Canada, 2019



4.2 Technology-related Occupations

We classify occupations according to their role in the production and use of digital technologies. The production side is comprised of occupations involved in the development of digital infrastructure. Regarding the use of digital technologies, we characterize occupations according to their possibility for remote work and their automation risk. Jobs that allow people to work from home and that are at low risk of automation are complementary to technology. In all these classifications, we exclude jobs related to health care—group 3 in the NOC and some other titles (managers in health care, and health information management occupations). The reason is that these jobs might have acted very differently in responding to specific demands of the pandemic.

Production of Digital Infrastructure

We use the STATCAN (2019) working definitions for estimating the digital economy, which is in line with the international standards used by the OECD countries. Statistics Canada classifies products on its Canadian Supply and Use Tables (SUTs) within the national accounts in order to obtain measures of the output and the jobs associated with these activities.

We adapt Statistics Canada's definitions to single out occupations related to the digital infrastructure; i.e., the production of hardware, software and supporting services. A detailed list of the NOC codes we included in this category are provided in Appendix B. All of the remaining sectors are included in the so-called non-digital category.

Use of Digital Technologies

We use the definitions of the categories that are related to the feasibility of working from home (Dingel and Neiman, 2020) and the automation risk (Chernoff and Warman, 2020). These definitions are based on O*NET descriptor data. Developed under the sponsorship of the US Department of Labor, O*NET is a database of attributes and characteristics of occupations, the so-called *descriptors*.

We mapped the 4-digit NOC categories to the O*NET categories—based on the US Standard Occupation Classification—using a crosswalk designed by the Brookfield Institute (Vu, 2019).[13] 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 the feasibility of working from home and of the automation risk across O*NET categories.

Measuring the possibility of an occupation accommodating working from home, according to Dingel and Neiman (2020), requires using 17 questions from the O*NET, version 24.2's questionnaires on the work context and the generalized work activities. 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 to one NOC category. Occupations are considered feasible in terms of working from home if the average is 0.5 or above, and if the average is below 0.5, then these jobs cannot be performed from home.

To determine the automation risk based on Chernoff and Warman (2020), we standardize 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 the NOC categories with the associated multiple O*NET categories, we consider that occupations are at low automation risk if the index is below 0.5 and at high risk when it is 0.5 or more.

Further details about the construction of the measure of the possibility of working from home and the automation risk are found in Appendix B. It is worth mentioning that the occupation classifications, particularly those related to the ability of working from home,

[13] 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, manually adjusting the matching such that there are no unmatched NOC codes.

correspond to the time during which the O*NET survey was completed. However, many occupations changed and transformed in response to the pandemic. We discuss this matter in Appendix B. We highlight some changes between the O*NET version 24.2 used in Dingel and Neiman (2020), which corresponds to February 2020, and version 25.2, which corresponds to May 2021. We observe changes in the descriptors of many occupations that confirm shifts favoring working 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 on this front.

4.3 Trends in Technology-related Job Postings

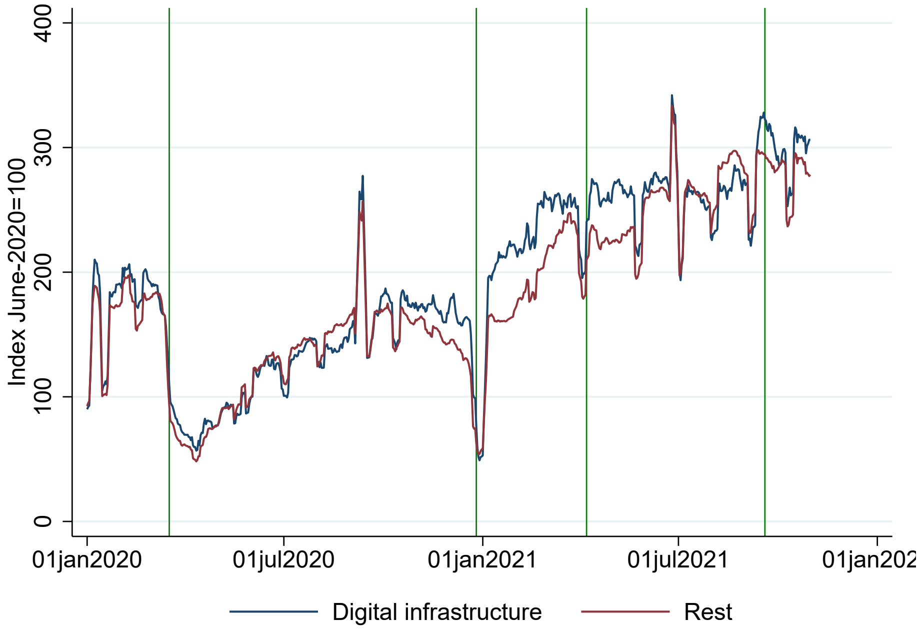
In this section, we observe the evolution of new job postings for occupations related to technology, as described in the previous section. All figures show the seven-day moving averages of these job postings, indexed to June 1, 2020, after the first big drop at the beginning of the pandemic. The vertical lines indicate the lockdowns based on the dates they were implemented in Ontario.

Figure 7 compares the new job postings in digital infrastructure and the rest of the postings. The job postings in digital infrastructure represent 8.4% of the total job postings in our data. Since the first wave and its corresponding lockdown, new job postings for employment in digital infrastructure seem to have outpaced job postings in the remaining sectors. By the end of October 2021, they had grown by almost 30 percentage points more than the rest of the postings, compared to June 2020.

Figure 8 shows the evolution of job postings in occupations that can be done from home and the rest of the job postings. The job postings with the possibility of working from home represent 53% of the total job postings. For Canada, researchers at Statistics Canada calculated that 38.9% of these jobs could be performed from home, using the same methodology we use here and employment data for 2019 (Deng et al., 2020). These numbers compare nicely to the 37% of teleworkable jobs documented by Dingel and Neiman (2020) for the US. The disproportionate growth in job postings that allow people to work from home is also apparent, having grown 50 percentage points more than the rest of the job postings, from June 2020 to October 2021.

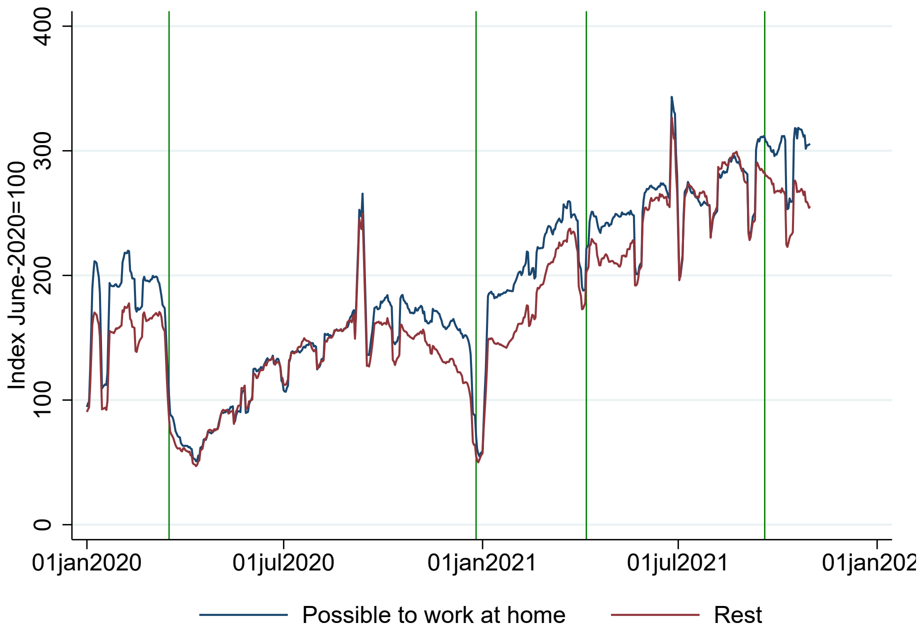
Figure 9 compares job postings in occupations at low risk of automation to the rest of the job postings. Those in occupations at low automation risk represent half of all job postings. This compares to the 39.7% of workers who are subject to high and moderate risk of automation-related transformation (probability of 50% or more) in 2016, according

Figure 7: Job postings related to digital infrastructure versus the rest of jobs



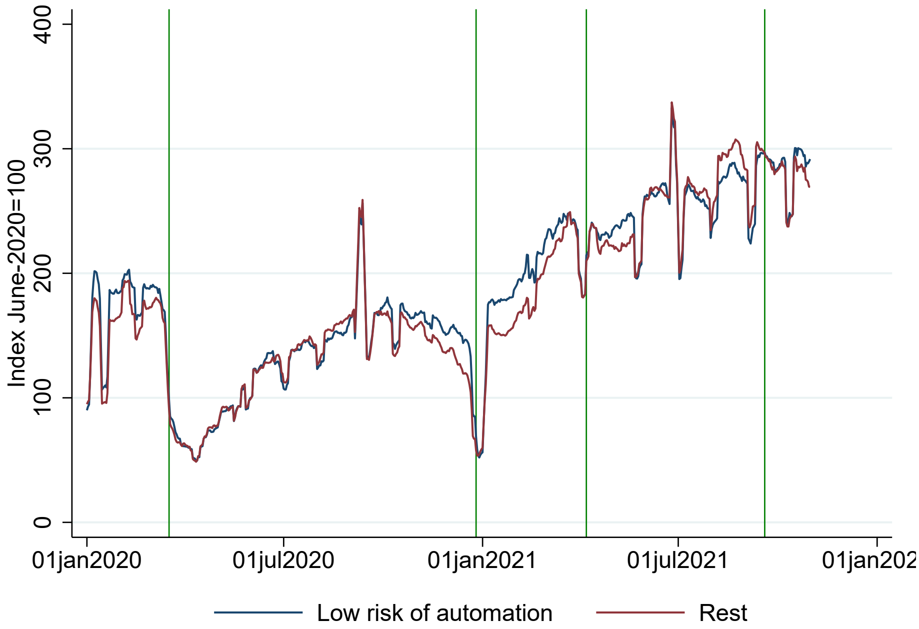
Note: Job postings in health-related occupations are excluded. Seven-day moving averages of job postings, indexed to June 1, 2020=100. The green vertical lines correspond to the beginning of the lockdowns between the first and fourth waves, using Ontario as a reference.

Figure 8: Job postings in occupations that can be performed from home versus the rest of jobs



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

Figure 9: Job postings in occupations with low risk of automation versus the rest of jobs



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

to Statistics Canada, using a similar methodology (Frenette and Frank, 2020). Since June 2020, new job postings in occupations at low automation risk have outpaced those at high risk by 22 percentage points to the end of October 2021.

