# Jobs During the Pandemic: Re-Evaluating the Importance of Teleworkability, Contact-Intensity, and Being 'Essential'

Nina Zi Wei Low

April 2023

At the start of this decade, SARS-CoV-2, or more commonly known as COVID-19, swept across the globe, bringing profound and uneven changes to the composition of the labor market in its wake. From the time COVID-19 was declared a public emergency by the World Health Organization (WHO), the Canadian unemployment rate at its peak rose to 13.4% on May 2020 and was above the typical 6.0% for 21 consecutive months[1]. The strong contractions in the labor force and high unemployment rates could be attributed to the provincial government's attempt to 'flatten the curve' and reduce virus transmission. The strictly enforced social and physical distancing policies accompanied by the shut-down of non-essential businesses seriously inhibited business activity. As a result, some occupations and the populations involved in those occupations were relatively more sheltered by job and earning loss compared to other occupations and populations.

This paper will investigate the disproportionate labour demand impacts from the government's large-scale emergency policy response to COVID-19, identify what occupational characteristics predict strong reactions from COVID-19 policies, and evaluate the allocation efficiency of federal business assistance programs during COVID-19.

*Significance.* Leveraging a generalized Pareto distribution, Marani and colleagues (2021) estimated that the yearly probability of extreme pandemics may triple in the coming decades. Factors such as population growth, changes in food systems, environmental degradation, increasing emergence of viral disease from animals, and increase contact between humans and disease-harboring animals, lead researchers, epidemiologists Madhav et al. (2017), and other environmental engineering researchers Marani et al. (2021) alike to speculate outbreaks to happen more frequently. To better prepare and harbour the negative shocks extreme pandemics bring, it warrants continued exploration to quantify

Furthermore, six separate subsidy programs, which costs a total of 112.2 billion CAD, were launched at the federal level at different periods of the pandemic with different target populations. The subsidy reallocation and distribution among different industries and occupation groups may have accelerated the recovery of businesses and industries, but considering that some occupations are likely more sheltered by the COVID-19 Emergency Response policies, it is important to investigate if occupations most vulnerable and negatively impacted were also most subsidized. In extension, this helps to answer if the government was able to refine the subsidies and response to achieve the same results at a lower cost.

[1] Values derived from Statistics Canada Labor Force Survey

*Related Literature.* This paper mainly contributes to two strands of literature. First, it contributes to the literature on examining the immediate labor market impacts of social-distancing policies during the pandemic. Since early 2020, there has been an influx of research to quantify the economic consequences of the pandemic and corresponding policies. Interested in uncovering what occupations can be done from home, Dingel and Neiman (2020) used the Occupational Employment Statistics (OES) to identify job characteristics that clearly rule out the possibility of working entirely from home to deduce teleworkable feasibility. Messacar, Morissette, and Deng (2020) conducted the same analysis in the Canadian context and found similar figures for teleworkable feasibility. Leibovici, Santacreu, and Famiglietti (2020), along the same lines, conducted analysis considering an occupation's physical-proximity rather than work-from-home feasibility in the US. Their results reinforced the analysis of Dingel and Neiman (2020) but also underscored the non-negligible aspect of high contact-intensity occupations in the US in terms of employment and total labor income. Basso et al. (2020) built their own proximity-index with predetermined thresholds used European data based on pre-determined thresholds with O*NET and matched it with European occupations. One consistent trend among these papers is the use of standardized occupational indices, such as O*NET or NOC, and employment statistics, such as OES or the Labor Force Survey. The focus of this paper is to understand which occupation group - considering teleworkability, contact-intensity, and essential versus non-essential - is most sheltered during the pandemic in terms of employment and validate the measures by showing that they are consistent with measures from existing datasets. This requires a crosswalk between O*NET and the NOC and further integration with data containing total employment, such as the Labor Force Survey or LMIC's Job Trends Dashboard.

Other papers in this literature, such as Mongey, Pilossoph, and Weinberg (2021), Brugiavini, Buia, and Simonetti (2021), and Adams-Prassl et al. (2020), focuses on specific population groups that may have been disproportionately impacted looking at the dimensions of teleworkability and contact-intensity. By using data containing worker characteristics, such as CPS and the PSID, analyses repeatedly show that vulnerable populations, such as women, less educated workers, and individuals who were originally working on temporary contracts, are more likely to lose their jobs and experience disruption with their employment across the US and UK during the pandemic. They have reached such conclusion by identifying the occupational groups that are most affected by the pandemic according to teleworkability and contact-intensity dimensions. Yet, there are occupations that suffered disproportionately that differ solely based on the essential classification. This paper will attempt to understand whether being classified as essential is a significant indicator in influencing the employability of certain occupations and occupations.

Furthermore, Mongey, Pilossoph, and Weinberg (2021), in particular, looked into the relationship between physical proximity and employment losses and concluded that the relationship flattened as social distancing mandates expired. However, due to data availability constraint, this conclusion was reached only with data between February and August 2020 [2], which implied the conclusion risked the possibility of being premature. Considering other mechanisms and factors, such as COVID-19 fatigue and additional subsidies funneled into individual industries, it would be important to re-evaluate the conclusion reached by Mongey, Pilossoph, and Weinberg (2021). With additional time frames and high-frequency data, this paper will observe whether a similar conclusion holds for comparable time frames in the United States and validate whether the conclusion continues to hold as the pandemic intensified in subsequent phases.

