Remote Work and Employment Dynamics under Covid-19: Evidence from Canada*

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Abstract

We find that 41 percent of jobs in Canada can be performed remotely, with significant variation across provinces, cities, territories and industries. We complement this with labor micro data and document facts on the relationship between remote work and income inequality, gender, age and other worker characteristics. We then show that workers in occupations (and sectors) less likely to be able to work remotely experienced larger employment losses between February and March but not between March and April. This suggests that the pandemic shock hit harder and sooner those workers that could not work from home. As the crisis spread to the rest of the economy, the speed of job destruction converged across occupations, in line with occupation/sector complementarity and input-output linkages.

Keywords: Covid-19, Canada, labor markets, remote work, job destruction.

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1 Introduction

“Social distancing" is costly since some jobs cannot be performed at home. A key estimate to assess the economic impact of the Covid-19 pandemic is the percentage of jobs can be done remotely. Motivated by this, in this paper we focus on Canada and estimate the feasibility of working from home, as well as the heterogeneity of this variable along several dimensions. We then measure the employment changes during March and April 2020 and compare these changes with the computed feasibility of working remotely.

In Section (2) we provide a literature review and describe our contribution. In Section (3) we compute the percentage of jobs that can be performed at home. We find that 41 percent of jobs in the Canada can be performed remotely, with significant variation across provinces, cities, territories, industries and worker characteristics. In Section (4) we use labor micro data and document that female workers and immigrants tend to work in occupations with more possibility of working remotely. On the other hand, poorer workers, younger workers, part-time workers, small firm workers, seasonal/contractual workers, single workers and workers without a college degree tend to be employed in jobs that are less likely to be performed at home. We then show that workers in occupations (and sectors) less likely to be able to work remotely experienced larger employment losses between February and March but not between March and April.

2 Literature Review

We follow the methodology in Dingel and Neiman [2020] to measure the percentage of jobs that can be done at home. This methodology has been since applied to other countries. For instance, Saltiel [2020] focuses on a sample of developing countries. We complement this methodology with worker characteristics. The worker characteristics and distributional aspect has been studied among others by Mongey et al. [2020] and Yasenov [2020] the USA, Lekfuangfu et al. [2020] in Thailand and Bonavida Foschiatti and Gasparini [2020] in Argentina.

We contribute to this literature by adding Canadian estimates. Our results are in line with all these findings. However, we go beyond this and study the link with the recent employment dynamics data.

In terms of employment dynamics, our paper is closest to the ones studying job vacancies. Lange and Warman [2020] reports that in Canada there were very rapid declines in vacancy postings as the COVID-19 crisis brought the economy to a halt in mid-March. Postings declined by up to 50% until mid-April. Kahn et al. [2020], study the changes in job vacancies and unemployment insurance claim for different occupations and industries during the pandemic in the USA.

Relative to these two papers, we focus on actual employment losses, not vacancy postings nor UI claim and are also able to observe representative labor market data for the entire country.

We view our paper as complementary to the increasing macroeconomic literature (see Baqaee and Farhi [2020] and references there in) that incorporates complementarities between occupations and sectors, as well as input-output linkages. We think that models and empirical estimations that incorporate and measure these crucial network effects will be important to better understand the current unfolding crisis.

3 Remote Work Estimation

We apply the methodology of Dingel and Neiman [2020] (DN henceforth) to Canadian data. The main idea in DN is to classify the feasibility of working at home for all occupations and merge this classification with occupational employment counts. The feasibility measure is based on responses to two Occupational Information Network (O*NET) surveys.[1] DN estimate that up to 37% of jobs can be plausibly done from home in the USA, and provide estimates for a large sample of countries (but not Canada).

We use the Stats Canada's Employment Income Statistics (EIC henceforth), a tabulation from the 2016 Census that contains 4-digit occupation classification employment counts at the provincial, city and territorial level (51 geographic areas in total). The classification code corresponds to the National Occupational Classification (NOC). The EIS also contains average income, which we will use to compute percentage of wages (in addition to percentage of jobs).

We use the Brookfield Institute for Innovation + Entrepreneurship (BII+E) crosswalk of O*NET with NOC. We then merge with O*NET's binary index computed by DN. We call this "benchmark" remote-work index.[2]

As robustness check, we then manually assign values for the NOC categories, using introspection (as in the robustness check in DN) and call this the "alternative" remote-work index.[3] For a small set of occupations, however, the two methodologies do reach opposite conclusions. Appendix Table (A1) reports the 4-digit occupation codes for which the two measures differ more than 0.75 or more. According to our benchmark classification based on O*NET (and DN), engineers and journalists cannot work from home, whereas our manual classification says that they can. Our benchmark classification codes photographers, painter, air traffic controllers, administrative assistants, land survey technologists and technicians and forestry professionals as able to work from home, whereas the manual classification says that they cannot.

[1] These are the"Work Context" and "Generalized Work Activities", which provide data on whether an occupation required daily work outdoors, operating vehicles, mechanized devices, equipment, physical activities and other characteristics relevant for the possibility of remote work.

[2] One issue that we faced was that the O*NET occupation classification in BII+E and DN have some discrepancies. After merging with the NOC data, there were 17 occupations dropped. Please refer to the replication package for details

[3] Two of our research team manually assigned values of 0, 0.5 and 1 to each 4-digit NOC code, which we then averaged.

3.1 Results

Table 1: Share of jobs that can be done at home

Unweighted	Weighted by Wages
0.41	0.51

According to our estimates, 41% of jobs can be done from home in Canada. When weighted by wages, this percentage increases to 51%. The robustness check estimates for our alternative specification are in line with these, but somewhat lower: 37% and 48%, respectively (all robustness checks are available in the replication package). The higher estimate when weighting by wages indicates that higher wage jobs tend to be associated with jobs that can be more easily performed remotely. We will go back to this point later with the micro data. DN document that the former numbers is 37% in the USA. Even though DN do not report Canadian estimates, our results are consistent with DN's international evidence.[4]

Table 2: Share of jobs that can be done at home, by province

Province	Unweighted	Weighted by Wages
Ontario	0.44	0.55
Quebec	0.42	0.51
British Columbia	0.41	0.48
Alberta	0.39	0.47
Manitoba	0.38	0.45
Nova Scotia	0.38	0.45
New Brunswick	0.37	0.43
Saskatchewan	0.35	0.41
Prince Edward Island	0.35	0.43
Newfoundland and Labrador	0.32	0.38

As can be seen in Table (2), there is considerable heterogeneity among Canadian provinces. While Ontario has a high share of jobs that can be done at home (44%), Newfoundland and Labrador is the province in which the least amount of jobs can be done at home, with 32%.

