Automation and Reallocation:
The Lasting Legacy of COVID-19 in Canada

Joel Blit*
Department of Economics
University of Waterloo
jblit@uwaterloo.ca

Aug 2020

Abstract

Recent evidence suggests that recessions play a crucial role in promoting automation and the reallocation of productive resources. Consistent with this, I show that in the three previous Canadian recessions, routine jobs were disproportionately lost. COVID-19 is likely to have a similar impact, but bigger because superimposed onto the usual recessionary transformational forces are health-specific incentives to automate. Using O*NET data, I construct an index of COVID-19 health risk and of routine task intensity to measure health incentives to automate and the feasibility of doing so. Across occupations, income groups, industries, and regions, the two indices are strongly negatively correlated, suggesting that automation will not be overly focused and that it may penetrate into hitherto relatively unaffected sectors like health and education. Nevertheless, office and health support workers are likely to be disproportionately affected, as will the retail and hospitality industries. The impacts will also be primarily felt by families toward the bottom of the income distribution and in smaller cities.

Keywords: COVID-19, recessions, productivity, innovation, automation
JEL Classifications: O33, O40, E32, J24

1. Introduction

COVID-19 is both a health and an economic crisis. As a result of the crisis, Canadian real gross domestic product fell an unprecedented 11.5% in the second quarter of 2020. Between February and April, 5.5 million Canadians either lost their job or were working fewer than half of their regular work hours. Worse, the impacts were primarily felt by those financially most vulnerable: low-wage workers, part-time workers, the self-employed, and recent immigrants.

While over half of lost jobs have now been recovered, the recovery has been uneven and a full recovery remains distant. In fact, one of the enduring legacies of the crisis may be the permanent disappearance of certain types of jobs due to automation and reallocation. In no sector is this transformation more apparent than in retail trade, where there has been a surge in both within-firm automation (ex: Walmart Canada investing $3.5 billion in e-commerce and its U.S. parent announcing the first fully cashierless store) and between-firm reallocation (resources and market share flowing from brick and mortar to online retailers). According to Statistics Canada, retail e-commerce sales totaled $3.8 billion in May, an increase of 113% from a year earlier. Even in industries like mining, where the threat of automation is less formidable, firms like Agnico Eagle are accelerating automation to avoid further health-related shutdowns of their operations.

That the COVID-induced economic downturn is likely to accelerate technological transformation should not be surprising. Since the beginning of the information and communications technology (ICT) revolution in the mid-1980's (but importantly not before), every U.S. recession has resulted in the permanent loss of routine jobs (Jaimovich and Siu, 2020). Non-routine jobs, on the other hand, either remained relatively unaffected during the downturns or subsequently bounced back. Canada has experienced a similar, and in fact even more pronounced, pattern of permanent routine job loss during recessions (Blit, 2020). As shown in Figure 1, all the routine job losses over the last 33 years occurred during the three economic downturns. This, along with the fact that those routine jobs never returned, suggests that recessions play a crucial role in fostering automation and reallocation in the Canadian economy.

The current crisis is likely to result in a more significant technological transformation than previous downturns, both because of its scale and because superimposed onto the usual recessionary incentives to automate are the health-related incentives. The best way for firms to protect workers and mitigate risks to their operations is to replace worker-worker interactions with worker-machine interactions, or better yet to dispense with workers altogether. Similarly, firms that are more highly automated are likely to experience fewer disruptions to their operations and are thus likely to gain market share (and resources) at the expense of less automated firms. Technological transformation will therefore be particularly severe in sectors of the economy where workers are at higher risk of infection. However, not all of these jobs can feasibly be automated given today's technology, and the transformation is thus likely to be most significant in jobs and sectors that both present significant health risks and where many tasks are routine.

To examine the likely impacts of COVID-19 on economic automation and reallocation, I use data from the Occupational Information Network (O*NET) to construct indices of routine task intensity (feasibility of automation) and of COVID-related health risks (incentives to automate). I show that, consistent with Figure 1, routine intensive jobs were disproportionately lost in the three previous recessions. However, during the first months of this crisis it has not been routine jobs that have been primarily lost, but rather jobs that pose significant risks of COVID-19 transmission (jobs that require close physical proximity, involve face to face interaction, are primarily indoors, and/or entail exposure to infection). This is consistent with the fact that initial job losses were the result not of market forces, as in previous recessions, but of government-imposed shutdowns in response to the health emergency. Many of these jobs, and in particular the ones that are feasibly automated, are likely never going to return.