Secondly, this paper builds on the growing literature that uses online job posting data to analyze labor market outcomes. Turrell et al. (2019) leverage online vacancies from Reed, a UK job site, to study the labor mismatch

[2] August 2020 marked a close end to the first phase of the pandemic for the United States; However, a second phase quickly ensued in November followed by even stricter policies.

related to productivity in the UK. They concluded that regional mismatch was a greater contributing factor than occupational mismatch in determining producitivity. Hensvik, Le Barbanchon, and Rathelot (2021) analyze real-time data on the largest onling job board in Sweden operated by the Swedish government to undersetand how job seekers' job search behaviors are impacted by the pandemic. Additionally, Marinescu and Wolthoff (2020) use data from CareerBuilder.com, a worldwide employment websites with offices in United States, Canada, Europe, and Asia (as of Nov 2022), to explain the relationship between job titles and wage variance. Indeed, which has its own data repository covering job postings in over 60 markets and has over 300 million unique visitors [3] every month, made appearances in numerous studies, including Adrjan and Lydon (2019), Bellatin and Galassi (2022), and Sinclair and Gimbel (2020). The topics of these studies ranged from tightness in the labor market (Adrjan and Lydon (2019)) to US employer and job seeker mismatch (Sinclair and Gimbel (2020)) to the evolution of technology-related occupational postings (Bellatin and Galassi (2022)). This paper would add to the pool of growing literature and help understand the potential measurement error of using online job posting data. A limitation of using job posting data is its ability to reflect employer decisions and reflect changes in quantity of labour demand. Using the novel Canadian job posting data powered by LMIC, this paper will attempt to uncover whether the online job posting data is enough as a proxy for labour demand controlling for occupational characteristics and other covariates directly affected by the pandemic.

# 1 Conceptual Framework

On March 10th, the Canadian government followed the World Health Organization's footsteps to announce strong recommendations for businesses to transition to a work-from-home model. The promotion of remote work and a more socially distanced lifestyle created a division among occupations that were able to successfully transition to an online environment and those who failed. Subsequently over the next few weeks, each province announced their list of essential workers or essential workplaces limiting the operation of business to those who are not included. As a result, for disease preventive measures, any contact-intensive occupations that are non-essential, such as food and beverage servers, find themselves vulnerable for layoffs and earning loss.

To interpret the economic intuition behind change in labour demand as a result of COVID-19's interaction with occupational characteristics, the labour market can be visualized as a venn diagram shown in Figure 1. This paper would predict positive increase in labour demand for teleworkable occupations during the pandemic considering business feasibility as a result of pandemic policies. In comparison to labour demand prior to the pandemic, occupations that are teleworkable would continue being able to provide goods and services online with minimal disruptions relative to occupations that are non-teleworkable. Furthermore, due to changes in consumer taste and restrictions with in-person contact, goods and services that are able to make the transition to an online environment will likely also face an increase in demands for goods and services relative to their non-teleworkable business counterparts. For businesses with contact-intensive occupations, due to preventative measures and restrictions, they will likely face temporary or permanent shut-downs if they are unable to transition easily to an online environment. Employability or labour demand for contact-intensive occupations will thus experience negative growth. For essential occupations, which broadly include occupations that support public health and safety, essential products, and other infrastructure support [4], they are likely going to experience an increase in labour demand compared to the occupations not included in the list of essential occupations. These essential occupations will continue to provide

[3] Referenced Indeed Internal data, average monthly unique visitors between April to September
[4] Referenced Bureau of Labour Statistics article

goods and services during the pandemic, and for some, they may even experience an even stronger demand for their goods and services as people begin to hoard essential products.

To summarize, when considering how pandemic policies impact business feasibility, this paper predicts that teleworkability and being classified as essential improves labour demand during the pandemic whilst being contact-intensive decreases an occupation's demand.

## 2 Data

This section outlines the fundamental components and classifications involved in constructing a dataset (Section 2.1) and presents descriptive statistics (Section 2.2).

### 2.1 Dataset Construction

This paper leverages a variety of publicly available data to assemble the final dataset. In order to proxy quantity of labor demand for each occupation reliably, similar to Bellatin and Galassi (2021), this paper utilizes high-frequency Canadian online job postings data provided by the Labour Market Information Council (LMIC) and the Future Skills Centre (FSC). The data repository consists of online job postings collected from thousands of Canadian websites and job boards [5] per month, per province, and at the 4-digit unit National Occupation Classification (NOC) level. Starting from January 2018 to September 2022, the dataset consisted of 55 months and 385 unique occupations.

To subset job postings based on teleworkability, contact-intensity, and essential or non-essential characteristics, this paper uses existing classifications or indices. All indices are coded as a binary variable. The 'Teleworkability' dimension references Dingel and Neiman's (2020) classification and paper. The authors utilized O*NET's Work Context Questionnaire and Generalized Work Activities Questionnaire to provide an upper-bound estimate of occupations that are teleworkable. The classification clearly rules out the possibility of working-at-home and may have ignored occupational characteristics that would make working-at-home difficult. Of 141 unit-level NOC occupations (excluding healthcare workers), 63 occupations have been identified as teleworkbale according to the index. The 'Contact-Intensity' dimension references the Federal Reserve at St. Louis' Leibovici, Santacreu, and Famiglietti (2020) classification. Leibovici and colleages (2020) combined individual-level data from the 2017 American Community survey with O*NET's index of Occupational Contact-Intensity to compute the egree to which job tasks are performed in close physical proximity to others. Three levels of intensity were identified in the final classification. To observe clear differences in COVID-19's impact on contact-intensive jobs, this paper only takes into account occupations that are either high contact-intensive or low contact-intensive according to the classification. Medium contact-intensive occupations will be excluded. Of the 977 6-digit unit Standard Occupation Code, the US equivalent of NOC 4-digit, 159 occupations are identified as contact-intensive while 272 are identified as a low-contact occupation. Lastly, the 'essential' dimension references the Labour Market Information Council's Rosenbaum (2020) Pan-Canadian List of Essential Services and Related Occupations, which documented provincial announcements of essential services to match occupational titles at the NOC 4-digit unit level. For example, the essential service

[5] The data repository cleaned and organized all job posting data using AI and big data technology powered by Vicinity. In particular, the firm used cascading style sheet selectors to retrieve job market information followed by feature extraction to process raw data into a form conducive to further statistical analysis. Then natural langauge processing was leveraged to remove fake and duplicate job postings (95% duplicates per month). Finally, machine learning and text classifiers were used to organize cleansed data into a specific set of NOC classification. It is important to note that 10-15% of job postings lacked enough detial to be matched.

”Pharmacies” would match NOC 4-digit unit level occupation ”pharmacist (3131),” ”other medical technologists and technicians (3219),” ”pharmacy clerks (6421),” etc. Of 59 essential services announced during the pandemic, the Pan-Canadian List of Essential Services found 273 unique NOC 4-digit unit level occupations. Using the same list, this paper excludes occupiations associated with the healthcare sector due to their unique development associated with the ongoing pandemic.