We also observe heterogeneity at the city level. In Table (3) we report the estimates for the 10 largest cities. Ottawa, Toronto and Montreal lead this telecommuting ranking (with roughly half of jobs being able to do from home). We also included in the last row the aggregated smaller cities estimates.

The full sample of cities can be seen in Table (A2). Figure (1) shows the relationship between the estimated share of jobs that can be performed remotely and city size. As can be observed, there is a positive, non-linear relationship.

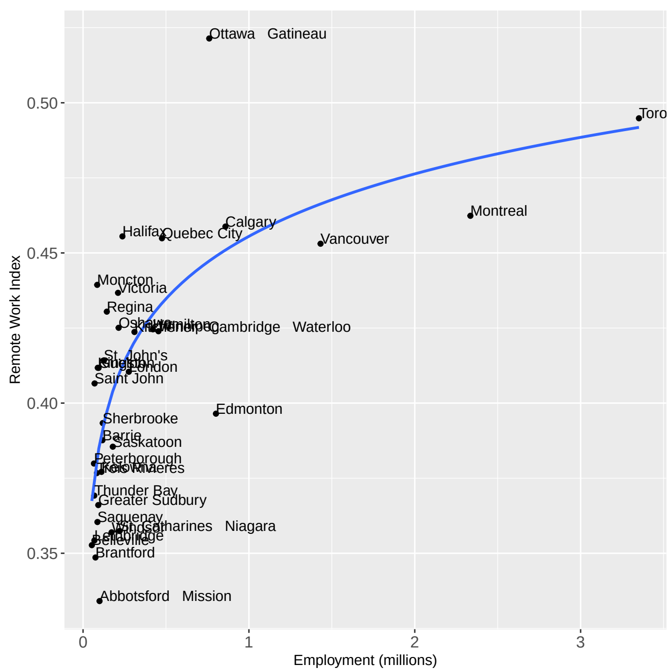
Lastly, Table (A3) reports the territorial distribution. Northwest Territories, Yukon and Nunavut don't show much differences, with roughly 42%. We also provide an estimate for rural areas: rural areas have a

[4]See Figure 2 in DN and recall that Canada's GDP per capita is around 46,000 USD

Table 3: Share of jobs that can be done at home, 10 largest cities and (aggregated) smaller cities

City	Unweighted	Weighted by Wages	National Employment Share
Ottawa Gatineau	0.52	0.63	0.04
Toronto	0.49	0.63	0.17
Montreal	0.46	0.56	0.12
Calgary	0.46	0.59	0.04
Quebec City	0.45	0.54	0.02
Vancouver	0.45	0.55	0.07
Hamilton	0.42	0.52	0.02
Winnipeg	0.42	0.50	0.02
Kitchener Cambridge Waterloo	0.42	0.52	0.02
Edmonton	0.40	0.45	0.04
Rest of smaller cities	0.40	0.46	0.16

Figure 1: Remote-Work Index and City Size



remote work index of 32% and contain 27% of Canada's employment.[5]

4 Worker Characteristics and Employment Dynamics

Next, we explore the Labor Force Survey (LFS), which contains Canadian labor micro data at the 2-digit occupation level. We assign remote index values by taking a weighted average across the 4-digit sub cate-

[5]The rural estimate was computed indirectly, since we only observe urban and aggregate employment: employment in Canada is the sum of rural and urban employment, $E_{CAN} = E_{Rural} + E_{Urban}$. Furthermore, the remote-work share for Canada S_{CAN} is a weighted average of the urban and rural shares, $S_{CAN} = \frac{E_{Urban}}{E_{Can}} \times S_{Urban} + \frac{E_{Rural}}{E_{Can}} \times S_{Rural}$. Using the first equation in the second and rearranging yields $S_{Rural} = \frac{E_{Can} \times S_{CAN} - E_{Urban} \times S_{Urban}}{E_{CAN} - E_{Urban}}$.

gories.

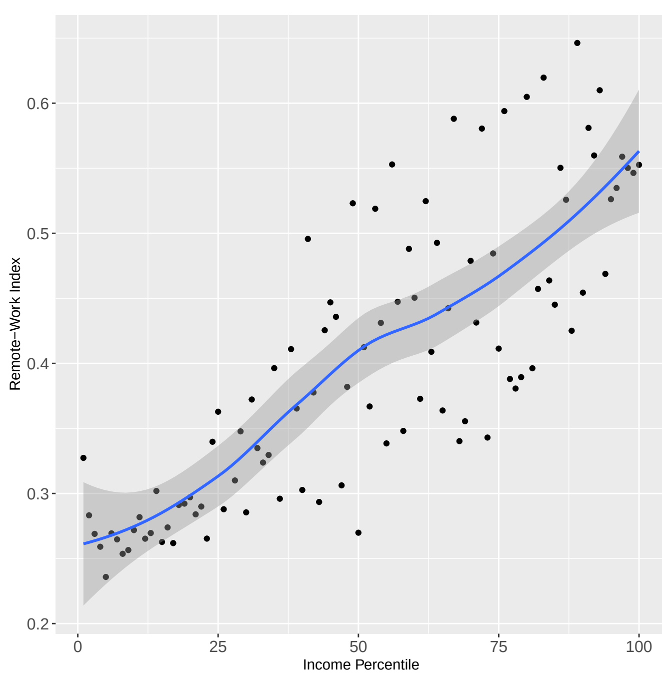
In Tables (A4) and (A5) we document that the provincial and city estimates using the LFS are consistent with those reported before. Additionally, in Table (A6) we report the estimation by industry: as can be observed, sectors such as Finance and Insurance report the largest percentage of ability to perform remote work, while Agriculture is the sector with the least amount of possibility of working from home.

4.1 Workers Characteristics

What type of workers are more vulnerable to this labor market shock? We use the 2019 LFS data to document correlations of worker characteristics and the possibility to work from home. We fist explore the distributional dimension. In Figure (2) we report the remote-work index by percentile of the income distribution. Each dot represents the average of the corresponding percentile, and the line represents the conditional mean with corresponding standard errors.

This figure shows that higher income workers are on average more likely to be able to work from home. This would suggest that social-distancing is regressive, in the sense that poorer workers tend to work in jobs that that are more difficult of being performed remotely. Note that this is consistent with the findings in the previous section on higher share of jobs that can be done at home when weighting by wages.[6]

Figure 2: Remote-Work Index and the Distribution of Income



[6]However, one can argue that if health outcomes are included, social-distancing might not be regressive, or at least not as much as this figure suggests. This is because poorer people are more vulnerable to Covid-19. We hope to explore this more in future work.