To understand the likely long-run impacts of COVID-19 on the Canadian economy, I examine which occupations, income groups, industries, and geographic regions are likely to experience the biggest COVID-induced technological transformation. I find that regardless of the level of analysis, units that face the strongest health incentives to automate are generally also the least automatable, and the converse, suggesting that the impacts are going to be widespread. The negative correlation further suggests that automation may make inroads into sectors that traditionally have had little automation like health and education, since those are sectors where COVID-19 health incentives tend to be highest.

There are, however, some units that stand out as being particularly exposed due both to strong incentives and high feasibility. Health technicians, health support workers, sales support, office support, distribution coordinators, and manufacturing machine operators, are among the occupations that will be most impacted. Concerningly, lower-income families, earning between

$15,000 and $45,000, will also be disproportionately affected. The two industries likely to be most impacted are retail and hospitality, two industries where we have already seen a significant transformation. However, sectors like health that have traditionally been less subject to automation are also likely to see significant changes in efforts to mitigate the health risks of patients and workers alike. Finally, while absolute differences across cities are not large, smaller cities are likely to be more impacted than Canada's larger cities.

The paper proceeds as follows. The next section summarizes the previous literature on the impact of recessions on automation. Section 3 describes the data and the indices. Section 4 uses these indices to examine the impact of the three previous recessions and the current downturn on employment. Section 5 describes which occupations, income groups, industries and geographic regions are likely to be most impacted and Section 6 concludes.

2. Recessions and Automation

Aggregate productivity growth is the result of both within-firm productivity increases and between-firm reallocation, with their relative contribution depending on the sector and the historical period in question (Foster, Haltiwanger, and Krisan, 2001). While Foster, Haltiwanger, and Krisan (2006) find that productivity increases in the 1990s retail industry were primarily driven by reallocation between firms, Garcia-Macia, Hsieh, and Klenow (2019) conclude in their broader thirty-year study that within-firm innovations are relatively more important. Baldwin and Gu (2011) find that in Canada within-firm productivity growth is relatively more important in manufacturing, while the opposite is true in retail. Both mechanisms thus play a crucial role in economic transformation.

A related and equally important subject of inquiry has been on when this productivity-enhancing transformation occurs during the business cycle. The prominent role of recessions in accelerating change has been posited since at least as far back as Schumpeter (1934). In "Depressions: Can we learn from past experience?", he writes that "depressions are not simply evils, which we might attempt to suppress, but … something which has to be done, namely, adjustment to … change." (Schumpeter 1934, p.16).

More recently, Davis and Haltiwanger (1992) empirically showed that job reallocations (especially job losses) tend to primarily occur during recessions, and are not industry-wide but rather focused in specific plants. To the extent that productivity-enhancing efforts like technological upgrading, reorganizations, and training are disruptive to operations, such activities are more likely to be undertaken during economic downturns when opportunity costs are lower (Hall, 1991; Saint-Paul, 1993; Aghion and Saint-Paul, 1998). They are also more likely to be undertaken by firms that face a more significant risk of failure (Gibbons and Roberts, 2012) or firms with higher abilities to innovate.

The experience of the Great Recession, which accelerated not just the ICT revolution but also the adoption of emerging robotics and artificial intelligence technology, re-energized inquiry into the role of recessions in technological transformation. Informing this research, were the earlier insights of Autor, Levy, and Murnane (2003), Goos and Manning (2007), Autor, Katz, and Kearney (2008), and Autor and Dorn (2013) on the phenomenon of job polarization arising from technology displacing routine employment in the middle of the skill and wage distribution. A model by Kopytov, Roussanov, and Taschereau-Dumouchel (2018) explains the greater share of investments going towards automation (software, information processing equipment, and robots) during the Great Recession, and the associated job polarization.

A number of important empirical papers have also examined these trends. Jaimovich and Siu (2020) find evidence of accelerating job polarization during each of the three most recent U.S. recessions. They show that since the beginning of the ICT revolution (but crucially not before) each recession has resulted in the disproportionate and permanent loss of routine jobs. In fact, the three recessions account for 88% of all routine job losses between 1990 and 2007. Blit (2020) finds similar impacts of recessions in Canada. Between 1987 and 2020, while non-routine employment increased, routine employment per capita declined by 5.4% percentage points and the entirety of the decrease happened during the three Canadian recessions.

In a particularly influential paper, Hershbein and Kahn (2018) examine the differential impact of the Great Recession across U.S. regions. They find that regions that were harder hit by the recession experienced more investment in automation technology and a permanent increase in the job skill requirements. Anghel, De la Rica, and Lacuesta (2014) document accelerating routine job losses and job polarization in Spain during the Great Recession. Zhang (2019) examines publicly traded U.S. firms and finds that during recessions, firms that have higher shares of routine labour relative to their industry peers, invest more in machines and decrease routine employment more sharply.