*Covariates.* Outside of the job posting data and the characteristics used to subset the labour market, this paper includes ‘COVID-19 stringency’ to control for how policy stringency during the pandemic period may have affected job postings independent of the job characteristics. ‘COVID-19 stringency’ is a continuous variable extracted from the Bank of Canada’s COVID-19 stringency index, which references the Oxford COVID-19 Government Response Tracker’s (OxGRT) methodology to construct the index. This dataset begins on Jan 1, 2020 to July 25, 2022 across each province and computes a value for daily stringency. Due to the granuarlity of the job posting data at the monthly level, average stringency is used as a covariate.

*Government Business Subsidies.* Finally, the main data source to investigate Canadian business subsidies during the pandemic is from the Canadian government website. This paper uses three of the four largest business subsidies - Canadian Emergency Wage Subsidy (CEWS), Canadian Emergency Rent Subsidy (CERS), and Canadian Recovery Hiring Program (CRHP) - to gain insight into the allocation efficiency of these subsidies. All three data sets uses NAICS to organize total amount approved to each industry and average employee.

### 2.2 Summary Statistics

Table 1 summarizes the key statistics for each occupational sub-group considering the three binary dimensions. Prominent examples are listed for intuitive interpretation of each sub-group. To maintain quality assurance, the job posting data is truncated at the 25 job posting level, which contributed to the panel data being unbalanced.

## 3 Methods

Let $S$ denote the state of the world, where $S = 1$ is when the state of the world has COVID-19 at time $t$ and $S = 0$ is the state of the world when there is no COVID-19 at time $t$. The parameter of interest in this paper would be to estimate $E[JobPostings_{i,t}^{S=1} - JobPostings_{i,t}^{S=0}|covid = 1]$, which can be interpreted as the average difference in number of job postings if the pandemic has happened compared to if the pandemic has never happened or the average treatment effect (ATE). However, it is impossible to observe the counterfactual $E[JobPostings_{i,t}^{0}|covid = 1]$ because COVID-19 has impacted all occupations despite varying levels of magnitudes. There is no dataset that measured what happened to job posting levels if COVID-19 did not spiral out of control starting March 2020. Therefore, this paper uses an identification assumption that average job postings before pandemic levels should continue after the pandemic, or $E[JobPostings_{i,t}^{S=0}|covid = 1] = E[JobPostings_{i,t}^{S=0}|covid = 0]$. In other words, to estimate the ATE of COVID-19, the parameter of interest $E[JobPostings_{i,t}^{S=1} - JobPostings_{i,t}^{S=0}|covid = 1]$ can be rewritten as $E[JobPostings_{i,t}^{S=1}|covid = 1] - E[JobPostings_{i,t}^{S=0}|covid = 0]$ instead.

Since the dimensions - teleworkability, essential or non-essential, and contact-intensity, varies among occupations but not over time, a random effects regression clustered at the NOC 4-digit unit level will be used to estimate the potential outcome ATE. Specifically, the following Random Effects regression model will be used:

$$JP_{i,t} = \beta_0 + \beta_1 tel_i + \beta_2 ess_i + \beta_3 CI_i + \beta_4 covid_t + \beta_5 covid * tel + \beta_6 cov * ess + \beta_7 cov * CI + \beta_8 ess * tel + \beta_9 ess * CI + \beta_{10} CI * tel + \beta_{11} covid * ess * tel + \beta_{12} cov * ess * CI + \beta_{13} cov * tel * CI + \beta_{14} CI * ess * tel + stringency + \epsilon \tag{1}$$

where $tel_i$ is a binary variable that takes value 1 if occupation $i$ is teleworkable, $ess_i$ is a binary variable that takes value 1 if occupation $i$ is essential, $CI_i$ is a binary variable that takes value 1 if occupation $i$ is contact-intensive, and $covid_t$ is a binary variable that takes value 1 if $t$ is equal or after March 2020.

# 4 Results

This section outlines the regression results and interpretation for each occupational sub-group to identify which occupational sub-group was impacted by the pandemic and its policy (Section 4.1). Secion 4.2 investigates which occupational characteristic could have strongly influenced labour demand towards a particular direction. Section 4.3 explores the allocation efficiency of government business subsidies using changes in labour demand as a metric.

## 4.1 Labour Demand of Each Occupation Sub-group

Running the specified econometrics random effects model clustered at the NOC 4-digit unit level yields coefficient values and robust standard errors shown in Table 2.

Following these coefficient results, a before and after solution calculation yields estimates for the average job postings (AJP) levels before COVID-19, during COVID-19, and the ATE or average job posting difference as a result of COVID-19 as shown in table 3. Significance shown is based on Wald test testing the significance of beta values for individual occupational sub-group prior to COVID-19 and during COVID-19. It can be noted that the ATE for some occupational groups is double the amount of pre-pandemic level average job-posings, which suggests that some occupations had a economic significant change as a result of the pandemic.

The treatment AJP lends insights to how employers were hiring during the pandemic compared to pre-pandemic levels. Intuitively, employers who are unable to sustain their business will not demand more workers or would even lay-off current workers. From the figures, occupations that are essential, contact-intensive, and non-teleworkable, such as transport truck drivers, are most negatively impacted by the pandemic relative to all other sub-groups. This is followed by occupations that are essential, non-contact-intensive, but essential, such as postal and courier service managers. Interestingly, from the figures derived in table 3, no dimension strongly dominates the change in labour demand negatively or positively as a result of pandemic policies. To investigate this further, a comparison between sub-groups conditional on other characteristics are used as seen in tables 4 to table 6.

## 4.2 Labour Demand of Each Occupational Characteristic

Table 4 shows the importance of contact intensity holding other occupational characteristics, teleworkability and essential classification, constant. Observable in the difference of the average job postings when varying contact-intensity, the signage and significance of contact-intensity is unclear and insignificant. This suggests that contrary to prior beliefs that occupations classified as contact-intensive likely faced a decrease in labour demand, the relationship is not strong. Contact-intensity's influence on labour demand is dependent on other characteristics.