We then explore other worker characteristics. Here we follow the methodology in analysis in Mongey et al. [2020] (MPW henceforth), which focused on the USA. We run a simple regression as in MPW. Let y_{ij} be a characteristic of a worker i that reports that they mostly worked in occupation j in 2019. We construct binary variables based on the worker characteristics of LFS 2019 (following MPW); for example we construct a variable y_{ij} if the continuous variable 'wage' is above the median. We then estimate the following regression for each of our observables, where S_j is the 2-digit occupation index remote-work score:

$$y_{ij} = \alpha_y + \beta_y S_j + \varepsilon_{ij} \tag{1}$$

We then plot the values for $\hat{\beta}_y$ in Figure (3).[7] As an example to understand the interpretation of $\hat{\beta}_y$, let's take the case of below than median income: since $\hat{\beta}_y < 1$, then workers with below median income tend to be in occupations that are less likely to be able to remote work. This is consistent with the findings reported in Section 3 as well as the discussion of Figure (2).

Our results suggest that female workers and immigrations tend to work in occupations with more possibility of working remotely. On the other hand, younger (less than 50 years) workers, part-time workers, small firm workers, seasonal/contractual workers, single workers and workers without a college degree tend to be employed in jobs that are less likely to be performed at home.

The rest of characteristics can be analyzed in a similar fashion: female workers and immigrations tend to work in occupations with more possibility of working remotely. On the other hand, younger (less than 50 years) workers, part-time workers, small firm workers, seasonal/contractual workers, single workers and workers without a college degree tend to be employed in jobs that is less likely to be performed at home These results are overall consistent with the findings of MPW for the USA.

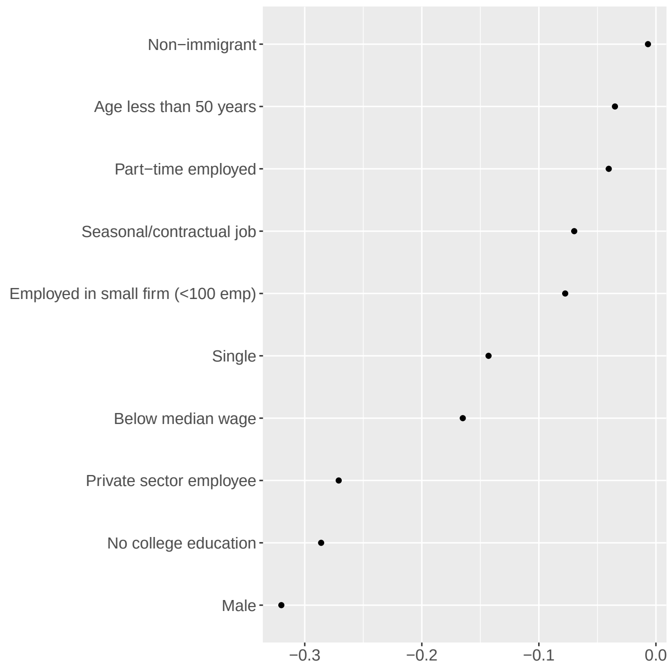
4.2 Employment Dynamics

We then obtain the March and April 2020 LFS data, and compare with the February 2020 (before the social distancing measures in Canada). In Figure (4) we can see that 2-digit occupations that have higher telecommuting index values experiences smaller employment declines. This holds for the February-March 2020 period (Figure (4a)) but not for the March-April 2020 period (Figure (4b)).

As can be observed in the Figures, we control for jobs deemed essential by public policy. For example,

[7] As explained in MPW, this sample moment gives $\hat{\beta}_y = \mathbb{E}\left[y_{ij}\middle|S_j = 1\right] - \mathbb{E}\left[y_{ij}\middle|S_j = 0\right]$ where $\mathbb{E}$ is the sample mean. Given that y_{ij} is binary, β_y simply gives the fraction of workers for which $y_{ij} = 1$ in low work-from-home occupations, relative to the fraction of workers for which y_{ij} in high work-from-home occupations. Note that $\hat{\beta}_y \in [0,1]$ and takes the maximum value of 1 when $y_{ij} = 1$ for all individuals for which $S_j = 1$, and $y_{ij} = 0$ for all individuals for which $S_j = 1$.

Figure 3: Worker characteristics and likelihood of having a job that can be done at home



front line medical workers have low jobs scores (0), but because they have been declared essential they can continue to work. For instance, “Occupations in front-line public protection services" has a 0 in the job score, but was the only occupation category to experience employment gains.

We construct an “Essential-Service" dummy variable to take this important caveat into account.[8] As a robustness check, we then also use the 4-digit essential service binary classification done by Labour Market Information Council (LMIC), and aggregate into 2-digit by taking employment weighted averages, thus having now an index that is no longer binary.[9]

We formally test this relationship. For an occupation j, let employment be q_j and denote $\triangle q_{j,t,\tau}$ as the percent change in employment between period t and τ. We then run the following OLS regression, where S_j is the remote-work score of occupation j and D is the “essential-service” dummy variable (or alternatively the “essential service" variable as described in the previous paragraph, which we will denote as ES_j):