5 Correlations between Job Postings and Containment Policies

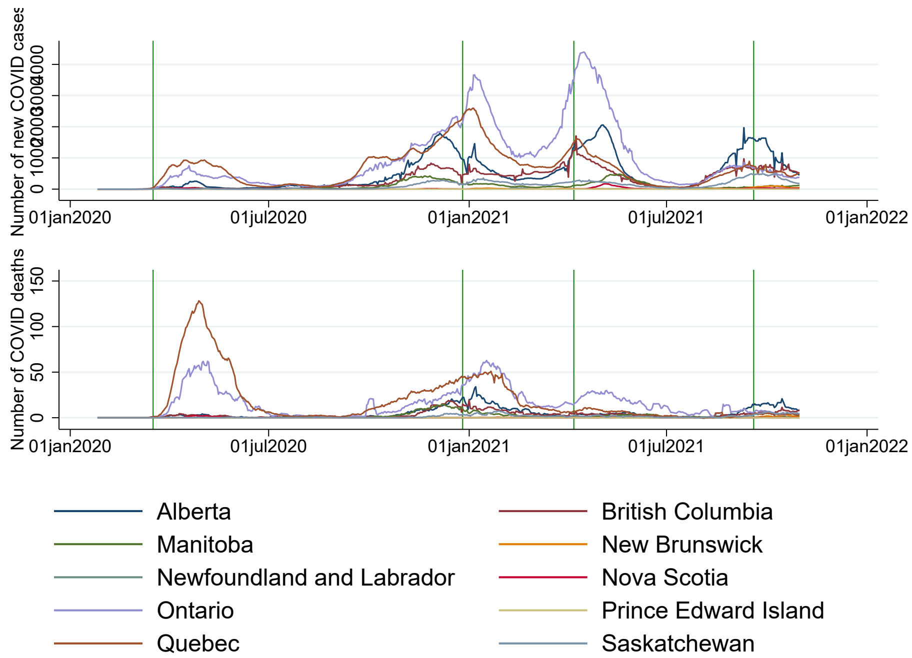
We leverage the variation in the spread of COVID-19 and the containment policies across different provinces over time (see, e.g., Correia et al., 2020) and we study how they correlate to technology-related occupations. We use weekly data to reduce the noise.

The spread of COVID-19 across Canadian provinces and the policies implemented in response varied across provinces and over time. Figure 10 shows the evolution of new confirmed cases and deaths related to COVID-19 by province.

We estimate the following model:

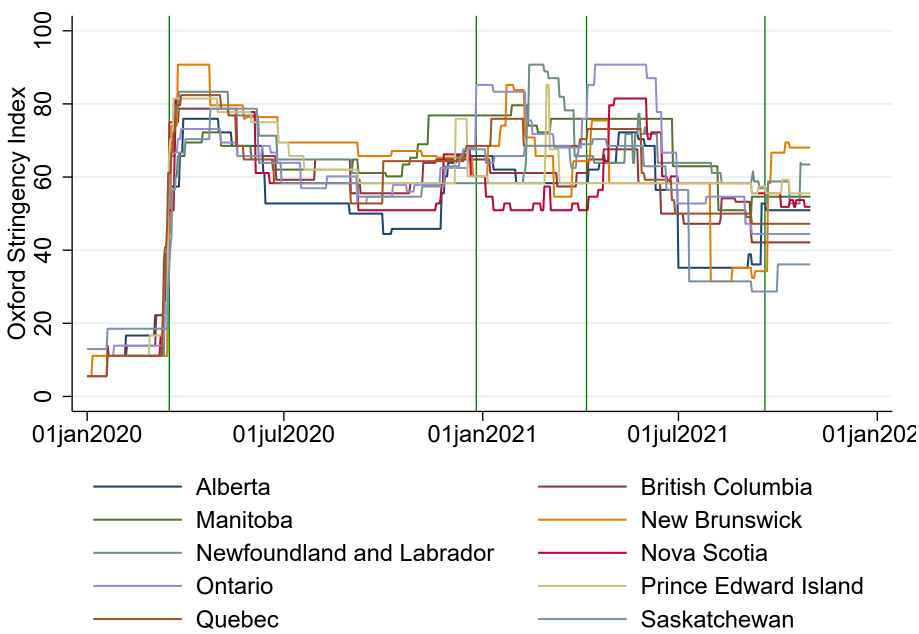
$$JP^{j}_{pt} = \delta L.log(Pol)_{pt} + \gamma L.log(Deaths)_{pt} + \lambda_{pm} + \epsilon_{pt}, \tag{1}$$

Figure 10: Evolution of new COVID-19 cases and deaths by province



Note: Seven-day moving averages of new COVID-19 cases and deaths. The green vertical lines correspond to the beginning of the lockdowns between the first and fourth waves, using Ontario as a reference.

Figure 11: Evolution of stringency as measured by Oxford University



Note: Oxford University Stringency Index. The green vertical lines correspond to the beginning of the lockdowns between the first and fourth waves, using Ontario as a reference.

where p is the province, t is the week, m is the month; JP^j is the year-over-year growth in job postings in occupation group j (i.e., the digital infrastructure, possibility of working from home, low automation risk, etc.), $log(Pol)$ is the logarithm of the Stringency Index as measured by Oxford University, $log(Deaths)$ is the logarithm of the number of deaths due to COVID-19, λ_{pm} represents the province-by-month fixed effects that absorb province-specific seasonal trends. All levels are smoothed with a three-week moving average. We use deaths instead of cases to ignore changes in testing capacity over time and across provinces. Deaths and stringency are included with a one-week lag to account for delayed adjustments in the labor market. The natural logarithm eases the interpretation of the coefficients in terms of growth rates. We show that these correlations are robust to changes in the specifications. Standard errors are bootstrapped at the province level.

Table 1 shows the estimation of Equation 1 for job postings in occupations for different groups. The changes in the stringency measures correlate significantly with the growth rate of the job postings. The changes in the number of deaths affect the growth in job postings for certain groups, after accounting for the changes in the stringency measures.

The first panel shows the results for the job postings related to the production of digital infrastructure and for the rest of the job postings. When the stringency measures double (increase by 100%), the number of job postings for positions in the production of digital infrastructure decrease by 25 percentage points. This compares to a 30 percentage point decline in the number of job postings for the rest of the categories. Also, when the number of deaths doubles, the job postings that are not related to digital infrastructure drop by 0.6 percentage points; however, the coefficient is not statistically significant for these job postings.

Similarly, the second panel indicates that doubling the stringency measures around COVID-19 is accompanied by a 29-percentage-point decline in the number of job postings that offer the possibility of working from home and a 31-percentage-point decline for the rest of the jobs. The deaths are related to a drop only in the job postings that do not allow people to work from home.

Finally, the last panel suggests there is a much smaller difference in the decline in the number of job postings for occupations with low and high automation risk. When the stringency measures double, the job postings in occupations with both low and high automation risk fall by 30 percentage points. The postings for jobs at low automation risk also seem to fall when the number of deaths increases.

Table 1: Dependent variable: year-over-year growth in job postings by group–JP^j

VARIABLES	Digital Infrastr.	No Digital Infrastr.	Work from Home	No Work from Home	Low Autom. Risk	High Autom. Risk
Stringency Ox (log), L1	-25.46***	-29.99***	-28.96***	-30.73***	-29.77***	-29.74***
	(7.269)	(1.424)	(1.911)	(1.724)	(2.559)	(1.024)
COVID-19 Deaths (log), L1	-0.64	-0.64*	-0.49	-0.78**	-0.61**	-0.64
	(1.050)	(0.306)	(0.311)	(0.309)	(0.270)	(0.348)
Observations	870	870	870	870	870	870
Number of Provinces	10	10	10	10	10	10
Adjusted R^2	0.75	0.93	0.93	0.91	0.91	0.93

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Overall, the results of this correlation analysis suggest that whenever policies become more stringent in response to changes in the spread of the disease, some job postings related to technology (i.e., in digital infrastructure and those that allow people to work from home) fare slightly better than the rest of the jobs. Further increases in deaths not related to policies also relatively favor job postings in these categories. There are no differences in the response to stringency measures in terms of job postings for positions with different automation risks.

Robustness Checks: Tables 8-11 in Appendix C show the results of estimating modified versions of Equation 1. Considering different delays in the responses of job postings to the stringency policies and the disease spread does not change the conclusions, as our regressions without lags and with a two-week lags suggest. These results are also maintained for a different normalization of job postings (a logarithm instead of year-over-year growth) or for the independent variables (levels instead of logarithms). Overall, the correlations do not seem to be affected by the particular specification we use to compute them.

5.1 Correlations by Demographic Compositions of Occupations

In this section, we estimate Equation 1, splitting the groups of job postings such that $j \in \{occupation\ group \times characteristic\}$. This means that the job postings are grouped according to their relation to technology and by their demographic composition. The characteristics we consider for these splits are the proportions of women and low-educated (up to high school) and low-wage workers (in the first two quintiles of the hourly wage distribution).

To characterize occupations according to the demographics, we compute the average proportion of each group (i.e., female, low-educated and low-wage workers) by occupations in the LFS, using the Public Use Micro-data File for 2018 and 2019. To account for the differences among the regional economies, the averages are provided at the province level. The occupation data in the LFS are coarser than our classifications using the Indeed data—there are 40 categories in the LFS that roughly correspond to the 2-digit NOC. Each occupation is considered to be highly populated by one group if the group size is above the average proportion. This categorization is then attached to the detailed occupations found in the job posting data. Table 12 in Appendix C shows the two most popular occupations in the subgroups—in terms of number of job postings—for illustrative purposes.

Tables 13-21 in Appendix C show the regressions for the resulting groups. Table 2 shows a summary of the results. The icons indicate whether the occupations with a proportion of *disadvantaged* workers (i.e., female, low-educated and low-wage) above the provincial average perform worse in terms of job postings than the rest of the occupations when the crisis deepens, as we expect (✓) or do not expect (✗). We do a simple comparison of the magnitude of the point estimates when they are statistically significant.

We see observations that contradict the expectation of typically disadvantaged groups being particularly affected by the pandemic. For instance, when stringency measures increase, there is a decline in the number of job postings in occupations that are typically held by low-wage workers but only in jobs not related to digital infrastructure or that do not favor remote work. Increased stringency is accompanied by decreased job postings for female-populated occupations but only if they are at high risk of automation. An increase in the number of COVID-19 deaths correlates with a stronger decline in the number of job postings for female-populated occupations compared to postings for the rest of the listed occupations but only if they are not related to digital infrastructure. In general, as we can see in the left-hand panel, there is more divergence in terms of expectations (in technology-related occupations, two thirds of the comparisons yield results that are contrary to our expectations) than we see in the right-hand panel (for non-technology-related occupations only one third of the results are contrary to our expectations). These divergences from the expectations may suggest a certain degree of *digital advantage for typically disadvantaged groups*: work opportunities are not biased against disadvantaged groups in technology-related jobs.