Table 5 shows the importance of being essential holding other occupational characteristics, teleworkability and contact-intensity, constant. Unlike contact-intensity, the signage for the difference in average job posting is consistent. At the 10% significance level, being essential decreases an occupation's quantity of labour demand. This goes against economic intuition previously established - even though essential occupations were guaranteed to be able to continue providing goods and services relative to their non-essential counterparts, they demanded less extra labour during the pandemic. This suggests that there are other mechanisms that may have influenced essential or non-essential employers' decisions that are not accounted for. For example, the large subsidies provided by the central government may have influenced the reactions and decisions on how employers would hire or lay-off.

Table 6 shows the importance of teleworkability holding other occupational characteristics, essential classification and contact-intensity, constant. Similar to results investigating the essential classification, the signages are consistently negative. However, specific to teleworkability, being teleworkable significantly influences an occupation's labour demand negatively, which suggests a teleworkable occupation was less desired by employers during the pandemic compared to a non-teleworkable job holding other occupational characteristics constant. These results goes against economic intuition - given that teleworkable businesses are able to continue sell their goods and services, if not, at a higher demand, teleworkable occupations should be more demanded. A likely explanation for the negative signage could be changes in turnover rates from the employee's end as a result of health considerations during the pandemic. Compared to teleworkable occupations, Non-teleworkable occupations have an increased likelihood of health risk during the pandemic. Employees may resign in hopes to find an occupation that jeopardizes their health and future income stream, which causes businesses that are non-teleworkable to constantly be seeking for more people to replace those employees that have resigned. Complementing this mechanism, existing employees who hold teleworkable occupations are relatively less likely to resign considering the non-teleworkable alternatives. Thus, results may show slower growth in labour demand for teleworkable jobs while non-teleworkable jobs faced higher labour demand.

### 4.3 Government Business Subsidy Allocation

Over the span of 27 months, 112 billion CAD total was spent from the central Canadian government to subsidize businesses in different forms, such as rent subsidy, wage subsidy, or recovery hiring, during the unprecedented time. As shown previously, different occupational sub-groups with varying occupational characteristics experienced the negative impacts of the pandemic and its policies with different magnitudes. To analyze government subsidy data which aggregates to the North American Industry Classification System (NAICS), this paper matched each occupation to its appropriate NAICS to observe how each industry's quantity of labour demand has been impacted by COVID-19. The results are available in Table 7. It is clear again that while some industries seem to continue demand more employees, others experienced negative change in labour demand.

Figures 2 and 3 showcases government business subsidy allocation per industry per subsidy. Figure 2 suggests the percentage subsidy allocated to particular businesses are generally non-targeted at differences in average job postings as a result of COVID-19 or exacerbating the inequality in financial impact COVID-19 has caused to different industries. The wage and recovery hiring programs, in particular, seem to increase their subsidy as certain industries experience more labour demand. An interpretation of this could be in extension of the non-intuitive results shown whilst investigating the effect of each occupational characteristic on labour demand. For industries or

occupations that experience higher labour demand during the pandemic, it could be entirely motivated by increase in turnover. Therefore, governments are funding those occupations or industries that experience high turnover rate more to subsidize businesses during the unprecedented period.
Figure 3 showcases the same subsidies but specifically looking into the average subsidy received by employees in each industry. The relatively steeper line of best fit for the rent subsidy implies that there seems to be targeting going on when approving the allocation where industries that happen to not hire as much labourers due to the pandemic receives more subsidy. However, similar to that of the previous figure (Figure 2), there is no targeting for the wage subsidy or the hiring program.

# 5 Conclusion

This paper analyzed how labour demand of occupational sub-groups, divided based on teleworkability, contact-intensity, and the 'essential' classification, have changed due to the COVID-19 pandemic. From estimated results, no particular sub-group experienced COVID-19 similar to another due to the differences in occupational characteristics. Interestingly, when uncovering the importance of specific occupational characteristics in influencing labour demand during COVID-19, none of the results fit prior economic intuition discussed in the conceptual framework section. Occupations classified as teleworkable or essential experienced a decrease in labour demand during the pandemic. This non-intuitive results could be attributable to the assumption that COVID-19 and its policies only influences labour demand changes from the business feasibility aspect. However, it failed to consider how reactionary employers may be with subsidies or how employees may be motivated to resign their current occupation for an occupation that exposes them to less health-risk during the pandemic. The failure to control for certain mechanisms that could have explained the non-intuitive changes in labour demand would bias the beta coefficients yielded when running the random effects regression. Therefore, the figures observed when investigating the government subsidy allocation efficiency also needs to be re-evaluated.

*Discussion.* Since the current model does not control for certain determinants and provides non-intuitive signage, this warrants further investigation that looks labour demand determinants need to be controlled to fully understand the uneven changes to the labour market. The beta estimates yielded could be heavily biased by omitting variables such as turn-over rates or number of employees at time $t$. Both variables will lend insight to the total labour demanded by the particular occupation at time $t$. Additionally, this paper could include amount of subsidy provided at time t for occupation i in the future to account for how employers may hire differently when provided extra financial support.
Aside from omitted variable bias, the current paper also exhibits measurement error with the dependent variable, online job postings. There is likely an underestimation to the actual job vacancy in the labour market based on three rationales. Firstly, online job postings are more likely to capture urban jobs relative to rural jobs. Compared to urban occupations, rural occupations are likely to get filled up through word of mouth or physical job boards. Contingent to this notion, jobs that require less technology or are not as technical, are likely to also not get publicized in an online environment. Secondly, one job posting could represent multiple job vacancy. Even though big data technology and AI tries its best to extract all job posting information, employers may use one job posting to hire for multiple positions. Lastly, when a job posting gets taken down, there is no information to whether this is as a result of the job position being filled or they are no longer able to hire.
If this paper is able to get access to wage and payroll data to account for changes in turnover rate or get more

granular job posting data to minimize measurement error, the model can better predict and understand which occupation was most impacted by COVID-19. This also helps to answer how did the governments fund the different industries or occupations and whether there is room to allocate the funds more efficiently.

# References

Adams-Prassl, Abi et al. (2020). "Inequality in the impact of the coronavirus shock: Evidence from real time surveys". In: *Journal of Public Economics* 189.C, S0047272720301092. URL: https://EconPapers.repec.org/RePEc:eee:pubeco:v:189:y:2020:i:c:s0047272720301092.