Overall, the empirical evidence suggests that recessions are important times of technological transformation, leading both to job upskilling and a permanent reduction in the number of routine jobs.

3. Data

This paper draws on three primary datasets: the Canadian Labour Force Survey (LFS), the 2016 Canadian Census, and the Occupation Information Network (O*NET) version 25.0 database.

Statistics Canada's LFS is a monthly survey of about 54,000 households measuring the state of the Canadian labour market. It is generally administered in the third week of every month and the results are published early the next month. While it can lack accuracy when examining questions that require too large a disaggregation of the data, it offers a frequent and up to date insight into Canada's labour market. I use the public use microdata files (PUMFs), which disaggregates monthly employment by 40 occupation categories, to examine which occupations were disproportionately impacted during past recessions and during the initial months of the COVID-19 crisis.

Statistics Canada's 2016 Census Individuals File PUMFs were used to construct the indices and to determine which income groups, education groups, industries and regions are likely to be most affected by the coming transformation.

The O*NET Database, sponsored by the U.S. Department of Labor, randomly surveys U.S. workers in each of 974 different occupations. The survey asks questions about the knowledge, skills, abilities, activities, tasks, and work context. Because O*NET's occupations are coded according to the Standard Occupational Classification, I employ a crosswalk developed by the Brookfield Institute[1] to convert O*NET-SOC occupations to one of 494 4-digit NOC codes.[2] For the cases where multiple O*NET-SOC codes map to the same 4-digit NOC code, I assign the average. When I aggregate from 4-digit NOC to the 40 LFS categories (which roughly correspond to 2-digit NOC codes) I take weighted averages, where the weights are employment shares obtained from the Census.

---

[1] The crosswalk is available at: https://github.com/BrookfieldIIE/NOC_ONet_Crosswalk

[2] There were 70 cases where the concordance mapped a more highly aggregated O*NET-SOC code than was in the O*NET data. In these cases, I first aggregated O*NET-SOC codes to the higher level of aggregation by taking an average, then corresponded to a 4-digit NOC.

Following Deming (2017), I construct an index of routine task intensity (feasibility of automating an occupation) using variables that describe the work context of each occupation. In particular, I use responses to five questions: (i) "how automated is the job?", (ii) "how important is repeating the same physical activities or mental activities over and over to performing this job?", (iii) "how important is being very exact or highly accurate in performing the job?", (iv) "to what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?", and (v) "how important is it to this job that the pace is determined by the speed of equipment or machinery?" Because responses are rated on an ordinal scale of 1 to 5[3], for each question I convert each occupation's score to a 0 to 1 scale that reflects that occupation's percentile rank among all 974 different occupations. The routine task intensity index for a particular occupation is then computed as the average of the five percentiles, so that the index too is bounded between 0 and 1 and has a mean of approximately 0.5.

The index of routine task intensity is similar to Deming's but more comprehensive in that it is the average of five questions instead of only two (Deming uses the first two). Reassuringly, the index's correlation with Blit's (2020) routine classification of the 40 LFS occupations, which itself is based on the classification of Cortes, Jaimovich, and Nekarda (2014), is 0.61. The index developed here has the advantage that it is available at a more disaggregated level (494 different 4-digit occupations instead of 40 categories) and that it assigns a routine task intensity value to each occupation instead of categorizing occupations as either entirely routine or non-routine.

The index of COVID-related health risk is created in a similar manner to the routine index using the following four questions that describe the work context: (i) "to what extent does this job require the worker to perform job tasks in close physical proximity to other people?", (ii) "how often do you have to have face-to-face discussions with individuals or teams in this job?", (iii) "how often does this job require working outdoors, exposed to all weather conditions?, and (iv) "how often does this job require exposure to disease/infections?"[4]. For question (iii) on

[3] For (i) degree of automation, the five possible responses were 1: not at all automated, 2: slightly automated, 3: moderately automated, 4: highly automated, and 5: completely automated (which reassuringly received no responses). For (ii) importance of repeating the same tasks, (iii) importance of being exact, and (v) pace determined by speed of equipment, the five possible responses were: 1: not at all important, 2: fairly important, 3: important, 4: very important, and 5: extremely important. For (iv) structured versus unstructured work, the five possible responses were 1: no freedom, 2: very little freedom, 3: limited freedom, 4: some freedom, and 5: a lot of freedom. Because more structured (less freedom) tasks are more easily automated, the percentile rank is computed for the negative of this average score and the variable is interpreted as the degree of structure.

[4] For (i) physical proximity, the five possible responses were 1: I don't work near other people (beyond 100ft.), 2: I work with others but not closely (e.g. private office), 3: slightly close (e.g., shared office), 4: moderately close (at

working outdoors, a higher score (working outdoors more often) implies a lower risk of infection so that the percentile rank for this question is computed based on the negative of the average score and the ensuing variable is referred to as "indoors".[5] As before, the index of health risk is computed as the average of the four percentiles, so that the index is bounded between 0 and 1 and has a mean of approximately 0.5.