5.2 Inertia at the City Level

Using a set of 37 cities for which we have consistent information across the time of the Indeed job postings and the COVID-19 cases—these cases comprise the only information we have

Table 2: Dependent variable: year-over-year growth in job postings in each group–JP^j, $j \in$ {Digit.-Fem., Digit.-No fem., No digit.-Fem., No-digit.-No fem., ...}

VARIABLE	Female	Low-educ.	Low-wage	Female	Low-educ.	Low-wage
	Digital Infrastructure			*No Digital*		
Stringency	✗	✓	✗	✗	✓	✓
COVID-19 Deaths				✓	✗	✓
	Work from Home			*No Work from Home*		
Stringency	✗	✓	✗	✗	✓	✓
COVID-19 Deaths		✗	✗	✓	✗	✓
	Low Automation Risk			*High Automation Risk*		
Stringency	✓	✓	✓	✗	✓	✓
COVID-19 Deaths		✗	✗		✓	✓

Note: The checks and X marks correspond to estimates that are significantly different from 0:
✓: the group associated with *disadvantages* fares worse than the rest of the workers.
✗: the group associated with *disadvantages* fares better than the rest of the workers.

on COVID-19 spread for the city level—we estimate the following model:

$$
\begin{aligned}
JP_{ct} =& \delta L.log(Pol)_{ct} + \delta_1 L.log(Pol)_{pt} \times C_j + \\
& \gamma L1.log(Cases)_{ct} + \gamma_1 L.log(Cases)_{ct} \times C_j + \lambda_{cm} + \epsilon_{ct},
\end{aligned} \tag{2}
$$

where c represents the city, t represents the week, m is the month, JP is the year-over-year growth in total job postings, $log(Pol)$ is the logarithm of the Stringency Index as measured by Oxford University at the provincial level, $log(Cases)$ is the logarithm of the number of confirmed COVID-19 cases, and λ_{cm} represents the province-by-month fixed effects used to control for seasonal trends at the provincial level. The variables are in three-week moving averages. C_j is an indicator that takes the value 1 if a city has a low proportion of job postings of type j, pre-pandemic, with $j \in$ {Digital Infrastructure, Work from Home, Low Automation Risk}. A city is considered to have a low pre-pandemic proportion of a specific type of job posting if the average proportion in the city in 2018 and 2019 is below the average of the entire sample in those years. As before, cases and stringency measures are introduced with a one-week lag, and we use the logarithm of the cases and the stringency for interpretation.

Table 3 shows the estimates. We observe a negative and statistically significant interaction coefficient for the stringency measures in cities with below average proportions of job postings for positions in digital infrastructure, pre-pandemic. This implies that there is a certain *inertia in cities*, with cities that start with low digital job creation creating less employment when stringency measures increase. The interaction term for COVID-19 cases and cities with low pre-pandemic proportions of digital job postings and those that allow people to work from home is positive and significant. This implies that cities with low proportions of these job postings, pre-pandemic, create more online vacancies when cases increase independent of the containment policies.

Table 3: Dependent variable: year-over-year growth in total job postings in cities–JP

VARIABLES	(1)	(2)	(3)
Stringency Ox (log), L1	-30.34***	-32.85***	-33.31***
	(2.134)	(2.532)	(2.573)
... × City with Low Prop. of JP in Digital Infrastructure	-6.09**		
	(2.595)		
... × City with Low Proportion of JP for Working from Home		0.31	
		(3.045)	
... × City with High Proportion of JP with High Automation Risk			1.78
			(3.064)
COVID-19 Cases (log), L7	-0.85*	-0.93	-0.59
	(0.497)	(0.571)	(0.554)
... × City with Low Prop. of JP in Digital Infrastructure	1.06***		
	(0.330)		
... × City with Low Proportion of JP for Working from Home		0.87*	
		(0.465)	
... × City with High Proportion of JP at High Automation Risk			0.39
			(0.420)
Observations	3,219	3,219	3,219
Number of cities	37	37	37
Adjusted R^2	0.73	0.73	0.73

Note: Variables are in three-week moving averages. Standard errors clustered at the city level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Differences between Lockdowns and Reopenings

In Canada, the provincial governments are in charge of implementing containment measures to slow the spread of COVID-19. In this section, we take advantage of differences in the timing of the policies across provinces to estimate the effects containment measures have on job postings related to positions in technology. This exercise allows us to analyze the asymmetry of the policies (increased stringency during lockdowns compared to decreased stringency during reopenings) and the persistence of the effects. We use the first and second lockdowns and their respective reopenings, as their dates are more defined than the lockdowns and reopenings that occurred later on.[14]

[14]Results are robust to including the third lockdown and reopening. Estimates are available upon request. The policies during the fourth wave are blurry because provinces implemented vaccine requirements.

We perform two exercises. First, we do a difference-in-differences approach with the two lockdowns and reopenings pooled together to estimate the average effect of each type of event. Second, we do an event study to observe how changes in job postings evolve in time.

6.1 Difference-in-Differences

We compare the evolution of the job postings for each of the groups defined in relation to digital technologies before and after each lockdown and reopening. The period of the first lockdown ends at the first reopening. The period of the first reopening ends at beginning of the second lockdown, and so on. We estimate the following equation:

$$JP^{j}_{pt} = \delta Event^{k}_{pt} + \lambda_{pw} + \phi_{py} + \epsilon_{pt}, \tag{3}$$

where p is the province, t is the week, w is the week number, and y is the year. JP^j represents the year-over-year growth in the three-week moving averages for job postings in occupation group j (i.e., digital infrastructure, possibility of working from home, high automation risk, etc.). $Event^k$, with $k \in \{Lockdown, Reopening\}$, is an indicator that equals one if week t occurs during the 1^{st} or 2^{nd} periods of lockdown or reopening, respectively. We include trends for province-by-week (λ_{pw}) to absorb the seasonal patterns and for province-by-year (ϕ_{py}) to absorb the macroeconomic fluctuations.

The results for job postings related to digital technologies are shown in Table 4. The first panel shows the estimates regarding the first and second lockdowns, and the second panel shows those of the first and second reopenings. We see that during these lockdowns, the job postings for positions in digital infrastructure decreased by less (-14 percentage points) than they did in the remaining sectors (-23 percentage points). Also, the subsequent reopenings brought about a faster recovery for digital job postings (+16.5 percentage points) than for jobs in the rest of the sectors (+10 percentage points).

The third panel in Table 4 presents a placebo exercise. We take the same weeks as for the first and second lockdowns but for one year prior; i.e., for 2019 and the beginning of 2020. We cannot do the same exercise for the reopenings as the weeks of the second reopening one year prior overlap the first lockdown. This exercise confirms that there is nothing special about the lockdown period driving the results, as the estimates for the same period one year ahead are not significant.

Table 5 presents the results for job postings according to the possibility of working from

Table 4: Dependent variable: year-over-year growth in job postings in digital infrastructure and the rest of jobs–JP^j

	Lockdown		*Reopening*		*Placebo Lockdown*	
VARIABLES	Digit.	No digit.	Digit.	No digit.	Digit.	No digit.
Lockdown	-13.60*	-23.37***				
	(6.783)	(5.934)				
Reopening			16.47*	9.80*		
			(8.550)	(4.606)		
Lockdown weeks, 1 year before					1.93	9.03
					(6.617)	(5.863)
Observations	1,220	1,220	1,220	1,220	1,220	1,220
Adjusted R^2	0.09	0.25	0.10	0.16	0.08	0.16

Note: Three-week moving averages of job postings. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

home. Similar to the previous case, job postings that allow people to work from home incur smaller declines during lockdowns than do jobs in the rest of the sectors: the former drop by 21 percentage points and the rest of the sectors drop by 25. Job postings that allow people to work from home do not seem to pick up faster during the reopenings. They increase by 10 percentage points, which is the same as for the rest of the job postings. The placebo test also confirms that there were no particular differences between the lockdown period and the reminder of the year.

Table 5: Dependent variable: year-over-year growth in job postings according to the possibility of working from home–JP^j

	Lockdown		*Reopening*		*Placebo Lockdown*	
VARIABLES	WAH	No WAH	WAH	No WAH	WAH	No WAH
Lockdown	-20.57***	-25.15***				
	(6.190)	(5.934)				
Reopening			10.05*	10.11**		
			(5.010)	(4.001)		
Lockdown weeks, 1 year before					7.48	9.92
					(6.160)	(5.748)
Observations	1,220	1,220	1,220	1,220	1,220	1,220
Adjusted R^2	0.22	0.25	0.16	0.16	0.15	0.16

Note: Three-week moving averages of job postings. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 shows the estimates for job postings according to automation risk. Job postings in occupations with low automation risk seem to not only slow by less than the rest of the job postings during the lockdowns but also to recover faster during the reopenings. The placebo test is also reassuring for these results.

Table 6: Dependent variable: year-over-year growth in job postings according to automation risk–JP^j

VARIABLES	*Lockdown* Low AR	High AR	*Reopening* Low AR	High AR	*Placebo Lockdown* Low AR	High AR
Lockdown	-20.27***	-24.96***				
	(5.880)	(6.455)				
Reopening			11.69*	8.31*		
			(5.788)	(4.058)		
Lockdown weeks, 1 year before					7.64	9.37
					(5.840)	(6.228)
Observations	1,220	1,220	1,220	1,220	1,220	1,220
Adjusted R^2	0.16	0.29	0.12	0.18	0.10	0.18

Note: Three-week moving averages of job postings. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.2 Event Study

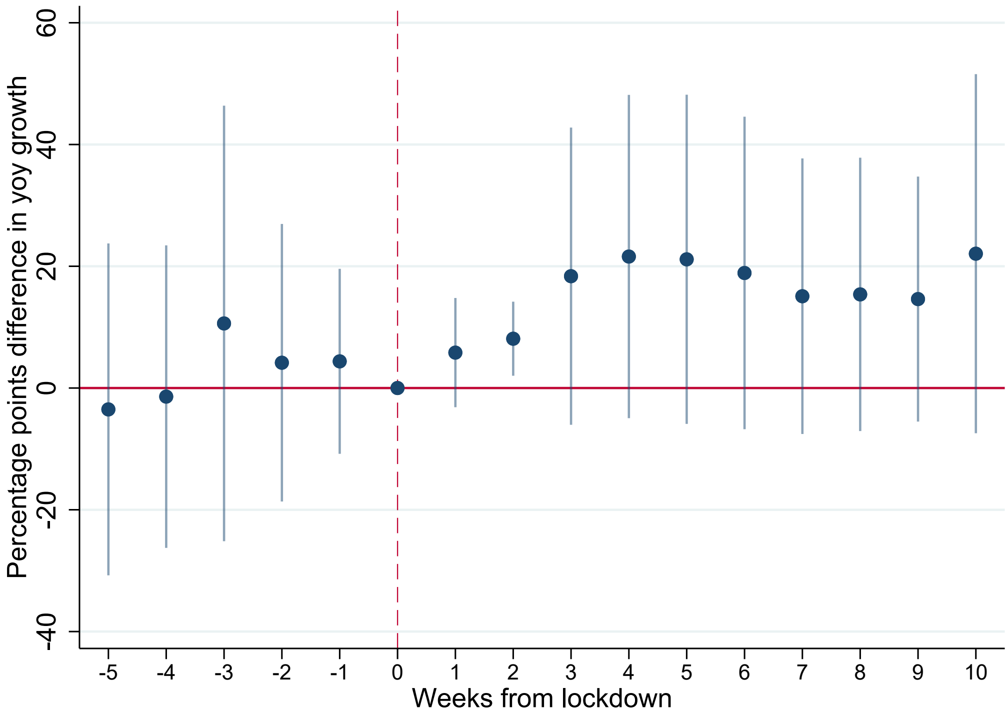
To observe how job postings for different technology-related categories changed over time when lockdowns and reopenings are implemented, we perform an event study. We show the results from the first lockdown and subsequent reopening. We estimate the following model:

$$\Delta JP^d_{pt} = \sum_{\tau=-5}^{10} \delta_\tau \mathbb{1}(Week_\tau)_t + \lambda_{pm} + \epsilon_{pt}, \tag{4}$$

where p represents the province, t is the week, and m is the month. The dependent variable is ΔJP^d; that is, the difference between the year-over-year growth in job postings—three-week moving averages—in *digital-oriented* groups of occupations d (i.e., digital infrastructure, possibility of working from home, low automation risk), minus the growth in the rest of occupations. The Appendix C provides the estimates for the separate groups. $\mathbb{1}(Week_\tau)_t$ is an indicator function that takes the value of 1 if week t is τ weeks from the event (first lockdown or first reopening). We include the province-by-month fixed effects, λ_{pm}, for seasonality. The interpretations of the estimates of the effects of the lockdowns and reopenings rely on the parallel trends assumption. In absence of the event (a lockdown or reopening), all job postings regardless of the 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 12 shows the event-study coefficients for the outcome of the difference in growth between job postings for positions in digital infrastructure. We see that the difference is positive and statistically significant two weeks after the lockdown and that it remains positive (though not significant) for two months.

Figure 12: Dependent variable: difference in year-over-year growth in job postings in digital infrastructure and the rest of jobs–ΔJP^d. First lockdown



Note: Three-week moving averages of job postings. Robust standard errors.

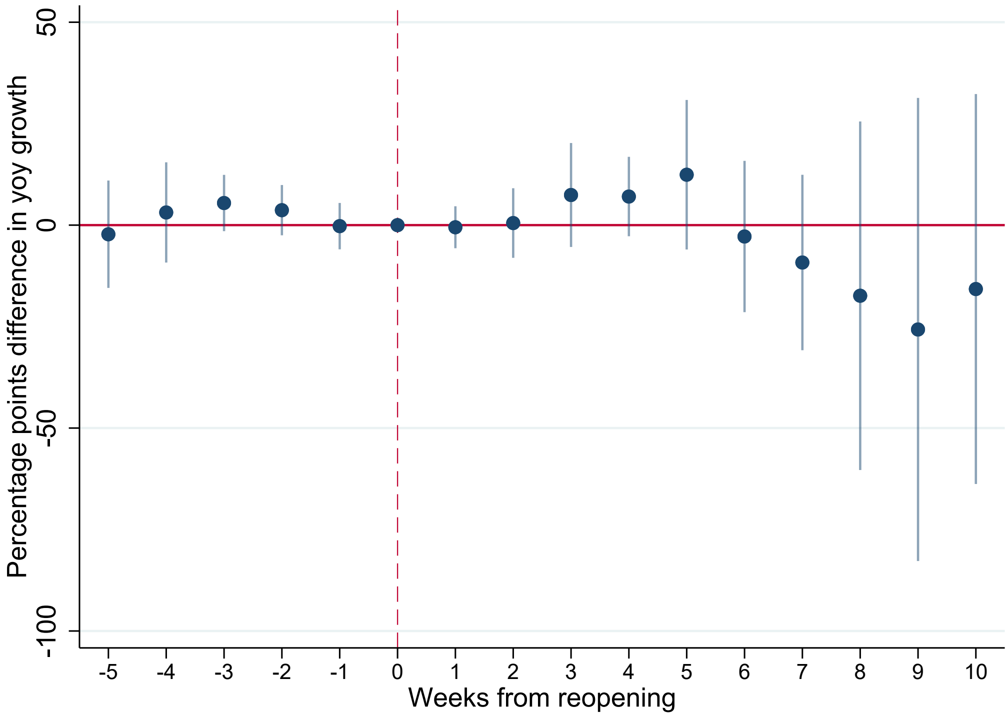
Figure 13 shows the coefficients for the first reopening. No coefficients are significant. Looking at the point estimates, although we see a positive difference between week three and week five after the reopening, this becomes negative thereafter.

In Figure 14, we see that after the first lockdown, job postings that offer the possibility of working from home grew at a faster pace than those without such a possibility. However, the difference is not statistically significant and becomes negative—and still not significant—after six weeks. Figure 15 for the first reopening is not very informative. Before the reopening, job postings offering the potential of working from home were already growing faster than the rest of the jobs.

Figures 16 and 17 show the results corresponding to the first lockdown and reopening, respectively, for job postings with low versus high automation risk. Whereas no coefficient is significant around the lockdown, job postings for positions with low automation risk seem to pick up relative to the rest of the jobs after the reopening. The coefficients are positive and statistically significant during the four weeks after the event.

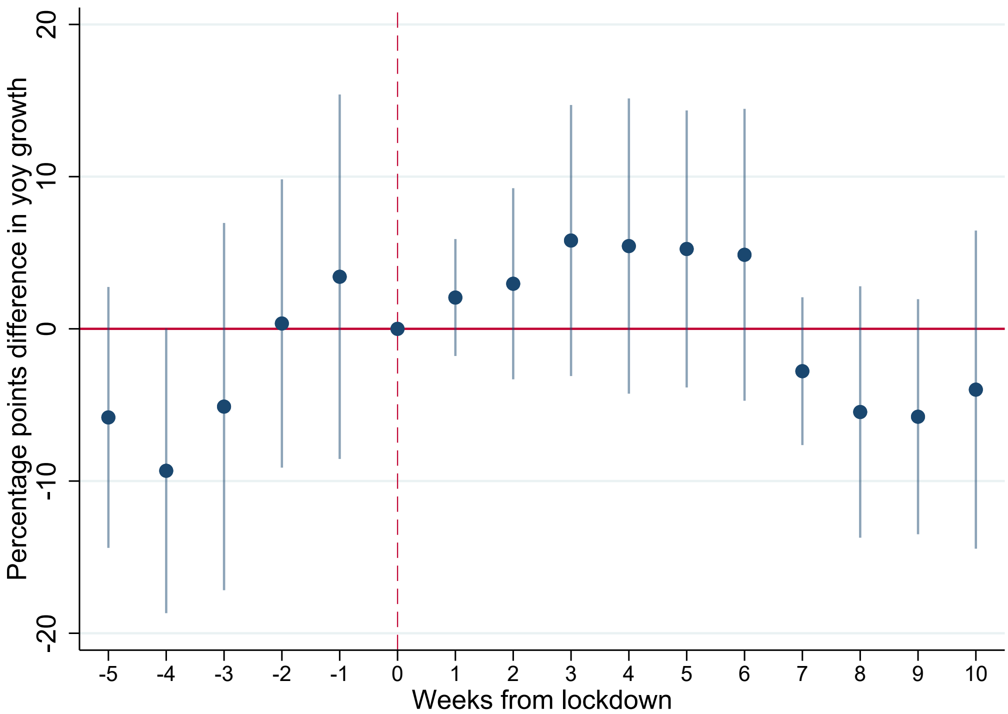
Overall, this analysis suggests that when the stringency of the policies changes, firms

Figure 13: Dependent variable: difference in year-over-year growth in job postings in digital infrastructure and the rest of jobs–ΔJP^d. First reopening



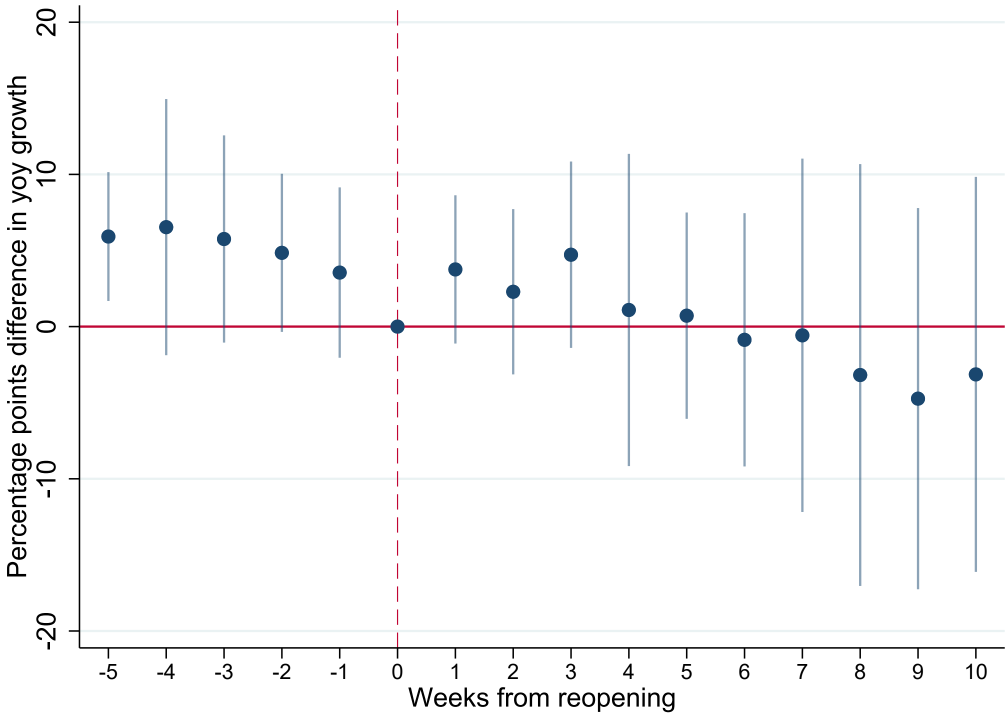
Note: Three-week moving averages of job postings. Robust standard errors.