Adrjan, Pawel and Reamonn Lydon (2019). *Clicks and jobs: measuring labor market tightness using online data.* Tech. rep. 6. Central Bank of Ireland. URL: https://www.centralbank.ie/docs/default-source/publications/economic-letters/vol-2019-no-6-clicks-and-jobs-measuring-labour-market-tightness-using-online-data-(adrjan-and-lydon).pdf.

Basso, Gaetano et al. (July 2020). *The new hazardous jobs and worker reallocation.* OECD Social, Employment and Migration Working Papers 247. OECD Publishing. DOI: 10.1787/400cf397-en. URL: https://ideas.repec.org/p/oec/elsaab/247-en.html.

Bellatin, Alejandra and Gabriela Galassi (Apr. 2022). *What COVID-19 May Leave Behind: Technology-Related Postings in Canada.* Research rep. Bank of Canada. URL: https://www.bankofcanada.ca/wp-content/uploads/2022/04/swp2022-17.pdf.

Brugiavini, Agar, Raluca E. Buia, and Irene Simonetti (2021). *Occupation and working outcomes during the Coronavirus Pandemic.* Working Papers 2021:09. Department of Economics, University of Venice "Ca' Foscari". URL: https://ideas.repec.org/p/ven/wpaper/202109.html.

Dingel, Jonathan and Brent Neiman (2020). "How many jobs can be done at home?" In: *Journal of Public Economics* 189.C, S0047272720300992. URL: https://EconPapers.repec.org/RePEc:eee:pubeco:v:189:y:2020:i:c:s0047272720300992.

Hensvik, Lena, Thomas Le Barbanchon, and Roland Rathelot (2021). "Job search during the COVID-19 crisis". In: *Journal of Public Economics* 194, p. 104349. ISSN: 0047-2727. DOI: https://doi.org/10.1016/j.jpubeco.2020.104349. URL: https://www.sciencedirect.com/science/article/pii/S0047272720302139.

Leibovici, Fernando, Ana M. Santacreu, and Matthew Famiglietti (2020). *Social Distancing and Contact-Intensive Occupations.* Tech. rep. Federal Reserve at St. Louis.

Madhav, Nita et al. (2017). *Chapter 17 Pandemics: Risks, Impacts, and Mitigation.* Tech. rep. The World Bank.

Marani, Marco et al. (2021). "Intensity and frequency of extreme novel epidemics". In: *Proceedings of the National Academy of Sciences* 118.35. DOI: 10.1073/pnas.2105482118. eprint: https://www.pnas.org/doi/pdf/10.1073/pnas.2105482118. URL: https://www.pnas.org/doi/abs/10.1073/pnas.2105482118.

Marinescu, Ioana and Ronald Wolthoff (Apr. 2020). "Opening the Black Box of the Matching Function: The Power of Words". In: *Journal of Labor Economics* 38.2. URL: https://www.journals.uchicago.edu/doi/full/10.1086/705903?af=R&mobileUi=0.

Messacar, Derek, René Morissette, and Zechuan Deng (June 2020). *Inequality in the feasibility of workingfrom home during and after COVID-19.* Research rep. 45280001. Statistics Canada. URL: https://www150.statcan.gc.ca/n1/en/pub/45-28-0001/2020001/article/00029-eng.pdf?st=MwZJob-T.

Mongey, Simon, Laura Pilossoph, and Alexander Weinberg (Sept. 2021). "Which workers bear the burden of social distancing?" In: *The Journal of Economic Inequality* 19.3, pp. 509–526. DOI: 10.1007/s10888-021-09487-. URL: https://ideas.repec.org/a/spr/joecin/v19y2021i3d10.1007_s10888-021-09487-6.html.

Rosenbaum, Zoe (2020). *Essential Services and Occupations: A Pan-Canadian List.* Tech. rep. Labour Market Information Council.

Sinclair, Tara and Martha Gimbel (2020). *Mismatch in Online Job Search*. Working Papers. The George Washington University, Institute for International Economic Policy. URL: https://EconPapers.repec.org/RePEc:gwi:wpaper:2020-1.

Turrell, Arthur et al. (2019). "Transforming Naturally Occurring Text Data Into Economic Statistics: The Case of Online Job Vacancy Postings". In: *NBER Working Paper Series*.

# 6 Appendix

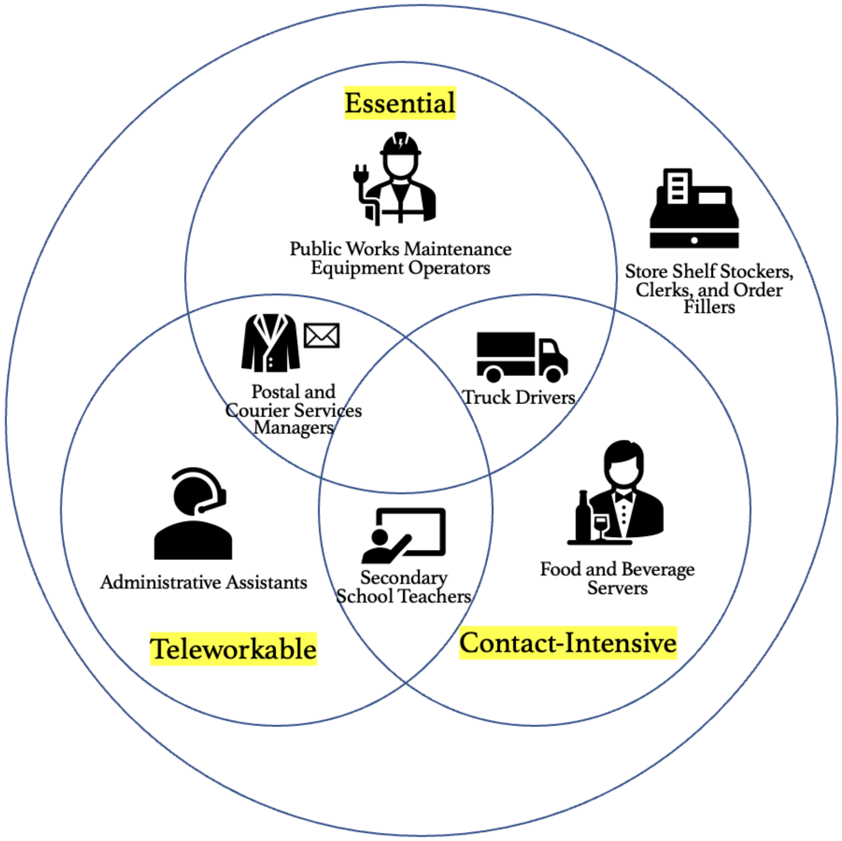


Figure 1: Figure 1. Division of Labour Market Based on Occupational Characteristics with Prominent Examples.