$$\triangle q_{j,t,\tau} = \alpha_j + \beta S_j + D_j + \varepsilon_j \tag{2}$$

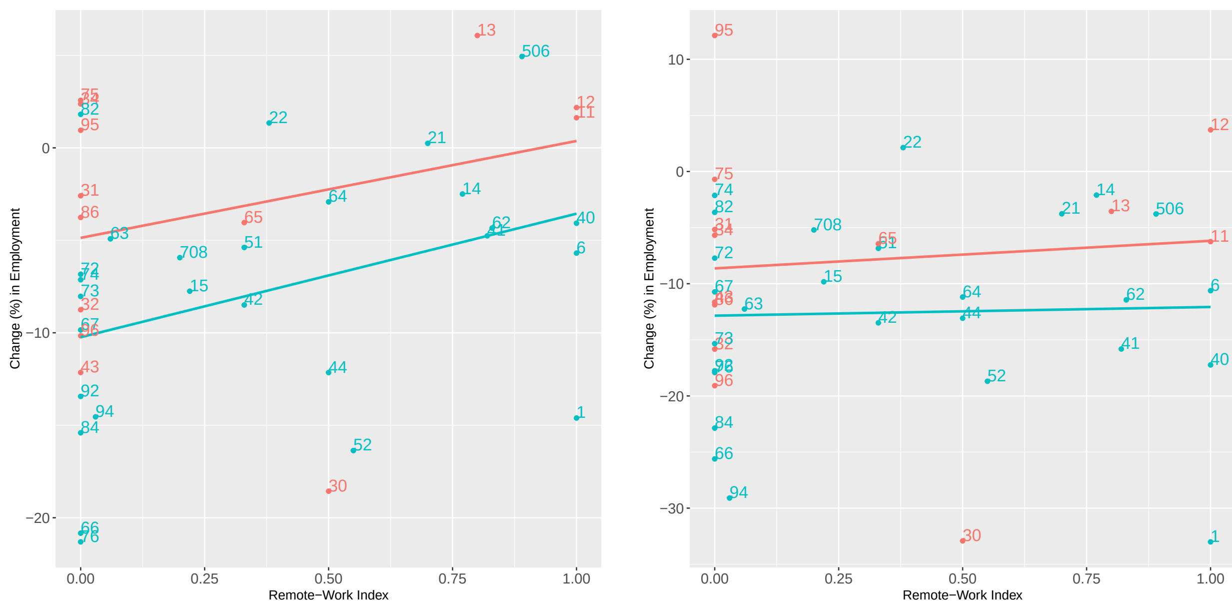
In Table (4) we can see the regression results. As can be observed, the remote-work index score variable

[8]We intuitively match the 2-digit occupations to the essential service sectors as listed by Public Safety Canada: Energy and Utilities, Information and Communication Technologies, Finance, Health, Food, Water, Transportation, Safety, Government, Manufacturing. We are aware of the subjectivity involved in the construction of this dummy variable. We thus complement this with the alternative essential service variable as robustness check (as described next).

[9]These two essential-service measures turn out to have some differences. For instance, occupations linked with “finance" and “manufacturing" were labelled as essential by us but had a low value in the LMIC score. We treated them as essential because of Public Safety Canada linked both “Finance" and “Manufacturing" as essential-service sectors.

Figure 4: Employment Dynamics and Remote Work Index (2-digit occupation)

(a) February - March 2020 (b) March - April 2020



Note: in red are the essential service occupations and in green are the non-essential service occupations.

is positive and statistically significant only for the February-March change.

The lack of statistical significance for the January-February change (the “before the social distancing” observation) is expected, but is surprising in the March-April case. One interpretation is that the shock hit first (during March) the workers that could not remote-work. This patterns holds across all regression specifications, as seen in robustness check in Tables (A7) (alternative remote work index), (A8) (alternative essential service variable) and (A9) (both alternative remote work index and alternative essential service variable).

This suggests that the pandemic shock hit harder and sooner (in terms of job destruction) those workers that could not work from home.[10] As the crisis spread to the rest of the economy, the speed of job destruction converged across occupations, in line with occupation/sector complementarity and input-output linkages.[11]

Figure (A2) shows the correlations at the NOC 10 broad occupations level. The broad occupations that have low remote-work index (for example, occupations in manufacturing and utilities) experienced larger

[10] In terms of income, instead of job loss, the shock is mitigated via policy measures. For example, the Canada Emergency Response Benefit (CERB) gives financial support to employed and self-employed Canadians who are directly affected by COVID-19. This replacement income is a considerable part of low-wage workers income. Eligible people can receive $2,000 for a 4-week period. We leave for future research the impact on income.

[11] The interpretation of this intuition is as follows: If one thinks of the production process being a function of different occupation/tasks and different intermediate inputs, then shocks to specific occupations propagate to the rest of the economy (and hence rest of occupations) via two channels: complementarity in production and input-output linkages. Furthermore, complementarity in consumption might reinforce these supply side channels.

Table 4: Employment Change and Remote Work Index: 2-digit level

	Monthly Percentage Change in Employment							
	$\triangle q_{j,Jan,Feb}$		$\triangle q_{j,Feb,Mar}$		$\triangle q_{j,Mar,Apr}$		$\triangle q_{j,Feb,Apr}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	4.417	4.290	5.465*	6.178**	−1.850	−1.769	0.677	1.363
	(3.033)	(3.090)	(2.827)	(2.706)	(2.747)	(2.801)	(4.023)	(3.991)
D_j		0.879		−4.923**		−0.556		−4.739
		(2.506)		(2.195)		(2.272)		(3.237)
Constant	−2.062	−2.612	−8.207***	−5.129**	−2.504*	−2.157	−11.291***	−8.328***
	(1.553)	(2.219)	(1.448)	(1.944)	(1.407)	(2.012)	(2.060)	(2.867)
Observations	40	40	40	40	40	40	40	40
R^2	0.053	0.056	0.090	0.198	0.012	0.013	0.001	0.055
Adjusted R^2	0.028	0.005	0.066	0.155	−0.014	−0.040	−0.026	0.004

Note: *p<0.1; **p<0.05; ***p<0.01
$\triangle q_{j,t,\tau}$ is the percentage change in employment between month t and τ in occupation j,
$S_j(Benchmark)$ is the Remote Work Index and D_j is the Essential Service Dummy variable.
Source: author's calculations.

employment declines between February and March 2020 except for health occupations (Figure (A2a)). A similar pattern continued in the March-April variation and in this period, some high remote-work index occupation like management occupations experienced higher employment loss compare to the February-March, as seen in Figure (A2b). Regression results presented in Table (A10) however indicate that the variation in employment was not statistically explained by the remote-work index (we are not controlling for essential service occupations here).

We also report the correlation plots at the sectoral level in Figure (A3). For example, accommodation and food services is highly impacted by employment loss as it has low remote-work index value, and this declined continued until April. Regression results are presented in Table (A11), where as in the NOC-10 case there is not a statistically significant relationship.

At the provincial level, the relationship is less clear, as seen in Figure (A4) and Table (A12). The lack of relationship also holds at the city level, as seen in Figure (A5) and Table (A13): this however makes sense when one takes into account that many other factor affect employment losses, such as the severity of Covid-19 infections and the subsequent magnitude of social distancing (for instance Toronto has a high work from home index, but also was one of the worst hit cities due to -probably- being an international travel hub).

5 Conclusion

The magnitude of the Covid-19 shock on labor markets is historic. Policy makers around the world are responding as fast as possible to mitigate this shock. Understanding and designing policy during the crisis and after it (ease of lockdown and relaxing of social distancing) is crucial. This paper might help policy makers design better options.