All four of the questions used to construct this health risk index are also used by the Vancouver School of Economics COVID-19 Research Group to develop the measure of viral transmission risk for their COVID-19 Risk Assessment Tool.[6] They validate their use by showing that their measure of occupation viral transmission risk is correlated with absences from work due to "own illness or disability" during the flu season.

The values of the routine task intensity and health risk indices and their components for each of the 40 LFS Occupation categories are listed in Table 1 and 2, respectively. A more complete list at the 4-digit NOC level is available upon request.

4. Patterns of Job Losses

4.1 Job Losses During Recessions

To provide further support for the evidence presented in Figure 1, I more formally examine the extent to which job losses were primarily in occupations with high routine task intensity during the three most significant economic downturns since the beginning of the ICT revolution. I define these recessions using data from the Federal Reserve Bank of St. Louis, that in turn is based on OECD Composite Leading Indicators of GDP turning points in the growth cycle.[7] A recession is defined as starting in the month that follows the month containing the peak and ending in the month containing the trough. The three longest downturns since 1987 occurred from June 1989 to May 1992, September 2007 to July 2009, and October 2014 to June 2016. The last was a relatively milder downturn, not always considered an official recession.

---

arm's length), and 5: very close (near touching). For (ii) face to face discussions, (iii) outdoors, and (iv) exposed to disease or infections, the five possible responses were: 1: never, 2: once a year or more but not every month, 3: once a month or more but not every week, 4: once a week or more but not every day, and 5: every day.

[5] Alternatively, I could have used a question on "working indoors in an environmentally controlled environment", "working indoors in a non-environmentally controlled environment", or "working outdoors under cover". But all of these could pose higher risks of infection and the three questions cannot easily be combined.

[6] The project and tool is described at https://covid19.economics.ubc.ca/projects/project-1/

[7] Data is available at https://fred.stlouisfed.org/series/CANRECD. Information on the OECD data is available at http://www.oecd.org/sdd/leadingindicators/oecdcompositeleadingindicatorsreferenceturningpointsandcomponentseries.htm

For each of the three recessions, I compute the peak to trough percentage change in employment per capita (including both full and part-time) for each of the 40 occupation categories. Pooling across the three recessions, I obtain a sample of 120 observations and estimate the following equation using both ordinary least squares (OLS) and weighted least squares (WLS) with employment per capita as weights:

$$\%\Delta\, Emppc_{ir} = \alpha + \beta_1 routine_i + \beta_2 healthrisk_i + \beta_3 trend_i + \gamma_r + \varepsilon_{it}$$

The dependent variable is the peak to trough percent change in employment for occupation *i* in recession *r*. The key explanatory variables are the *routine* and *healthrisk* indices. I control for the overall *trend* of each occupation, measured as the change in employment per capita between January 1987 and February 2020, to ensure that I capture recession-specific changes over and above the occupation's long-term trend. γ_r are recession fixed effects and robust standard errors clustered by occupation are reported throughout.

Table 3 presents the results. Across all three specifications, the coefficient on the index of routine task intensity is negative and significant indicating that more routine occupations suffered larger declines during the recessions. In the preferred specification (3), with full controls and using weighted least squares, the estimated coefficient of -0.20 predicts that the most routine occupation (index of 0.71) on average suffers a 4 percentage point larger decline in employment than the average occupation (index of 0.51) and a 9.8 percentage point larger decline than the least routine (index of 0.22). When not controlling for trend (column 1), the difference is a greater 5.6 and 13.7 percentage points, respectively.

Figure 2 plots the relationship between average percent change in employment per capita over the three recessions and routineness, for each of the 40 occupations. Consistent, with the regression results, a clear downward sloping relationship can be observed.

The results also suggest that during past recessions the types of occupations that pose higher risks of COVID-19 infection have suffered a smaller decline or even increased employment relative to lower risk occupations. As can be seen in Figure 3, this is in part driven by the highest risk occupations (health professionals, nurses, and health technicians) having experienced large increases in employment. However, the relationship remains significant even when health occupations are excluded.

4.2 COVID-19 Job Losses

Between February and April 2020, Canadian employment fell by an unprecedented 3.0 million, of which 1.9 million were in full-time work and 1.1 million part-time. Unlike previous recessions, job losses were not driven by market forces but rather by a self-imposed generalized shutdown of the economy in response to COVID-19. As a result, the initial pattern of job losses is very different from that of previous recessions.