Figure 14: Dependent variable: difference in year-over-year growth in job postings in occupations that can be done from home and the rest of jobs–ΔJP^d. First lockdown



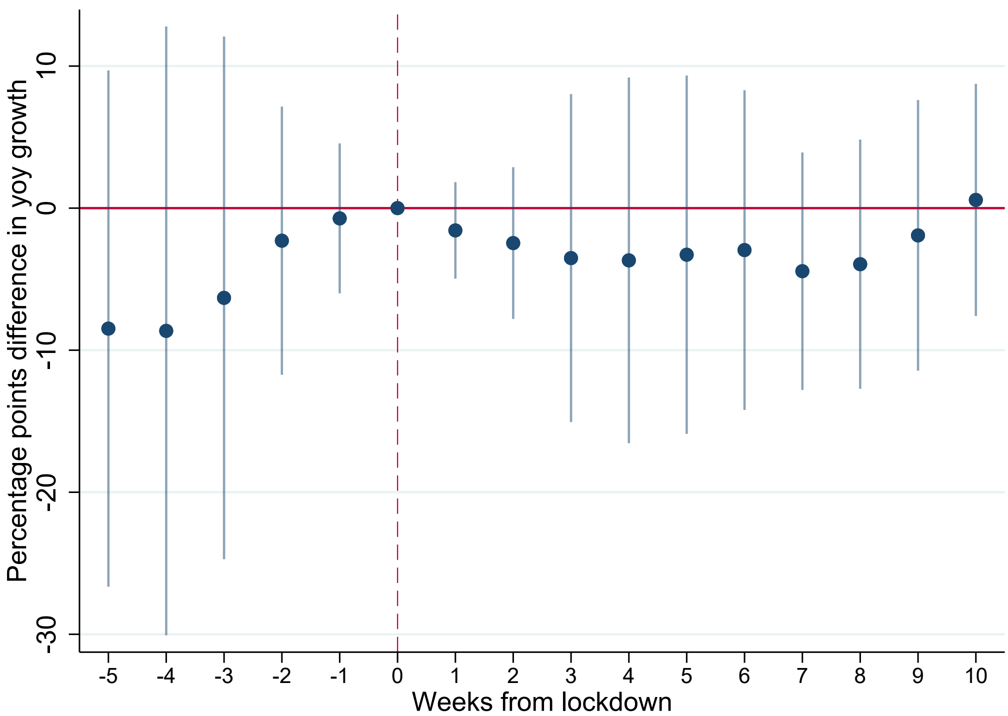
Note: three-week moving averages of job postings. Robust standard errors.

Figure 15: Dependent variable: difference in year-over-year growth in job postings in occupations that can be done from home and the rest of jobs–ΔJP^d. First reopening



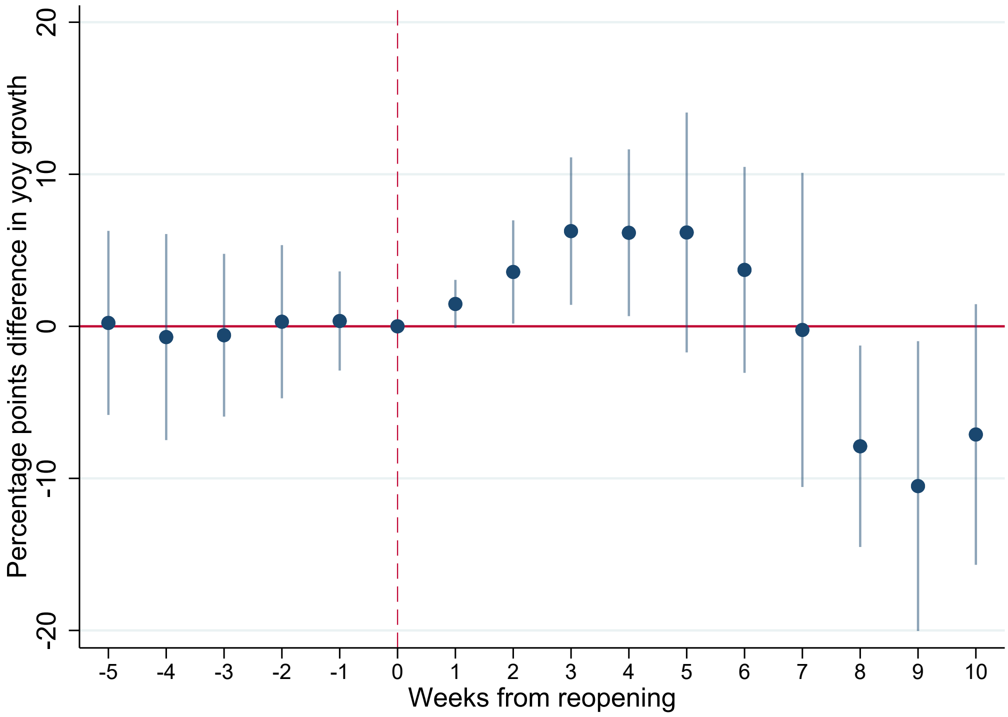
Note: Three-week moving averages of job postings. Robust standard errors.

Figure 16: Dependent variable: differences in year-over-year growth in job postings in occupations with low and high automation risk–ΔJP^d. First lockdown



Note: Three-week moving averages of job postings. Robust standard errors.

Figure 17: Dependent variable: differences in year-over-year growth in job postings in occupations with low and high automation risk–ΔJP^d. First reopening



Note: Three-week moving averages of job postings. Robust standard errors.

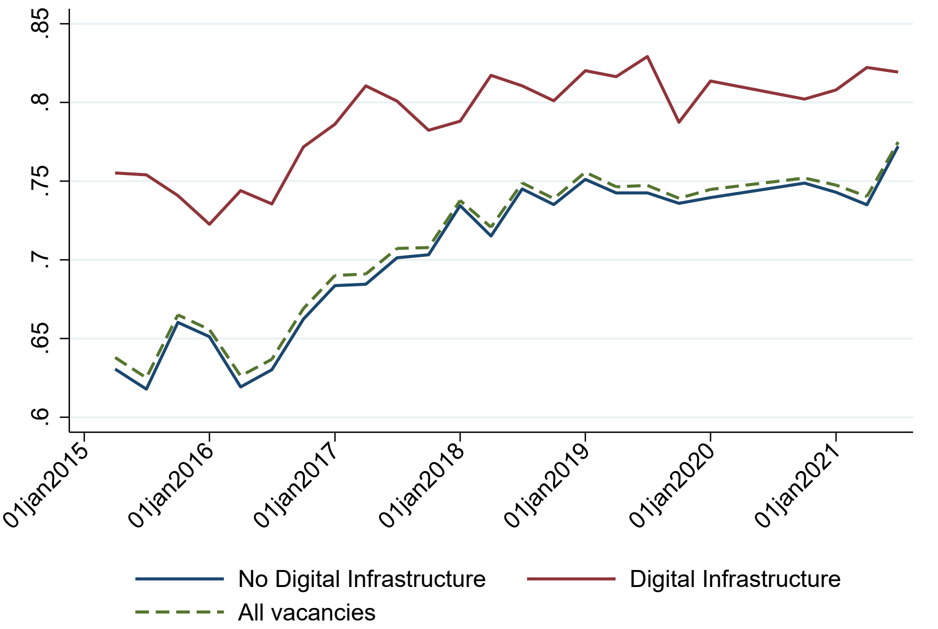
speed up their vacancy postings for certain jobs related to technology. In particular, job postings for positions in digital infrastructure and with the possibility of working from home proliferate after the lockdown, and occupations with low automation risk become more popular among firms after the reopening.

7 Digitalization of Vacancies

A potential source of bias in our results could come from changes in the proportion of vacancies advertised online across different occupation groups. We examine the Canadian Job Vacancy and Wage Survey (JVWS) data. The JVWS reports quarterly on recruitment strategies related to vacancies in industries listed at the NOC 4-digit level. The second and third quarters of 2020 are missing and the last data point corresponds to the third quarter of 2021. We observe the trends in the proportion of vacancies advertised in online job boards as a way to gauge whether the advertisement of vacancies in the technology-related groups we are analyzing has shifted toward digital posting.

Figure 18 shows the proportion of online vacancies posted for jobs in digital infrastructure, compared to the rest of the jobs. This proportion has remained roughly stable since the

Figure 18: Proportion of vacancies listed on online job boards for jobs in digital infrastructure and the rest of jobs



beginning of 2020. At the same time, there is a slightly upward trend in the proportion of online vacancies overall and for jobs not in digital infrastructure. The proportion of vacancies in jobs related to digital infrastructure has remained above the rest of jobs for the whole observation period. However, the gap seems to have been closing in the last few years.

Figure 19 shows that the proportion of vacancies posted online increased slightly more for those occupations that allow people to work from home, compared to the rest of the jobs during 2020. However, we observe a catch-up between these two types of occupations by the end of the third quarter of 2021. At that point, the proportions are equal across occupation groups. Figure 20 shows a similar relative trend for occupations with low automation risk as for those with the potential of working from home.

Figure 20 shows a decline in the proportion of online vacancies for occupations at high risk of automation in the second half of 2020. However, this proportion climbed in 2021. There does not seem to be a differential change in the proportion of online vacancies according to the automation risk of the various occupations for 2020 and 2021 taken together.

In sum, differential trends in vacancy posting online versus offline across occupations do not seem likely to drive our results.

Figure 19: Proportion of vacancies listed on online job boards for occupations that permit people to work from home and the rest of jobs

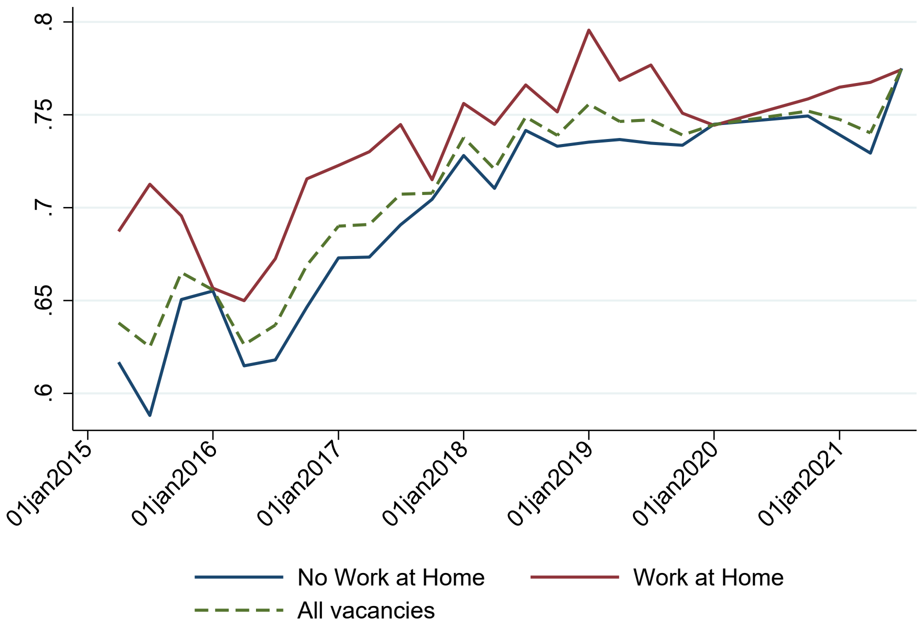
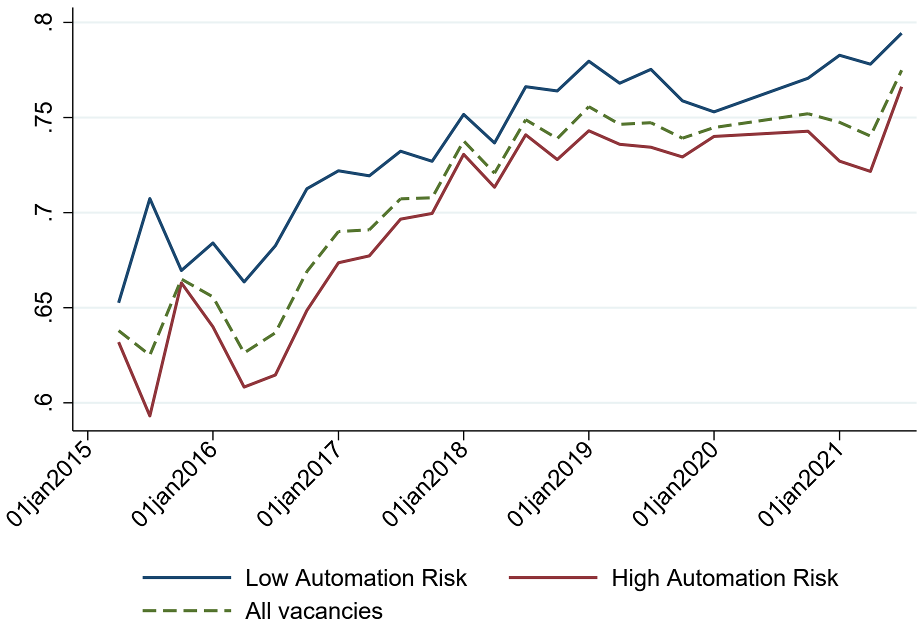


Figure 20: Proportion of vacancies listed on online job boards for occupations with low and high automation risk



8 Conclusion

The turbulence caused by the COVID-19 pandemic has given rise to much debate around the potential acceleration of technology use and technological change. Previous research shows that this occurred in past recessions. However, the COVID-19-induced recession is special in that digital technologies have been instrumental in keeping economic activity afloat while respecting physical distancing requirements.