In this paper we have provided three main set of results:

1. We find that 41 percent of jobs in the Canada can be performed remotely, with significant variation across provinces, cities, territories and industries.

2. We complement this with labor micro data and documents facts on the relationship between remote work and worker characteristics: our results suggest that female workers and immigrations tend to work in occupations with more possibility of working remotely. On the other hand, poorer workers, younger workers, part-time workers, small firm workers, seasonal/contractual workers, single workers and workers without a college degree tend to be employed in jobs that are less likely to be performed at home.

3. We then show that workers in occupations (and sectors) less likely to be able to work remotely experienced larger employment losses between February and March but not between March and April.

We argued that the last finding suggests that the pandemic shock hit harder and sooner those workers that could not work from home. As the crisis spread to the rest of the economy, the speed of job destruction converged across occupations, in line with occupation/sector complementarity and input-output linkages. This seems like an important channel for future research.

Future work with updated data could also extend and improve on the empirical findings. For instance, measuring the share of productivity or output instead of jobs seems. Also studying the impact of policy, such as the CERB financial support.

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A Plots and Tables

Table A1: Remote Work Index: Benchmark vs. Alternative Example Comparison

Occupation	Benchmark	Alternative
0621 Retail and wholesale trade managers	1	0
1222 Executive assistants	1	0
2254 Land survey technologists and technicians	1	0
1211 Supervisors, general office and administrative support workers	1	0
1214 Supervisors, mail and message distribution occupations	1	0
4422 Correctional service officers	1	0
5232 Other performers, n.e.c.	1	0
5221 Photographers	1	0
1215 Supervisors, supply chain, tracking and scheduling co-ordination occupations	1	0
0632 Accommodation service managers	1	0
6232 Real estate agents and salespersons	1	0
5252 Coaches	1	0
5241 Graphic designers and illustrators	1	0
5231 Announcers and other broadcasters	1	0
5136 Painters, sculptors and other visual artists	1	0
1241 Administrative assistants	1	0
4423 By-law enforcement and other regulatory officers, n.e.c.	1	0
2174 Computer programmers and interactive media developers	1	0
1435 Collectors	1	0
2272 Air traffic controllers and related occupations	1	0
2115 Other professional occupations in physical sciences	1	0
9472 Camera, platemaking and other prepress occupations	1	0
5132 Conductors, composers and arrangers	1	0
2122 Forestry professionals	1	0
1314 Assessors, valuators and appraisers	0	1
2132 Mechanical engineers	0	1
6222 Retail and wholesale buyers	0	1
2241 Electrical and electronics engineering technologists and technicians	0	1
2141 Industrial and manufacturing engineers	0	1
2232 Mechanical engineering technologists and technicians	0	1
5243 Theatre, fashion, exhibit and other creative designers	0	1
5123 Journalists	0	1

Figure A1: Index Comparison

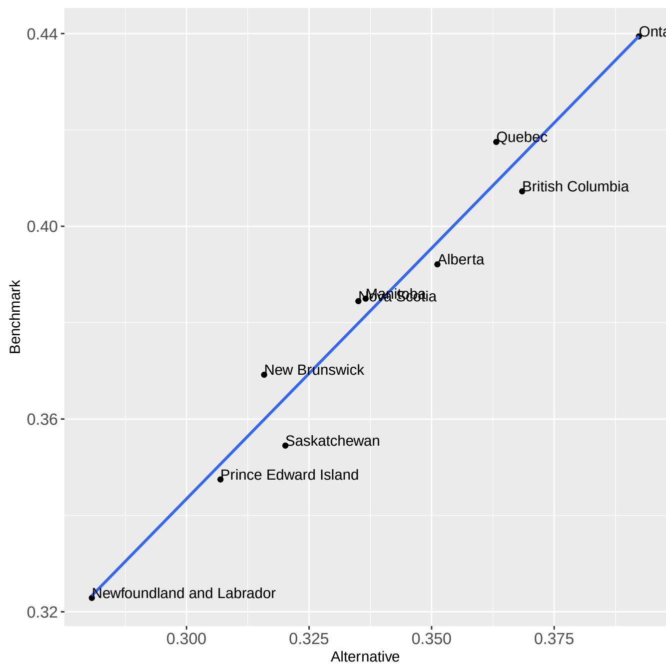
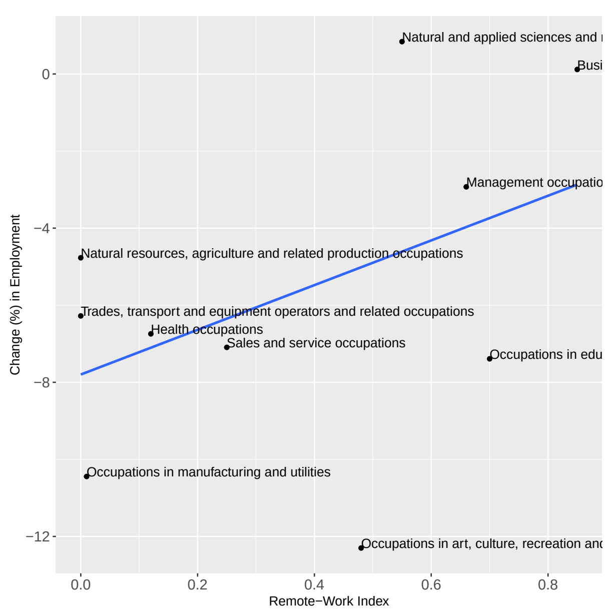


Figure A2: Employment Dynamics and Remote Work Index (10 NOC broad occupation groups)