As shown in Figure 4, while more routine occupations on average experienced bigger losses, the relationship is so far weaker than in the previous recessions. In terms of COVID-19 health risks, Figure 5 suggests that there was a very weak negative (effectively no) relationship between the extent of job losses and the health risk associated with a particular occupation (dashed fit line). The weakness of the relationship is partly driven by the fact that shutdowns were generalized and did not specifically target higher risk sectors and occupations. However, upon closer inspection it also becomes apparent that the weak overall relationship is the result of four outliers: the four health occupations (health professionals, nurses, health technicians, and health support workers), which not surprisingly present the highest health risks. Given the exceptionality of health occupations during a health crisis (changes in employment are driven by the nature of the crisis), these are unlikely to fairly reflect broader trends in the economy and it may thus make sense to exclude them from the analysis.

When we restrict the analysis to the 36 non-health occupations, we see that occupations posing bigger health risks suffered bigger declines (dotted line). This is in sharp contrast to the three previous recessions, where the same higher health risk occupations saw smaller drops (or even increases) in employment. It would thus seem that government shutdowns were to some degree targeted on riskier economic activities, or individuals chose to scale back work in accordance to their perceived risk.

To more formally examine these relationships for the 36 non-health occupations, I estimate the same equation as before but with the peak to trough (February to April 2020) percentage decrease in employment per capita as the dependent variable. I control for trend as before and report robust standard errors.

The results, presented in Table 4, are consistent with Figures 4 and 5. More routine occupations experienced bigger drops in employment, but the relationship is not significant.

However, the point estimates are relatively large. In the preferred specification the most routine occupation is predicted to suffer a decline that is 8.8 percentage points bigger than the least routine occupation.

In spite of the small sample, the relationship between changes in employment and health risks is significant in two of the three specifications. The preferred specification predicts that the highest-risk occupation (service supervisors and specialized service occupations, with an index of 0.72) suffers an employment decline 8.9 percentage points bigger than the average occupation (index of 0.48) and 16.3 percentage points bigger than the lowest risk one (workers in natural resources, agriculture, and related production, with an index of 0.28).

Occupations presenting higher health risks suffered more severe drops in employment in the initial shutdown phase of the COVID-19 crisis. The next section discusses which occupations, income groups, industries, and geographic regions are likely to experience the biggest long run economic transformations as a result of the crisis.

5. Predicted Patterns of Permanent Job Losses

While job losses between February and April were due to a generalized shutdown of the economy, it is clear that the reopening does not imply a return to normal. Employment made a dramatic recovery in the three months to July, recovering 71% of peak to trough job losses or 2.1 million jobs, but the rate of recovery is slowing. The Bank of Canada forecasts that a full recovery will not occur until 2022. Effectively, we are now in the midst of an economic downturn that was COVID-induced, but which is now governed by the same types of market forces as previous recessions.

However, an important difference with previous recessions is the ongoing threat of further waves of COVID-19 and the impact that it would have on the economy and firms' operations. Not surprisingly, firms are proactively transforming their activities to better protect the health of workers and mitigate operational risks. Some of these changes involve working from home or deploying protective equipment. However, more radical changes are also taking place. The best way to prevent transmissions is to replace worker-worker interactions with worker-machine interactions, or better yet to altogether replace workers with machines.

Incentives to automate will be greatest in occupations where transmission risks are highest, which I measure using our index of COVID-19 health risk. However, just because an occupation presents significant incentives to automate does not mean that it can feasibly be automated given current technologies. I use our index of routine task intensity to measure the extent to which a given occupation can be automated.

Sectors with high health risks and routineness are likely to experience not just the most automation, but also the greatest reallocation. High health risk sectors, like air travel, hospitality, and education have already seen big changes to their environment. This will lead to reallocation of market share and resources from less well adapted to better adapted or more resilient firms. Moreover, high health risk sectors where in addition significant automation is possible, will also see reallocation from firms whose operations are less automated (and therefore subject to more disruptions as workers get sick or governments impose shutdowns) to those that are more.

Together, automation and reallocation will transform many sectors. I first examine which occupations are most likely to be affected and how this might impact different parts of the income distribution and education groups. I then investigate which industries and which major Canadian cities are likely to be most affected.

5.1 Occupations

Figure 7 plots the COVID-19 related incentives for automation (health risk index) against the feasibility of automation (routine task intensity index) for the 40 LFS occupations. Occupations that are high in one dimension tend to be lower in the other. Their correlation across the different occupations is -0.25 and as shown in the first column of Table 5, their negative relationship is significant. This has potentially important implications in that COVID-induced technological transformation is likely to be more widely distributed across different occupations than previous waves of automation. Occupations where the health incentives to automate are highest (like health professionals, nurses, education professionals, and care providers), tend to be the very occupations where automation is most difficult, and therefore where automation has tended to lag.