In this paper, we compare the evolution of firms' recruitment needs in technology-related jobs throughout the pandemic. We use high-frequency data on online job postings collected by Indeed. We use text analytics to classify the data into standard occupational codes. We then group the occupations into those that are related to digital infrastructure and those that are not, those that allow people to work from home and those that do not, and those at low and high risk of automation.

We leverage the variation in time and space in the spread of COVID-19 and the policies introduced in response to it. We show that the demand for occupations that produce and use digital technology has intensified along the duration of the pandemic. Job postings in occupations related to digital infrastructure seem to proliferate during lockdowns. Those that are at higher risk of automation instead seem more popular when a reopening is in place.

Furthermore, we see that typically disadvantaged groups in the labor market, such as women and low-wage workers, may have a *technology advantage*. When jobs are associated to the us or production of technology, those that are more heavily occupied by these groups suffer smaller demand drops than those with low proportions of workers from these same groups.

Finally, there seems to be some inertia at the city level when stringency measures increase. Cities with low vacancy creation in digital infrastructure seem to create even fewer total vacancies when policies become more stringent.

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Appendix

A Classification Algorithm of Turrell et al. (2019)

We use the algorithm of Turrell et al. (2019), which classifies British job postings to the UK Standard Occupation Classification (UK SOC). Their programs used to run the algorithm are available in GitHub. They use the job title, description and sector for 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 dictionary of UK SOC text data provided by the ONS, using term frequency-inverse document frequency (*tf-idf*).
3. Searching to see if there is an exact match between the job titles in the job postings and those in the UK SOC 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 of the UK SOC data.
5. For jobs that were not matched, calculating the cosine similarity between the string obtained in the previous step, and the information in the UK SOC dictionary, and selecting the five categories in the UK SOC 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. (2019) chose to classify jobs using the three-digit UK SOC. Their algorithm has an accuracy rate of 76%.

B Occupation Groupings

B.1 Production of Digital Infrastructure

The NOC categories we manually classify as related to the production of digital infrastructure are listed in Table 7.

Table 7: NOC categories related to digital infrastructure

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*, then the occupation is coded as one that cannot be done remotely.

Work Context Questionnaire:

- The average respondent says they use e-mail less than once per month.
- The average respondent says they deal with violent people at least once a week.
- The majority of the respondents say they work outdoors every day.
- The average respondent says they are exposed to diseases or infection at least once a week.
- The average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week.
- The average respondent says they spent the majority of their time walking or running.
- The average respondent says they spent the majority of their 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 or 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 classification in terms of automation risk provided by Chernoff and Warman (2020) is based on three questionnaires of the O*NET, version 24.3 (May 2020): the abilities questionnaire, the generalized work activities questionnaire, and the work context questionnaire. Through the addition of a set of standardized descriptors—$Standardized\ descriptor = \frac{descriptor - Mean(descriptor)}{Standard\ Deviation(descriptor)}$—these authors construct a set of variables that classify occupations into routine and non-routine jobs. The variables and corresponding descriptors are as follows:

- **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; spend time making repetitive motions.
- **Non-Routine Analytical (NRA):** analyzing data or information; thinking creatively; interpreting the meaning of the 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; spend time using hands to handle, control or feel objects, tools or controls; manual dexterity and spatial orientation.

After these five variables are constructed, they are combined in the Routine Task-Intensity (RTI) index for each occupation: $RTI = RC + RM - NRA - NRI - NRM$. The index is normalized between 0 and $1 - \frac{RTI - Min(RTI)}{Max(RTI) - Min(RTI)}$. This is the normalized index we finally use to categorize occupations. After averaging out those with multiple O*NET categories per one NOC category, we classify an occupation as being at a high automation risk when the averaged normalized RTI is 0.5 or more and at a 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 corresponds to characterizations of occupations at the beginning of the pandemic. This is especially important with respect to the possibility of working from home. We have seen how many occupations have shifted to accommodate the need to do physical distancing. This is the case for many physical instructors, for example. They have adapted by teaching online via conferencing applications.

We use the definition of work from home obtained from Dingel and Neiman (2020). We examine changes in the mean ratings of the questions the authors used to construct their work-from-home measure between the version of the O*NET in the original paper—version 24.2 from February 2020—and version 25.3 from May 2021. This is meant to verify the changes in the profiles of the occupations that are not being captured by the work-from-home measure we are using in this paper. We consider an upward change in the rating—by more than 10%—as an increase in the importance of this particular descriptor within a certain occupation. The opposite occurs with a decline in the rating—by more than 10%.

In general, in the work context questionnaire, we observe a decrease in the importance of dealing with physically aggressive people and being exposed to disease or infections. These are signs of an increased profile of work-from-home occupations. Also, more occupations have larger ratings for checking e-mails, being outdoors, and spending time walking and running.

In the work activities questionnaire, more occupations have increased ratings for 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.

One example that is in line with our expectation is *physical education specialists*, for whom the disease and infection exposure rating has decreased, as has the rating for repairing and maintaining electronic and mechanical equipment. This suggests these occupations have effectively become more prone to remote work.

C Additional Tables

Table 8: Dependent variable: year-over-year growth in job postings in each group–JP^j. No lags in independent variables

VARIABLES	Digital Infrastr.	No Digital Infrastr.	Work from Home	No Work from Home	Low Autom. Risk	High Autom. Risk
Stringency Ox (log)	-28.22***	-32.65***	-31.48***	-33.93***	-31.32***	-33.55***
	(5.456)	(1.519)	(2.287)	(1.673)	(2.138)	(1.323)
COVID-19 Deaths (log)	-0.48	-0.82***	-0.56	-1.04***	-0.71*	-0.87***
	(1.542)	(0.204)	(0.425)	(0.181)	(0.340)	(0.240)
Observations	870	870	870	870	870	870
Number of provinces	10	10	10	10	10	10
Adjusted R^2	0.75	0.93	0.93	0.92	0.91	0.93

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Dependent variable: year-over-year growth in job postings in each group–JP^j. Two-week lags in independent variables

VARIABLES	Digital Infrastr.	No Digital Infrastr.	Work from Home	No Work from Home	Low Autom. Risk	High Autom. Risk
Stringency Ox (log), L2	-30.10***	-32.04***	-31.33***	-32.12***	-33.46***	-30.22***
	(7.888)	(2.127)	(2.351)	(2.889)	(3.172)	(2.322)
COVID-19 Deaths (log), L2	0.69	-0.01	0.07	-0.06	0.11	-0.08
	(0.901)	(0.280)	(0.196)	(0.429)	(0.215)	(0.400)
Observations	870	870	870	870	870	870
Number of provinces	10	10	10	10	10	10
Adjusted R^2	0.75	0.93	0.92	0.91	0.90	0.92

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Dependent variable: year-over-year growth in job postings in each group–JP^j. Independent variables are not in logarithms

VARIABLES	Digital Infrastr.	No Digital Infrastr.	Work from Home	No Work from Home	Low Autom. Risk	High Autom. Risk
Stringency Ox, L1	-0.55***	-0.68***	-0.62***	-0.71***	-0.67***	-0.67***
	(0.111)	(0.046)	(0.042)	(0.062)	(0.051)	(0.055)
COVID-19 Deaths, L1	0.00	0.00	0.00	0.00	0.00	-0.00
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	870	870	870	870	870	870
Number of provinces	10	10	10	10	10	10
Adjusted R^2	0.75	0.93	0.92	0.91	0.90	0.92

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Dependent variable: natural logarithm of job postings in each group–JP^j

VARIABLES	Digital Infrastr.	No Digital Infrastr.	Work from Home	No Work from Home	Low Autom. Risk	High Autom. Risk
Stringency Ox (log), L1	-0.31***	-0.40***	-0.37***	-0.42***	-0.40***	-0.39***
	(0.065)	(0.030)	(0.039)	(0.029)	(0.038)	(0.027)
COVID-19 Deaths (log), L1	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.007)	(0.005)	(0.007)	(0.003)	(0.007)	(0.003)
Observations	870	870	870	870	870	870
Number of provinces	10	10	10	10	10	10
Adjusted R^2	0.78	0.91	0.88	0.91	0.88	0.91

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Occupations in technology-characteristics groups

DIGITAL INFRASTRUCTURE		NO DIGITAL	
High female	**Low female**	**High female**	**Low female**
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
High low-educated	**Low low-educated**	**High low-educated**	**Low low-educated**
Electricians (except industrial and power system)	Information systems analysts and consultants	Other customer and information services representatives	Lawyers and Quebec notaries
Assemblers and inspectors, electr. appl., apparatus and equip. manuf.	User support technicians	Retail salespersons	Corporate sales managers
High low-wage	**Low low-wage**	**High low-wage**	**Low low-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
WORK FROM HOME		**NO WORK FROM HOME**	
High female	**Low female**	**High female**	**Low female**
Other customer and information serv. repr.	Corporate sales managers	Cooks	Managers in cust. and pers. services, n.e.c.
Sales and account repr.-wholesale trade (non-technical)	Retail and wholesale trade managers	Retail salespersons	Transport truck drivers
High low-educated	**Low low-educated**	**High low-educated**	**Low low-educated**
Other customer and information serv. repr.	Information systems analysts and consultants	Retail salespersons	Home support workers, housek. and related
Sales and account repr.-wholesale trade (non-technical)	User support technicians	Transport truck drivers	Social and community service workers
High low-wage	**Low low-wage**	**High low-wage**	**Low low-wage**
Other customer and information serv. repr.	Corporate sales managers	Retail salespersons	Managers in cust. and pers. serv., n.e.c.
Sales and acc. repr.-wholesale trade (non-technical)	Retail and wholesale trade managers	Cooks	Transport truck drivers
LOW AUTOMATION RISK		**HIGH AUTOMATION RISK**	
High female	**Low female**	**High female**	**Low female**
Sales and acc. repr.-wholesale trade (non-technical)	Corporate sales managers	Other customer and inf. serv. repr.	Transport truck drivers
Social and community service workers	Retail and wholesale trade managers Cooks	User support technicians	
High low-educated	**Low low-educated**	**High low-educated**	**Low low-educated**
Sales and acc. repr.-wholesale trade (non-technical)	Information systems analysts and consultants	Other cust. and inform. serv. repr.	Home supp. workers, housek. and related
Security guards and related sec. serv. occup.	Corporate sales managers	Retail salespersons	User support technicians
High low-wage	**Low low-wage**	**High low-wage**	**Low low-wage**
Sales and acc. repr.-wholesale trade (non-technical)	Corporate sales managers	Other cust. and inform. serv. repr.	User support technicians
Social and community service workers	Retail and wholesale trade managers	Retail salespersons	Administrative officers

Note: Each group displays the top two occupations that have the most job postings in the analysis period.