(a) February - March 2020, % change



(b) March - April 2020, % change

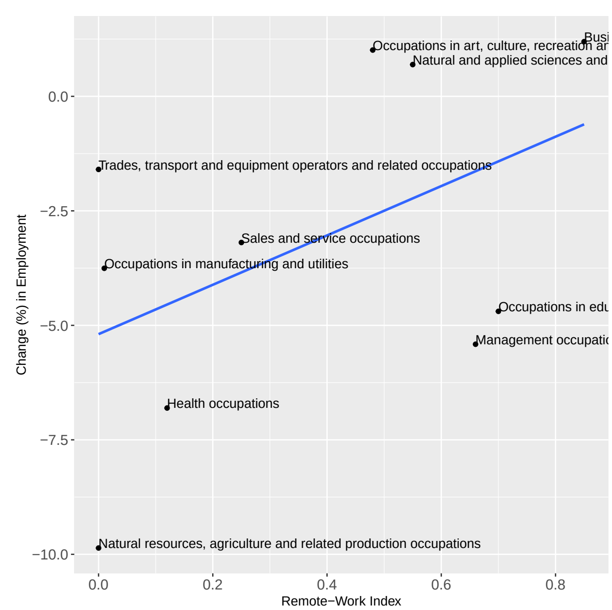


Table A2: Share of jobs that can be done at home, by city

City	Unweighted	Weighted by Wages
Ottawa Gatineau (Ontario part)	0.53	0.65
Ottawa Gatineau	0.52	0.63
Toronto	0.49	0.63
Ottawa Gatineau (Quebec part) City	0.49	0.58
Montreal	0.46	0.56
Calgary	0.46	0.59
Halifax	0.46	0.54
Quebec City	0.45	0.54
Vancouver	0.45	0.55
Moncton	0.44	0.52
Victoria	0.44	0.52
Regina	0.43	0.50
Oshawa	0.43	0.50
Hamilton	0.42	0.52
Winnipeg	0.42	0.50
Kitchener Cambridge Waterloo	0.42	0.52
St. John's	0.41	0.49
Kingston	0.41	0.49
Guelph	0.41	0.51
London	0.41	0.49
Saint John	0.41	0.46
Edmonton	0.40	0.45
Sherbrooke	0.39	0.46
Barrie	0.39	0.45
Saskatoon	0.39	0.45
Peterborough	0.38	0.45
Kelowna	0.38	0.43
Trois Rivieres	0.38	0.44
Thunder Bay	0.37	0.41
Greater Sudbury	0.37	0.40
Saguenay	0.36	0.40
St. Catharines Niagara	0.36	0.43
Windsor	0.36	0.43
Lethbridge	0.35	0.40
Belleville	0.35	0.40
Brantford	0.35	0.42
Abbotsford Mission	0.33	0.38

Table A3: Share of jobs that can be done at home, by territory

Territory	Unweighted	Weighted by Wages
Northwest Territories	0.43	0.50
Yukon	0.42	0.48
Nunavut	0.42	0.53

Table A4: Share of jobs that can be done at home, by province (LFS estimates)

Provinces	Benchmark	Alternative
Ontario	0.41	0.39
Alberta	0.39	0.38
British Columbia	0.39	0.37
Nova Scotia	0.39	0.37
Quebec	0.39	0.37
Canada	0.39	0.37
Manitoba	0.38	0.36
New Brunswick	0.38	0.36
Newfoundland and Labrador	0.38	0.36
Saskatchewan	0.38	0.36
Prince Edward Island	0.37	0.35

Table A5: Share of jobs that can be done at home, by city (LFS estimates)

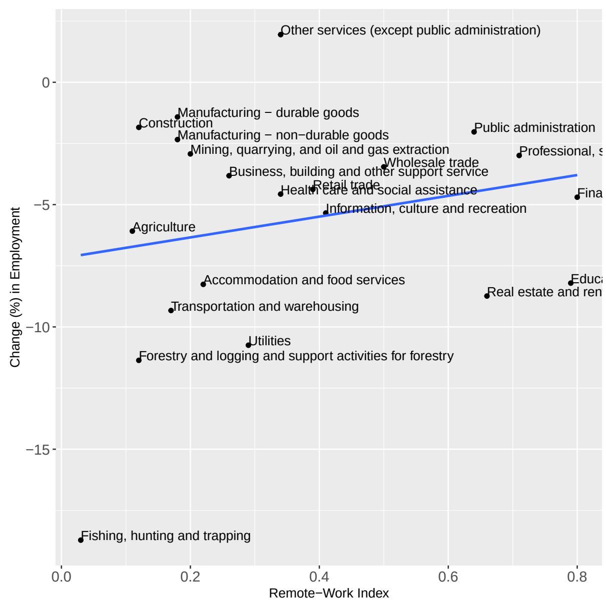
City	Benchmark	Alternative	National Employment Share
Ottawa	0.45	0.42	0.03
Hamilton	0.42	0.40	0.02
Montreal	0.42	0.40	0.11
Toronto	0.42	0.40	0.18
Calgary	0.41	0.39	0.04
Vancouver	0.41	0.38	0.07
Edmonton	0.39	0.37	0.04
Quebec	0.39	0.37	0.02
Winnipeg	0.39	0.37	0.02
Other CMA or nonCMA	0.38	0.36	0.46

Table A6: Share of jobs that can be done at home, by industry (LFS estimates)

Sector	Benchmark	Alternative
Finance and insurance	0.62	0.57
Real estate and rental and leasing	0.46	0.42
Wholesale trade	0.44	0.41
Professional, scientific and technical services	0.43	0.41
Educational services	0.42	0.40
Health care and social assistance	0.41	0.38
Information, culture and recreation	0.41	0.39
Utilities	0.39	0.38
Construction	0.39	0.38
Retail trade	0.39	0.36
Transportation and warehousing	0.39	0.38
Accommodation and food services	0.39	0.35
Total	0.39	0.37
Other services (except public administration)	0.38	0.36
Manufacturing - durable goods	0.37	0.36
Public administration	0.37	0.35
Manufacturing - non-durable goods	0.35	0.33
Business, building and other support service	0.34	0.32
Mining, quarrying, and oil and gas extraction	0.32	0.32
Forestry and logging and support activities for forestry	0.25	0.27
Fishing, hunting and trapping	0.18	0.19
Agriculture	0.17	0.22

Figure A3: Employment Dynamics and Remote Work Index (by industry)