However, there are some outliers where we should expect to see the greatest amount of automation. Occupations toward the top right of the figure include health technicians, health support workers, sales support, office support, distribution coordinators, and manufacturing machine operators. The latter four occupations have for decades been the target of automation, and this is likely to continue in the wake of the pandemic. On the other hand, the first two, health technicians and health support workers, are not occupations that would traditionally have been considered at risk of automation. With the increased incentives to mitigate health risks we may see some degree of automation creep into the fringes of the health sector. For example, support workers that transit between different settings are particularly prominent vectors for the spread of COVID-19. As a result, many Canadian long-term care facilities have restricted their movement, resulting in staffing shortages and forcing different ways of delivering care.

5.2 Income Distribution

How are these transformations going to impact the wage distribution? Using the 2016 Census Individual Files PUMFs, I determine the occupation of individuals in each different family income range.[8] For each income range, I then compute an average routineness and health index by taking the average index of all individuals in that income range (where the index of a given individual is determined by their occupation).[9]

Figure 8 plots the routine task intensity index for each income range. It shows a remarkably smooth pattern, with the lowest income occupations being relatively difficult to automate, the feasibility of automation increasing with income until it peaks at the $55,000 to $60,000 range, and then dropping for higher income ranges. Consistent with the job polarization literature, I find that the most routine occupations are held by workers in the middle of the income distribution (though closer to the lower end) between $35,000 and $60,000. For reference, the median family income is in the $75,000 to $80,000 range.

Figure 9 breaks the analysis into the five individual components of the index. While degree of automation and importance of repeating tasks show a similar pattern to the overall routine task index, importance of being exact shows a clear upward trend, while degree of structure at work and role of equipment in setting the pace show decreasing relationships. Each component captures different aspects and together they create the inverse U relationship.

The forthcoming transformation has the potential to hollow out the middle of the income distribution, increasing inequality. However, health-related automation incentives across the income distribution differ markedly from that of feasibility, with the lowest health risks being toward the middle-upper range of the income distribution, between $45,000 and $90,000 (Figure

[8] In particular, I obtain a tabulation of the number of individuals holding each of 30 occupation major groups for each of 33 total income of Census family ranges. This income variable was preferable to using employment income which is not given in broad ranges and therefore has many values that are suppressed for reasons of confidentiality.

[9] These 30 occupation major groups are related to the 40 LFS occupation groups, but they are not the same. I compute the index for each of the 30 occupations in the same way that I did for each of the 40, by aggregating from 4-digit NOC taking a weighted average using employment shares.

10). Instead, health risks are high at the lower end of the income distribution, in occupations like service supervisors, sales support, care providers, and retail sales. The other extreme of the income distribution, like professional occupations in health and senior management, are also relatively high risk. As shown in Table 5 (column 2), the two indices have a negative relationship that is significant. Figure 11 shows how the different components of the index contribute to the relationship.

Consistent with the occupation level findings, incentives and feasibility paint a largely opposite picture as to what part of the income distribution will be most affected by automation and reallocation. One way to examine the two indices' joint effects is to compute their geometric mean.[10] Figure 12 presents the geometric mean of the two indices across the income distribution. The combined effects worryingly suggest that most of the economic transformation will be felt by individuals with low family incomes between $15,000 and $45,000. In this range, individuals tend to hold jobs that both face strong health-related incentives to automate and are feasibly automated.

5.3 Educational Attainment

A different way to examine the impacts of COVID-19 induced automation on individuals is to examine how it will differ by educational attainment. Using the 2016 Census Individual Files PUMFs, I compute for each level of educational attainment an average index of routineness and health risk based on the occupation of each individual within that level of attainment. Figure 13 presents the average routine task intensity and COVID-19 health risk for each of six different levels of educational attainment.

The figure suggests a surprisingly monotonic relationship, with routine task intensity decreasing, and COVID-19 health risks increasing, with the level of education. At the extremes, individuals with no formal postsecondary education exhibit the highest levels of routineness and lowest health risks, while those holding doctoral degrees exhibit the lowest routineness and highest health risks. Consistent with the income distribution findings, the highest overall risks of automation are faced by individuals with lower-middle levels of education holding secondary school diplomas and college degrees or vocational training in a trade. These individuals (college degree holders and trades in particular) are primarily in occupations where automation is feasible and health incentives are significant.

[10] An alternative, which effectively yields the same results, is to compute the average of the two indices

5.4 Industries

Using the Census, I compute for each of 19 industry sectors (based on NAICS 2012) an average index of routineness and health risk based on the occupation of individuals in that industry. The two indices are strongly negatively correlated (-0.47) across industries and regressing one index on the other (Table 5, column 3) confirms a significant negative relationship.