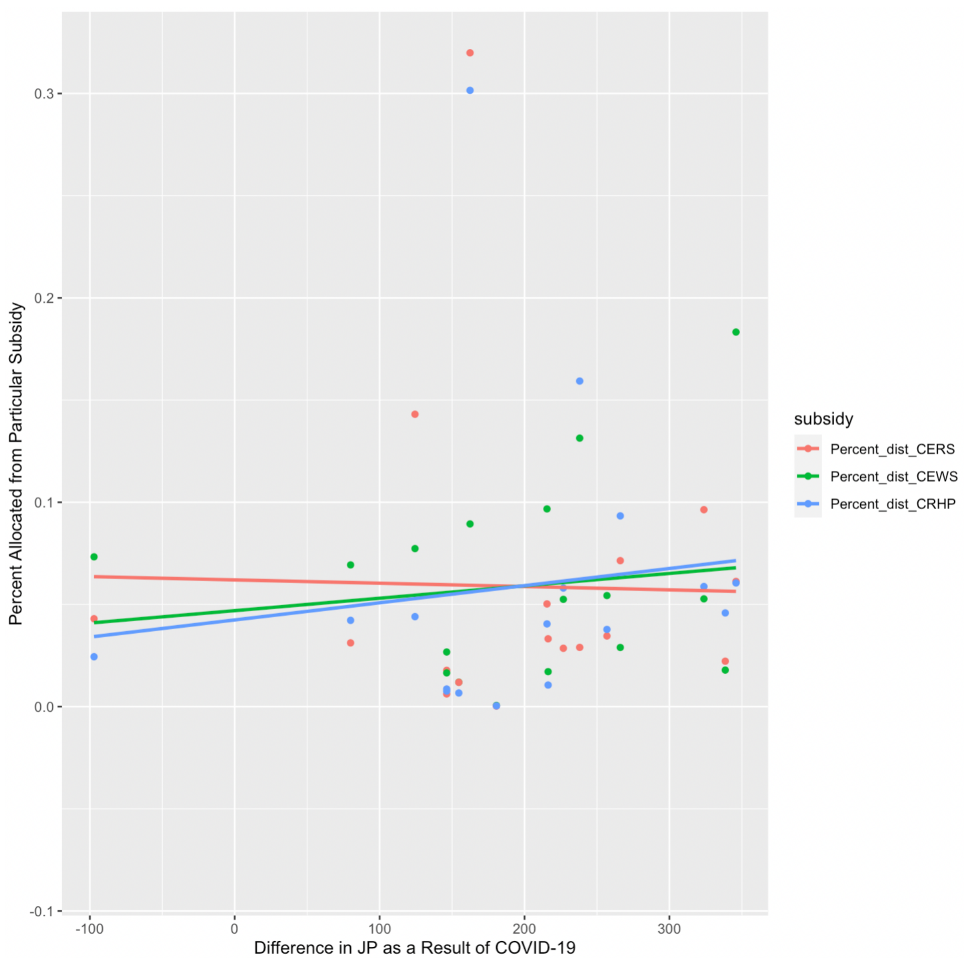


Figure 2: Relative Subsidy Allocated to Each Industry for Each Subsidy

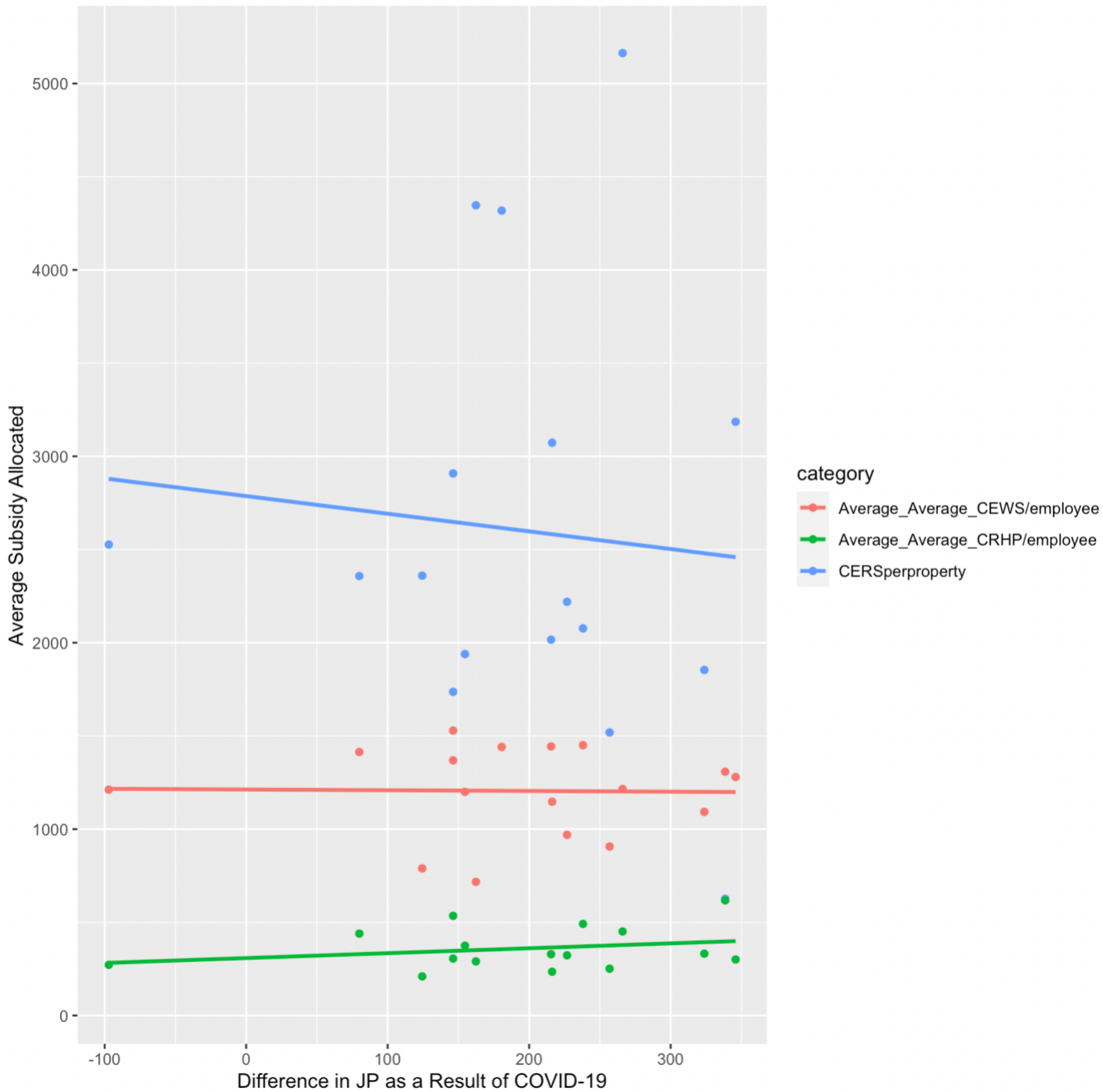


Figure 3: Average Subsidy per Employee to Each Industry for Each Subsidy

| # | CI | Tel | Ess | Prominent Examples | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | Material Handlers<br>Light Duty Cleaners<br>Store Shelf Stockers, Clerks, and Order Fillers | 1,486 | 501.0498 | 979.4756 | 25 | 7754 |
| 2 | 1 | 0 | 0 | Food and Beverage Servers<br>Bartenders<br>Other Assisting Occupations in Support of Health Services | 1,599 | 320.7011 | 384.909 | 25 | 2790 |
| 3 | 0 | 0 | 1 | Public Works Maintenance Equipment Operators and Related Workers<br>Railway and Motor Transport Labourers<br>Industrial and Manufacturing Engineers | 307 | 145.443 | 99.34172 | 25 | 504 |
| 4 | 1 | 0 | 1 | Registered Nurses and Registered Psychiatric Nurses<br>Delivery and Courier Service Drivers<br>Transport Truck Drivers | 220 | 2640.977 | 1236.849 | 642 | 5710 |
| 5 | 0 | 1 | 0 | Administrative Assistants<br>Administrative officers<br>Financial Sales Representatives | 2,594 | 568.2571 | 876.7018 | 25 | 7127 |
| 6 | 1 | 1 | 0 | Other Technical Occupations in Therapy and Assessment<br>Secondary School Teachers<br>Other Instructors | 318 | 163.7296 | 79.94077 | 26 | 513 |
| 7 | 0 | 1 | 1 | Retail and Wholesale Trade Managers<br>Technical Sales Specialists - Wholesale Trade<br>Postal and Courier Services Managers | 115 | 2004.374 | 2012.033 | 25 | 6777 |
| 8 | 1 | 1 | 1 | NA | 0 | | | | |

Table 1: **Summary Statistics and Prominent Examples of Each Occupational Sub-Group.**

| Input Variable | Estimate |
|---|---|
| constant | $287.11^{**}$ <br> 107.37 |
| teleworkability | 237.86 <br> (160.36) |
| essential | $-169.32$ <br> (115.50) |
| contact-intensity | $-7.18$ <br> (62.89) |
| covid | $345.93^{***}$ <br> (89.51) |
| covid # teleworkability | $-199.66^{*}$ <br> (79.48) |
| covid # essential | $-115.89.$ <br> (69.48) |
| covid # contact-intensity | $-44.27$ <br> (31.73) |
| essential # teleworkability | $1163.18^{*}$ <br> (1148.57) |
| essential # contact-intensity | $1139.90^{***}$ <br> (279.01) |