(a) February - March 2020, % change



(b) March - April 2020, % change

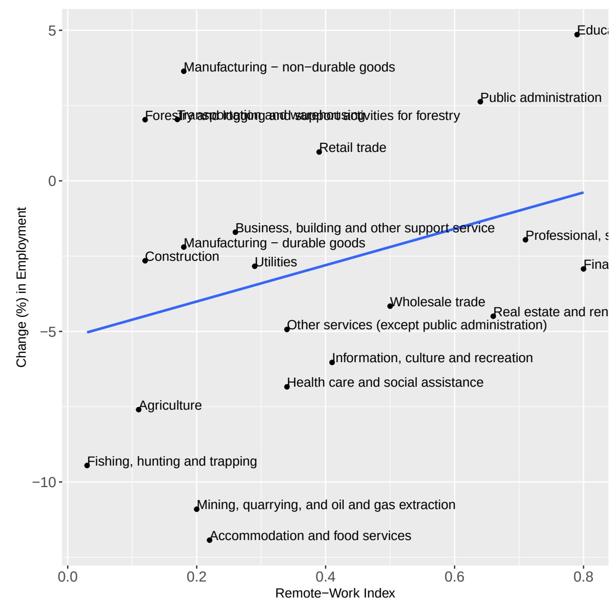
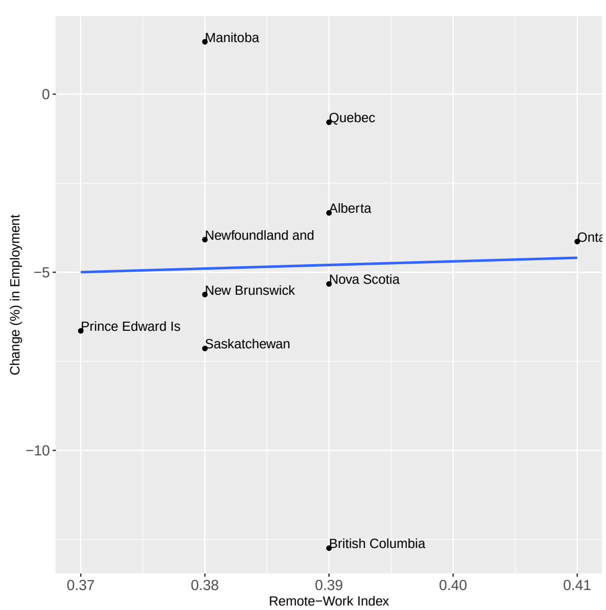


Figure A4: Employment Dynamics and Remote Work Index (by province)

(a) February - March 2020, % change



(b) March - April 2020, % change

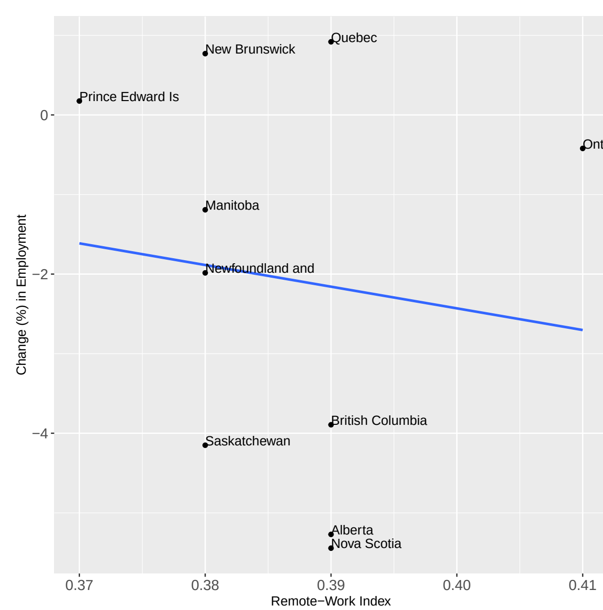
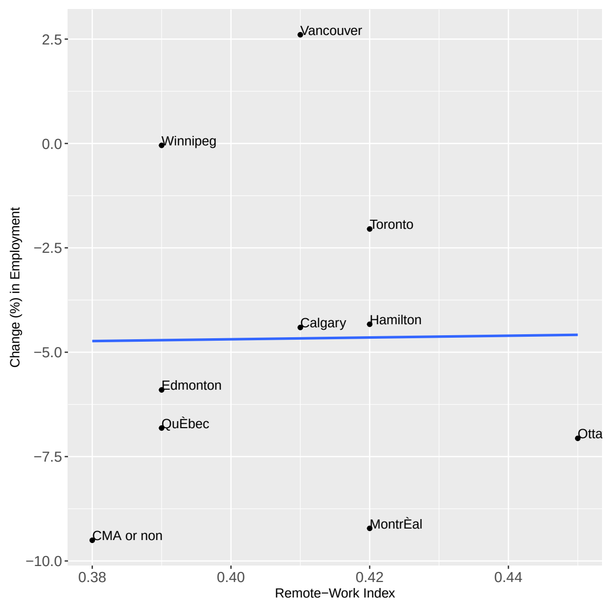
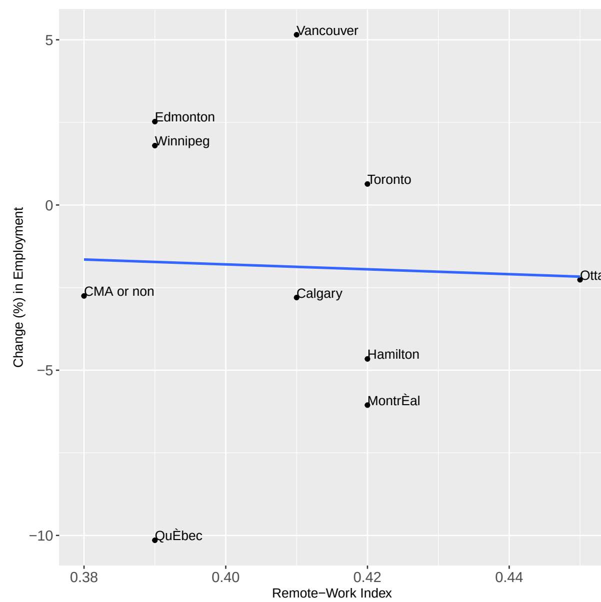


Figure A5: Employment Dynamics and Remote Work Index (by city)



(a) February - March 2020, % change



(b) March - April 2020, % change

Table A7: Employment Change and Remote Work Index: 2-digit level (Robustness Check: Alternative Remote Work Index)

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$		$\Delta q_{j,Feb,Mar}$		$\Delta q_{j,Mar,Apr}$		$\Delta q_{j,Feb,Apr}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Alternative)$	3.468	3.301	6.471**	7.300**	−2.840	−2.759	−0.369	0.406
	(3.454)	(3.519)	(3.157)	(3.018)	(3.069)	(3.131)	(4.519)	(4.491)
D_j		1.000		−4.970**		−0.484		−4.645
		(2.541)		(2.180)		(2.261)		(3.243)
Constant	−1.552	−2.178	−8.209***	−5.095**	−2.315*	−2.012	−10.952***	−8.041***
	(1.540)	(2.227)	(1.407)	(1.910)	(1.368)	(1.981)	(2.014)	(2.842)
Observations	40	40	40	40	40	40	40	40
R^2	0.026	0.030	0.100	0.210	0.022	0.023	0.0002	0.053
Adjusted R^2	0.0002	−0.023	0.076	0.168	−0.004	−0.030	−0.026	0.001
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A8: Employment Change and Remote Work Index: 2-digit level (Robustness Check: Essential Service Index)