Figure 14 maps industries along the routineness and health risk dimensions. Industries that are most feasibly automated, like manufacturing, transportation and warehousing, utilities, and mining and oil extraction, also tend to have relatively low health-related incentives for automation, and the converse is also true. However, there are some significant outliers. Retail trade and accommodation and food services, stand out as the only two industries where both the routine and health risk indices are above the mean. Retail, in particular, seems poised for a significant transformation. In response to COVID-19, not only are major retailers like Walmart piloting cashierless stores (following the lead of Amazon with its "Just Walk Out" technology), many are also shifting toward e-commerce, obviating the need for the thousands of staff that ring in sales or stock the showroom. A major reallocation is also underway in the form of market share and resources flowing from brick and mortar to online stores.

The hospitality industry is also undergoing technological transformations. Contactless check-in and keyless room entry in hotels may presage the end of hotel check-in clerks. Touchless digital menus in restaurants, perhaps along with self-pickup windows, may begin to replace waiters. Resources are migrating from restaurants to home meal delivery companies.

The health care and social assistance sector also stands out as a major outlier with by far the highest health risk of any industry (but less than average feasibility of automation). The significant risk reduction incentives presented by the COVID-19 pandemic may finally ignite transformation in what has been a relatively stagnant sector. As healthcare increasingly transitions to remote delivery, productivity enhancing possibilities are emerging. Activities like prescription refills that were largely done in office, often with physical paper, and with the support of staff, are quickly transitioning online through systems like Prescribe IT. In the process, such systems are reducing the workload of doctors and lessening the need for support staff. COVID-19 has also accelerated the diffusion of technology for taking vitals into people's homes (thermometres, blood pressure monitors, and increasingly also more advanced technologies like watches that can take an EKG), reducing the need for physical doctor visits and the administration and nursing staff that handle them.

Another important outlier is the education sector. It too, has traditionally been considered non-automatable (education is rated as being the least routine of all industries). Its notable lack of productivity increasing innovation has presented an ongoing challenge (along with health spending) for government budgets. COVID-19's risk to educators and pupils, due to the close physical proximity and exposure to infection associated with traditional teaching, has catalyzed a rethink of the sector. We have already witnessed a massive shift toward remote content delivery. Whether remote teaching will ultimately lead to more highly scalable online courses, particularly at the University level, remains to be seen.

5.5 Geographic Regions

We can also examine the extent to which different regions will be impacted by the oncoming wave of automation and reallocation. I first examine 23 of Canada's Census metropolitan areas (CMA) and census agglomerations that together account for 70% of the Canadian population. For each of these cities/regions, I compute an average index of routineness and health risk based on the occupation of individuals residing in that CMA. Once again, I find that the two indices are strongly negatively correlated (-0.59) across CMAs and regressing one index on the other (Table 5, column 4) confirms a significant negative relationship.

This same relationship can be seen in Figure 15, which maps regions along the dimensions of the two indices. Because larger urban areas tend to be relatively diversified across sectors, the likelihood of automation does not vary significantly from one city to the other. However, a few regions do stand out as being more prone to COVID-19 driven automation. Moncton, Winnipeg, Sudbury, Sherbooke-Trois Rivieres, and St. Catharines-Niagara, all smaller centres, are relative outliers in that they are above average in both dimensions. At the opposite extreme, Toronto, Vancouver, Montreal, and Hamilton are all below the average in both dimensions (Ottawa is average in terms of COVID health risk and well below in routineness). While differences across cities are not particularly large, it would seem that large cities are likely to experience less automation and reallocation than smaller centres. A regression of the likelihood of automation (as proxied for by the geometric mean of the two indices) on city size readily shows that the relationship is significant (results not shown here).

Figure 16 presents a similar analysis for the ten provinces. While the figure suggests that New Brunswick, and Newfoundland and Labrador are likely to see the most automation and reallocation, differences between provinces are small.

6. Conclusion

A consistent pattern across all recessions since the beginning of the ICT revolution, is that routine jobs are lost and never return. This, along with evidence of upskilling and increased investment in ICT, suggest that recessions play a crucial role in transforming our economy through automation and reallocation. The COVID-19 crisis will be no different, and in fact is likely to spur on an even bigger transformation due not only to its larger scale, but also to its health-specific incentives to automate in order to reduce risks of transmission and mitigate threats to operations.