Table 13: Dependent variable: year-over-year growth in job postings in digital infrastructure and the rest of jobs, according to the proportion of female workers

	Digital Infrastructure		No Digital	
VARIABLES	high prop. of women	low prop. of women	high prop. of women	low prop. of women
Stringency Ox (log), L1	-60.62	-22.13**	-27.45***	-34.06***
	(46.543)	(8.976)	(1.423)	(3.236)
COVID-19 Deaths (log), L1	-0.65	-0.73	-0.70*	-0.59
	(4.802)	(1.059)	(0.354)	(0.327)
Observations	863	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.49	0.74	0.92	0.90

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Dependent variable: year-over-year growth in job postings in digital infrastructure and the rest of jobs, according to the proportion of low-educated workers

	Digital Infrastructure		No Digital	
VARIABLES	high prop. of low-ed.	low prop. of low-ed.	high prop. of low-ed.	low prop. of low-ed.
Stringency Ox (log), L1	-169.63***	-23.00***	-32.54***	-27.66***
	(50.415)	(6.973)	(2.330)	(2.661)
COVID-19 Deaths (log), L1	3.74	-0.62	-0.35	-0.97**
	(6.739)	(1.006)	(0.287)	(0.386)
Observations	818	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.86	0.72	0.93	0.91

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Dependent variable: year-over-year growth in job postings in digital infrastructure and rest of jobs, according to the proportion of low-wage workers

	Digital Infrastructure		No Digital	
VARIABLES	high prop. of low-wage	low prop. of low-wage	high prop. of low-wage	low prop. of low-wage
Stringency Ox (log), L1	-13.02	-25.64***	-32.95***	-27.75***
	(14.627)	(7.600)	(1.589)	(2.400)
COVID-19 Deaths (log), L1	-0.62	-0.59	-0.66**	-0.62
	(2.001)	(1.073)	(0.290)	(0.377)
Observations	820	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	820	870	870	870

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Dependent variable: year-over-year growth in job postings with possibility of working from home and the rest of jobs, according to the proportion of female workers

	Work from Home		No Work from Home	
VARIABLES	high prop. of women	low prop. of women	high prop. of women	low prop. of women
Stringency Ox (log), L1	-28.60***	-29.03***	-26.37***	-35.36***
	(2.080)	(4.178)	(2.612)	(3.624)
COVID-19 Deaths (log), L1	-0.47	-0.62	-1.05**	-0.53
	(0.387)	(0.378)	(0.394)	(0.341)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.91	0.88	0.89	0.88

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Dependent variable: year-over-year growth in job postings with the possibility of working from home and the rest of jobs, according to the proportion of low-educated workers

	Work from Home		No Work from Home	
VARIABLES	high prop. of low-ed.	low prop. of low-ed.	high prop. of low-ed.	low prop. of low-ed.
Stringency Ox (log), L1	-30.42***	-28.24***	-34.21***	-24.25***
	(3.308)	(2.293)	(2.780)	(2.892)
COVID-19 Deaths (log), L1	0.17	-0.86**	-0.63*	-1.19**
	(0.401)	(0.309)	(0.308)	(0.525)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.92	0.91	0.92	0.83

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Dependent variable: year-over-year growth in job postings with the possibility of working from home and the rest of jobs, according to the proportion of low-wage workers

	Work from Home		No Work from Home	
VARIABLES	high prop. of low-wage	low prop. of low-wage	high prop. of low-wage	low prop. of low-wage
Stringency Ox (log), L1	-27.30***	-29.98***	-36.87***	-22.07***
	(2.158)	(2.811)	(2.037)	(2.249)
COVID-19 Deaths (log), L1	-0.07	-0.67*	-0.97**	-0.51
	(0.347)	(0.362)	(0.346)	(0.407)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.92	0.91	0.90	0.86

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Dependent variable: year-over-year growth in job postings with low and high automation risk, according to the proportion of female workers

	Low Automation Risk		High Automation Risk	
VARIABLES	high prop. of women	low prop. of women	high prop. of women	low prop. of women
Stringency Ox (log), L1	-30.57***	-27.81***	-25.25***	-39.61***
	(2.814)	(4.448)	(2.174)	(4.651)
COVID-19 Deaths (log), L1	-0.55	-0.78	-0.82**	-0.26
	(0.426)	(0.455)	(0.363)	(0.415)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.88	0.87	0.93	0.87

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 20: Dependent variable: year-over-year growth in job postings with low and high automation risk, according to the proportion of low-educated workers

	Low Automation Risk		High Automation Risk	
VARIABLES	high prop. of low-ed.	low prop. of low-ed.	high prop. of low-ed.	low prop. of low-ed.
Stringency Ox (log), L1	-32.75***	-28.57***	-32.95***	-24.44***
	(6.046)	(3.488)	(1.421)	(0.971)
COVID-19 Deaths (log), L1	0.33	-1.14***	-0.69	-0.63
	(0.378)	(0.346)	(0.405)	(0.375)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.89	0.90	0.93	0.88

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

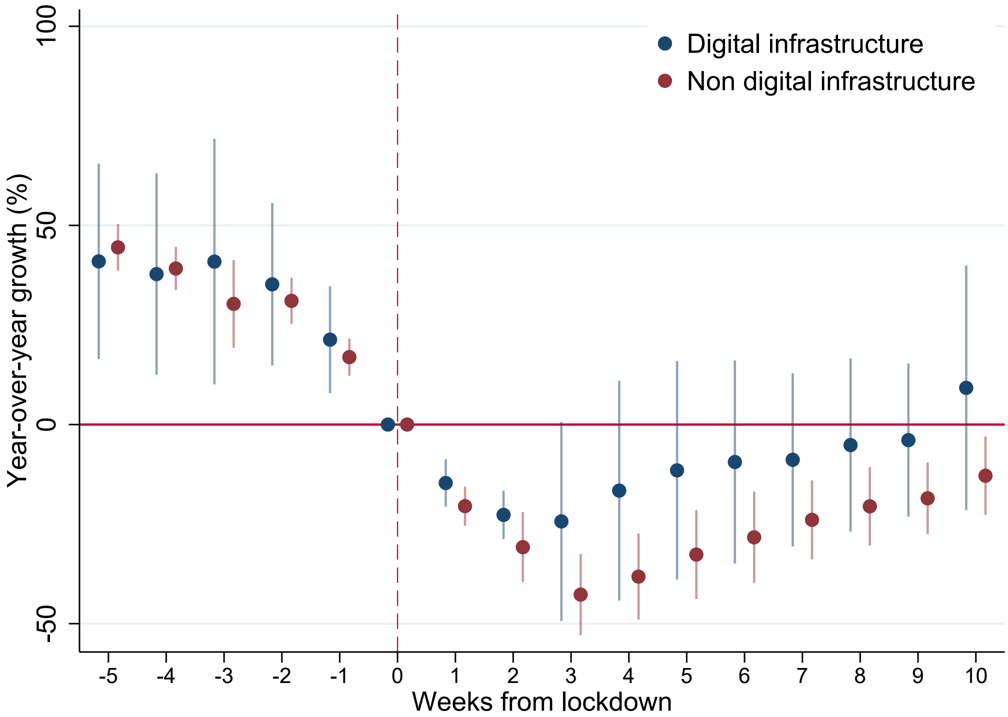
Table 21: Dependent variable: year-over-year growth in job postings with low and high automation risk, according to the proportion of low-wage workers

	Low Automation Risk		High Automation Risk	
VARIABLES	high prop. of low-wage	low prop. of low-wage	high prop. of low-wage	low prop. of low-wage
Stringency Ox (log), L1	-30.15***	-29.89***	-34.32***	-21.74***
	(2.830)	(2.714)	(1.768)	(1.808)
COVID-19 Deaths (log), L1	-0.52**	-0.62*	-0.70*	-0.55
	(0.206)	(0.303)	(0.365)	(0.467)
Observations	870	870	870	870
Number of provinces	10	10	10	10
Adjusted R^2	0.81	0.90	0.92	0.90

Note: Variables are in three-week moving averages. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

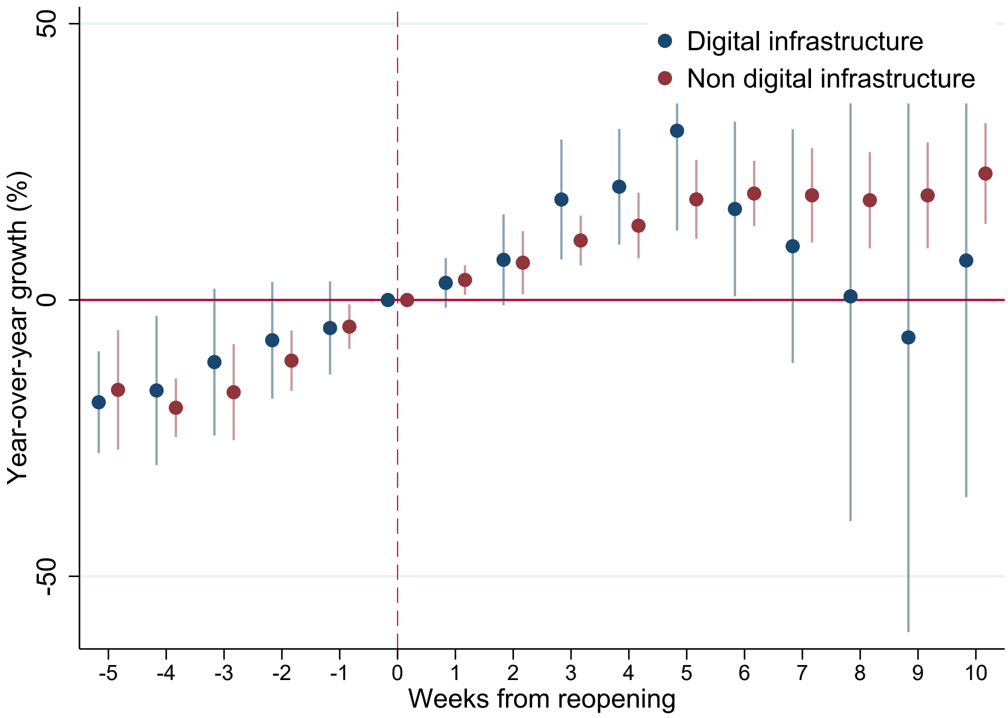
D Additional Figures

Figure 21: Dependent variable: year-over-year growth in job postings in digital infrastructure and the rest of jobs–JP^j. First lockdown