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$		$\Delta q_{j,Feb,Mar}$		$\Delta q_{j,Mar,Apr}$		$\Delta q_{j,Feb,Apr}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	4.290	4.238	6.178**	5.193*	−1.769	−1.900	1.363	0.372
	(3.090)	(3.016)	(2.706)	(2.712)	(2.801)	(2.781)	(3.991)	(3.945)
D_j	0.879		−4.923**		−0.556		−4.739	
	(2.506)		(2.195)		(2.272)		(3.237)	
ES_j		−4.798		−7.331**		−1.361		−8.207
		(3.895)		(3.502)		(3.592)		(5.095)
Constant	−2.612	−0.775	−5.129**	−6.241***	−2.157	−2.139	−8.328***	−9.090***
	(2.219)	(1.863)	(1.944)	(1.675)	(2.012)	(1.718)	(2.867)	(2.438)
Observations	40	40	40	40	40	40	40	40
R^2	0.056	0.090	0.198	0.186	0.013	0.016	0.055	0.066
Adjusted R^2	0.005	0.041	0.155	0.142	−0.040	−0.038	0.004	0.016
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A9: Employment Change and Remote Work Index: 2-digit level (Robustness Check: Alternative Remote Work Index and Essential Service Index)

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$		$\Delta q_{j,Feb,Mar}$		$\Delta q_{j,Mar,Apr}$		$\Delta q_{j,Feb,Apr}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Alternative)$	3.301	3.009	7.300**	5.794*	−2.759	−3.000	0.406	−1.192
	(3.519)	(3.459)	(3.018)	(3.065)	(3.131)	(3.121)	(4.491)	(4.451)
D_j	1.000		−4.970**		−0.484		−4.645	
	(2.541)		(2.180)		(2.261)		(3.243)	
ES_j		−4.670		−6.901*		−1.633		−8.385
		(3.978)		(3.525)		(3.589)		(5.118)
Constant	−2.178	−0.225	−5.095**	−6.249***	−2.012	−1.851	−8.041***	−8.570***
	(2.227)	(1.903)	(1.910)	(1.687)	(1.981)	(1.717)	(2.842)	(2.449)
Observations	40	40	40	40	40	40	40	40
R^2	0.030	0.061	0.210	0.184	0.023	0.027	0.053	0.068
Adjusted R^2	−0.023	0.010	0.168	0.140	−0.030	−0.025	0.001	0.017
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A10: Employment Change and Remote Work Index: 10 Occupation Group

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	9.888**	5.798	5.389	6.470				
	(4.271)	(4.070)	(3.485)	(5.023)				
$S_j(Alternative)$					11.979**	6.754	5.929	7.269
					(5.118)	(4.938)	(4.296)	(6.126)
Constant	−3.839*	−7.798***	−5.192**	−12.591***	−3.805*	−7.698***	−4.997**	−12.401***
	(2.029)	(1.934)	(1.656)	(2.387)	(2.002)	(1.932)	(1.681)	(2.396)
Observations	10	10	10	10	10	10	10	10
R^2	0.401	0.202	0.230	0.172	0.406	0.190	0.192	0.150
Adjusted R^2	0.326	0.103	0.134	0.068	0.332	0.088	0.091	0.043
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A11: Employment Change and Remote Work Index: Industry

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	10.754**	4.249	6.036	7.488				
	(5.041)	(4.221)	(4.308)	(6.008)				
$S_j(Alternative)$					11.938*	4.201	7.084	8.214
					(5.717)	(4.797)	(4.846)	(6.802)
Constant	−4.109*	−7.191***	−5.215**	−12.559***	−3.774*	−6.908***	−5.138***	−12.297***
	(2.142)	(1.793)	(1.830)	(2.553)	(2.044)	(1.715)	(1.732)	(2.431)
Observations	21	21	21	21	21	21	21	21
R^2	0.193	0.051	0.094	0.076	0.187	0.039	0.101	0.071
Adjusted R^2	0.151	0.001	0.046	0.027	0.144	−0.012	0.054	0.022
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A12: Employment Change and Remote Work Index: Province

	Dependent variable:							
	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$	$\Delta q_{j,Jan,Feb}$	$\Delta q_{j,Feb,Mar}$	$\Delta q_{j,Mar,Apr}$	$\Delta q_{j,Feb,Apr}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	33.664	10.095	−27.227	68.168				
	(96.075)	(125.633)	(80.594)	(148.440)				
$S_j(Alternative)$					−11.487	21.092	−50.026	53.455
					(89.659)	(116.281)	(73.141)	(138.133)
Constant	−11.740	−8.732	8.460	−35.513	5.470	−12.576	16.310	−28.818
	(37.098)	(48.511)	(31.120)	(57.318)	(32.920)	(42.694)	(26.855)	(50.718)
Observations	10	10	10	10	10	10	10	10
R^2	0.015	0.001	0.014	0.026	0.002	0.004	0.055	0.018
Adjusted R^2	−0.108	−0.124	−0.109	−0.096	−0.123	−0.120	−0.063	−0.104
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A13: Employment Change and Remote Work Index: City

	Dependent variable:							
	$\triangle q_{j,Jan,Feb}$	$\triangle q_{j,Feb,Mar}$	$\triangle q_{j,Mar,Apr}$	$\triangle q_{j,Feb,Apr}$	$\triangle q_{j,Jan,Feb}$	$\triangle q_{j,Feb,Mar}$	$\triangle q_{j,Mar,Apr}$	$\triangle q_{j,Feb,Apr}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_j(Benchmark)$	69.736	2.138	−7.408	9.620				
	(73.270)	(65.821)	(76.156)	(119.541)				
$S_j(Alternative)$					73.688	−12.472	−29.436	−21.206
					(81.399)	(72.639)	(83.598)	(131.998)
Constant	−26.628	−5.545	1.166	−11.345	−26.619	0.141	9.505	0.765
	(29.930)	(26.887)	(31.108)	(48.831)	(31.454)	(28.069)	(32.304)	(51.006)
Observations	10	10	10	10	10	10	10	10
R^2	0.102	0.0001	0.001	0.001	0.093	0.004	0.015	0.003
Adjusted R^2	−0.011	−0.125	−0.124	−0.124	−0.020	−0.121	−0.108	−0.121

Note: *p<0.1; **p<0.05; ***p<0.01