| contact-intensity # teleworkability | $-190.86$ <br> (86.68) |
| covid # essential # teleworkability | $-127.49$ <br> (171.92) |
| covid # essential # contact-intensity | $276.50^{*}$ <br> (122.94) |
| covid # teleworkability # contact-intensity | $98.88^{*}$ <br> (41.77) |
| contact-intensity # essential # teleworkability | omitted |
| covid # contact-intensity # essential # teleworkability | omitted |
| stringency | omitted |
| Time Dummies | Yes |
| $\sigma_u$ | 838.56 |
| $\sigma_e$ | 288.55 |
| $\rho$ | 0.89 |

Table 2: **Random Effects Regression estimates for total job postings.** Note: The robust clustered standard errors are in parentheses; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, . $p < 0.1$. All terms with # denotes interactions.

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | Treatment AJP |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | Material Handlers<br>Light Duty Cleaners<br>Store Shelf Stockers, Clerks, and Order Fillers | 287.1112*** | 633.0377*** | 345.9265*** |
| 1 | 0 | 0 | Food and Beverage Servers<br>Bartenders<br>Other Assisting Occupations in Support of Health Services | 279.928435*** | 581.582115*** | 301.65368*** |
| 0 | 0 | 1 | Public Works Maintenance Equipment Operators and Related Workers<br>Railway and Motor Transport Labourers<br>Industrial and Manufacturing Engineers | 117.7925*** | 347.8264*** | 230.0339*** |
| 1 | 0 | 1 | Registered Nurses and Registered Psychiatric Nurses<br>Delivery and Courier Service Drivers<br>Transport Truck Drivers | 1250.512735*** | 878.43342*** | −372.079315*** |
| 0 | 1 | 0 | Administrative Assistants<br>Administrative officers<br>Financial Sales Representatives | 524.9747*** | 671.240*** | 146.2653*** |
| 1 | 1 | 0 | Other Technical Occupations in Therapy and Assessment<br>Secondary School Teachers<br>Other Instructors | 326.930535*** | 527.807905*** | 200.87737*** |
| 0 | 1 | 1 | Retail and Wholesale Trade Managers<br>Technical Sales Specialists - Wholesale Trade<br>Postal and Courier Services Managers | 1518.834*** | 1421.7171*** | −97.1169*** |
| 1 | 1 | 1 | NA | 2460.692835*** | 2694.685005*** | 233.99217*** |