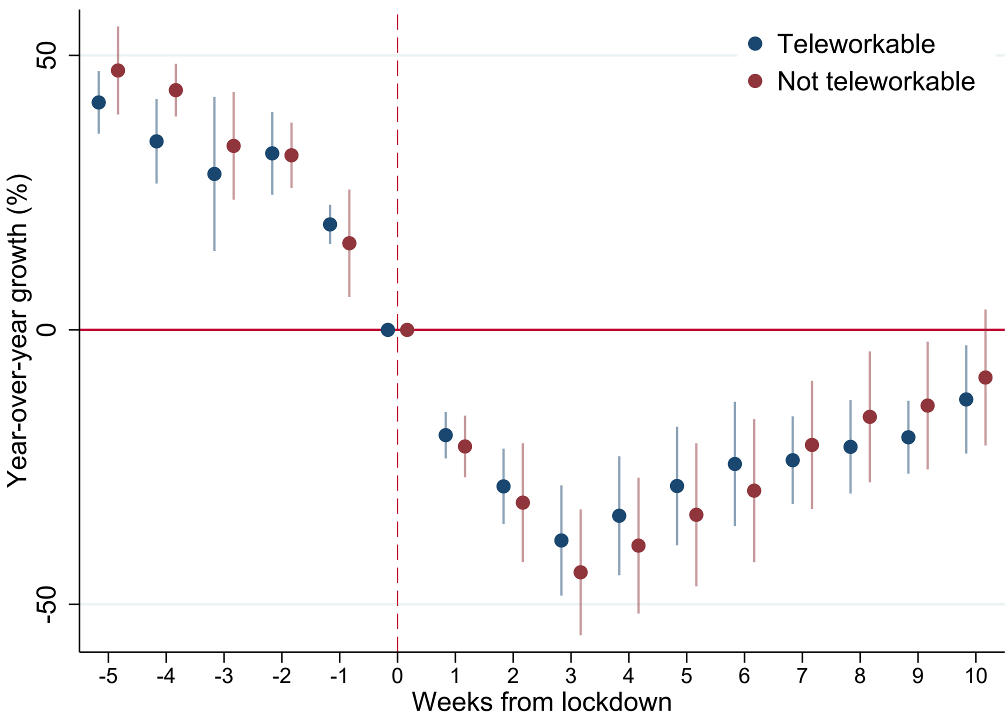
Note: 3-week moving average of job postings. Robust standard errors.

Figure 22: Dependent variable: year-over-year growth in job postings in digital infrastructure and the rest of jobs–JP^j. First reopening



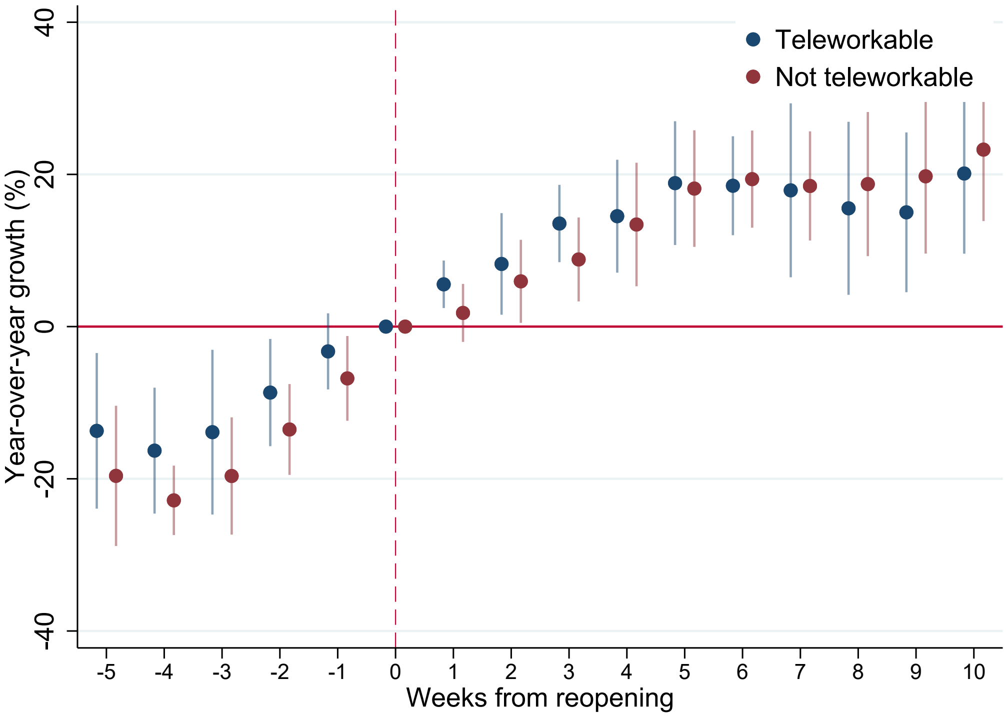
Note: Three-week moving averages of job postings. Robust standard errors.

Figure 23: Dependent variable: year-over-year growth in job postings in occupations that can be done at home and the rest of jobs–JP^j. First lockdown



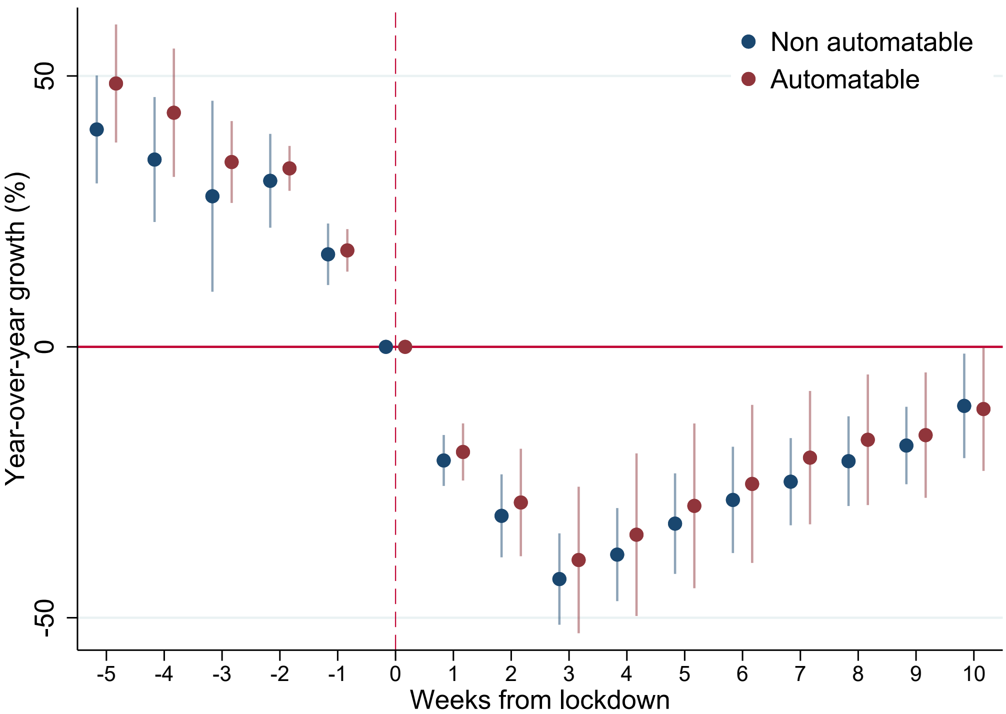
Note: Three-week moving averages of job postings. Robust standard errors.

Figure 24: Dependent variable: year-over-year growth in job postings in occupations that can be done at home and the rest of jobs–ΔJP^j. First reopening



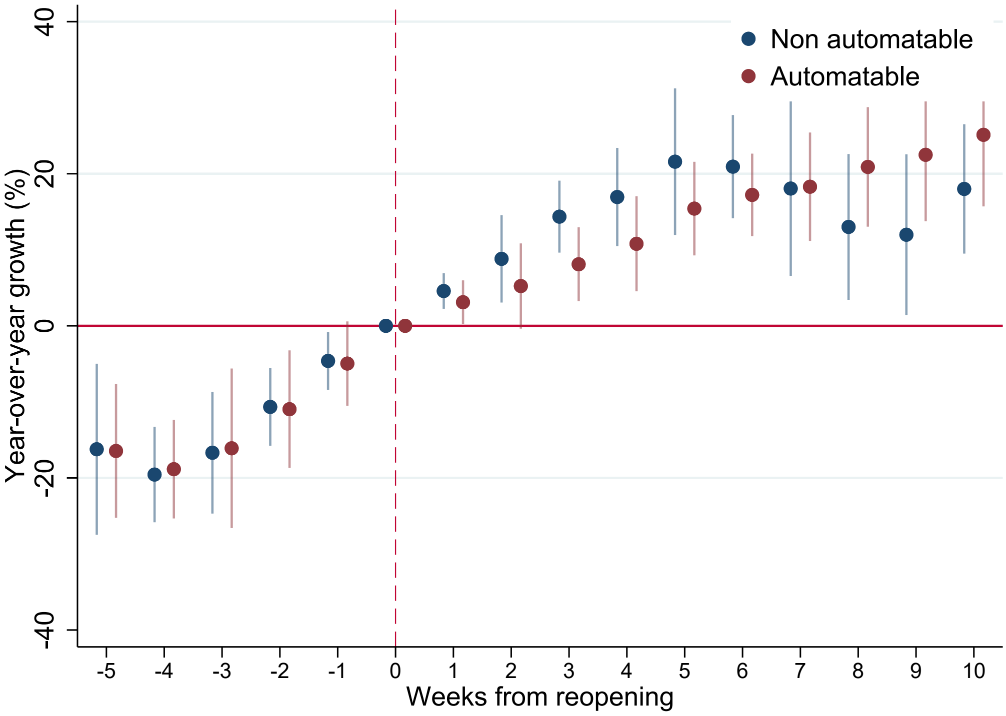
Note: Three-week moving averages of job postings. Robust standard errors.

Figure 25: Dependent variable: year-over-year growth in job postings in occupations with low and high automation risk–JP^j. First lockdown



Note: Three-week moving averages of job postings. Robust standard errors.

Figure 26: Dependent variable: year-over-year growth in job postings in occupations with low and high automation risk–ΔJP^j. First reopening



Note: Three-week moving averages of job postings. Robust standard errors.