Table 3: **Average Job Postings Estimates Per Occupational Sub-Group Before, After, and as a Result of COVID-19.** Note: The robust clustered standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, . $p < 0.1$

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 1 | 0 | 1 | Delivery and Courier Service Drivers<br>Transport Truck Drivers | 1250.512735*** | 878.43342*** | −372.079315*** |
| 0 | 0 | 1 | Railway and Motor Transport Labourers<br>Industrial and Manufacturing Engineers | 117.7925*** | 347.8264*** | 230.0339*** |
| | | | | | | −602.113215. |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 1 | 1 | 0 | Secondary School Teachers<br>Other Instructors | 326.930535*** | 527.807905*** | 200.87737*** |
| 0 | 1 | 0 | Administrative officers<br>Financial Sales Representatives | 524.9747*** | 671.240*** | 146.2653*** |
| | | | | | | 54.61207* |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | Bartenders<br>Other Assisting Occupations in Support of Health Services | 279.928435*** | 581.582115*** | 301.65368*** |
| 0 | 0 | 0 | Light Duty Cleaners<br>Store Shelf Stockers, Clerks, and Order Fillers | 287.1112*** | 633.0377*** | 345.9265*** |
| | | | | | | 44.27282 |

Table 4: **Significance of 'Contact-Intensity' Dimension Influence on Average Job Postings Before, After, and as a Result of COVID-19.** Note: The robust clustered standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, . $p < 0.1$

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 1 | 0 | 1 | Delivery and Courier Service Drivers<br>Transport Truck Drivers | 1250.512735*** | 878.43342*** | −372.079315*** |
| 1 | 0 | 0 | Bartenders<br>Other Assisting Occupations in Support of Health Services | 279.928435*** | 581.582115*** | 301.65368*** |
| | | | | | | −673.732995* |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 0 | 1 | 1 | Technical Sales Specialists - Wholesale Trade<br>Postal and Courier Services Managers | 1518.834*** | 1421.7171*** | −97.1169*** |
| 0 | 1 | 0 | Administrative officers<br>Financial Sales Representatives | 524.9747*** | 671.240*** | 146.2653*** |
| | | | | | | −243.3822· |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 0 | 0 | 1 | Railway and Motor Transport Labourers<br>Industrial and Manufacturing Engineers | 117.7925*** | 347.8264*** | 230.0339*** |
| 0 | 0 | 0 | Light Duty Cleaners<br>Store Shelf Stockers, Clerks, and Order Fillers | 287.1112*** | 633.0377*** | 345.9265*** |
| | | | | | | −115.8926· |

Table 5: **Significance of 'Essential' Dimension on Average Job Postings Before, After, and as a Result of COVID-19.** Note: The robust clustered standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, . $p < 0.1$

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 0 | 1 | 1 | Technical Sales Specialists - Wholesale Trade<br>Postal and Courier Services Managers | 1518.834*** | 1421.7171*** | −97.1169*** |
| 0 | 0 | 1 | Railway and Motor Transport Labourers<br>Industrial and Manufacturing Engineers | 117.7925*** | 347.8264*** | 230.0339*** |
| | | | | | | −327.1508*** |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 1 | 1 | 0 | Secondary School Teachers<br>Other Instructors | 326.930535*** | 527.807905*** | 200.87737*** |
| 1 | 0 | 0 | Bartenders<br>Other Assisting Occupations in Support of Health Services | 279.928435*** | 581.582115*** | 301.65368*** |
| | | | | | | −100.77631*** |

| CI | Tel | Ess | Prominent Examples | Pre-COVID AJP | COVID AJP | diff AJP |
|---|---|---|---|---|---|---|
| 0 | 1 | 0 | Administrative officers<br>Financial Sales Representatives | 524.9747*** | 671.240*** | 146.2653*** |
| 0 | 0 | 0 | Light Duty Cleaners<br>Store Shelf Stockers, Clerks, and Order Fillers | 287.1112*** | 633.0377*** | 345.9265*** |
| | | | | | | −199.6612*** |

Table 6: **Significance of 'Teleworkability' Dimension on Average Job Postings Before, After, and as a Result of COVID-19.** Note: The robust clustered standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, . $p < 0.1$

| NAICS | Pre-COVID AJP | COVID AJP | treatment AJP |
|---|---|---|---|
| 11 Agriculture, Forestry, Fishing & Hunting | 285.9140725 | 624.4617692 | 338.5476967 |
| 23 Construction | 261.917725 | 499.982625 | 238.0649 |
| 33 Manufacturing | 287.1112 | 633.037 | 345.9258 |
| 41 Wholesale Trade | 1518.83 | 1421.7171 | -97.1129 |
| 44 Retail Trade | 902.9706 | 1027.37705 | 124.40645 |
| 48-49 Transportation & Warehousing | 658.0685594 | 738.0242106 | 79.95565125 |
| 51 Information & Cultural Industries | 524.9747 | 671.24 | 146.2653 |
| 52 Finance & Insurance | 484.25648 | 638.89864 | 154.64216 |
| 54 Professional, Scientific & Technical Services | 424.7218392 | 640.2188062 | 215.4969669 |
| 55 Management of Companies & Enterprises | 524.9747 | 671.24 | 146.2653 |
| 56 Administrative Support, Waste Management & Remediation Services | 377.8231667 | 604.6034 | 226.7802333 |
| 61 Education Services | 377.2778883 | 593.54334 | 216.2654517 |
| 62 Health Care & Social Assistance | 349.826511 | 606.7069702 | 256.8804593 |
| 71 Arts, Entertainment & Recreation | 382.2566 | 648.3182 | 266.0616 |
| 72 Accommodation & Food Services | 527.364207 | 689.756884 | 162.392677 |
| 81 Other Services, except Public Administration | 283.5198175 | 607.3095575 | 323.78974 |
| 91 Public administration | 454.5356067 | 635.1214233 | 180.5858167 |

Table 7: **Estimated Average Total Job Postings per NAICS Industry**