The initial COVID-19 shutdown disproportionately impacted occupations presenting high risks of contagion. While many of these jobs will bounce back as restrictions are lifted, others may never return as firms find safer and more efficient ways of doing business. Particularly at risk are occupations that present significant health exposure (and hence strong incentives to automate) and also encompass routine tasks that are easily automatable. Among these are occupations in sales support, office support, distribution, and manufacturing, but also some health occupations including technicians and support workers. The impact will be uneven across the income distribution, with lower income families suffering the brunt of the transformation. Not only will their jobs be disproportionately impacted, lower income groups are also less likely to possess the types of skills that are complementary to technology and that will allow them to easily make the transition to the new economy.

In terms of industries, retail trade and hospitality, where both incentives to automate and the feasibility of doing so are high, are clearly the industries that are destined for the most significant change. In these sectors, transformation is already under way through the deployment of labour-replacing technologies that reduce customer exposure to staff (cashiers, check-in clerks, waiters), through the migration of physical services to online (e-commerce, online menus and ordering), and through the reallocation of market share and resources (brick and mortar to online stores, restaurants to home food delivery, less to more highly automated firms). Another important finding of this paper is that incentives to automate will be strongest in sectors that have not traditionally seen much automation. We may finally see productivity enhancing transformation in the health care and education sectors. Already, these sectors have been forced to adopt new ways of doing business like remote doctor visits, electronic prescription renewals, and online learning, to reduce the risk of infection. They may emerge from the crisis looking very different.

It is hard to imagine a silver lining from this crisis but the technological transformation that it will unleash may be a significant and lasting beneficial legacy. For that to occur, we must embrace change, while supporting Canadians through the transition and ensuring that all share in its rewards. In this regard, another silver lining emerging from the pandemic is the increased sense of solidarity and belief in the important role of government. This crisis presents an historic opportunity to reimagine our social safety net, to not only help Canadians through this crisis, but also to ensure that all Canadians benefit from technological change now and in the decades to come.

References

Aghion, P., and G. Saint-Paul. 1998. "Virtues of bad times interaction between productivity growth and economic fluctuations." *Macroeconomic Dynamics* 2(3):322-44.

Autor, D.H., F. Levy, and R.J. Murnane. 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly journal of economics* 118(4):1279-333.

Autor, D.H., L.F. Katz, and M.S. Kearney. 2008. "Trends in US wage inequality: Revising the revisionists." *The Review of economics and statistics* 90(2):300-23.

Autor, D. H. and D. Dorn. 2013. "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review* 103(5):1553-1597.

Anghel, B., S. De la Rica, and A. Lacuesta. 2014. "The impact of the great recession on employment polarization in Spain." *SERIEs* 5:143-171.

Blit, J. 2020. "Automation and reallocation: will COVID-19 usher in the future of work?" *Canadian Public Policy*, Special issue on COVID-19, 46(S2): S192-202.

Davis, S.J., and J. Haltiwanger. 1992. "Gross job creation, gross job destruction, and employment reallocation." *The Quarterly Journal of Economics*, 107(3):819-63.

Baldwin, J., and W. Gu. 2011. "Firm dynamics and productivity growth: a comparison of the retail trade and manufacturing sectors." *Industrial and Corporate Change*: 20(2):367-95.

Cortes, G.M., N. Jaimovich, C.J. Nekarda, and H.E. Siu. 2014. "The micro and macro of disappearing routine jobs: A flows approach." NBER Working Paper No. 20307.

Foster, L., J. Haltiwanger, and C.J. Krizan. 2001. "Aggregate productivity growth: lessons from microeconomic evidence." *New developments in productivity analysis* (pp. 303-72). University of Chicago Press.

Foster, L., J. Haltiwanger, and C.J. Krizan. 2006. "Market selection, reallocation, and restructuring in the US retail trade sector in the 1990s." *The Review of Economics and Statistics*, *88*(4):748-58.

Goos, M., and A. Manning. 2007. "Lousy and lovely jobs: The rising polarization of work in Britain." *The review of economics and statistics*, *89*(1):118-33.

Gibbons, R., and J. Roberts. 2012. "Economic theories of incentives in organizations." *Handbook of Organizational Economics*, Princeton, New Jersey, Princeton University Press, pp.56-99.

Garcia-Macia, D., C.T. Hsieh, and P.J. Klenow. 2019. "How destructive is innovation?" *Econometrica*, *87*(5):1507-41.

Hall, R.E. 1991. "Recessions as reorganizations." *NBER macroeconomics annual*, pp.17-47.

Hershbein, B., and L.B. Kahn. 2018. "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings." *American Economic Review* 108(7):1737-72.

Jaimovich, N., and H.E. Siu, 2020. "Job polarization and jobless recoveries." *Review of Economics and Statistics* 102(1):129-147.

Kopytov, A., N. Roussanov, and M. Taschereau-Dumouchel. 2018. "Short-run pain, long-run gain? Recessions and technological transformation." *Journal of Monetary Economics*, *97*:29-44.

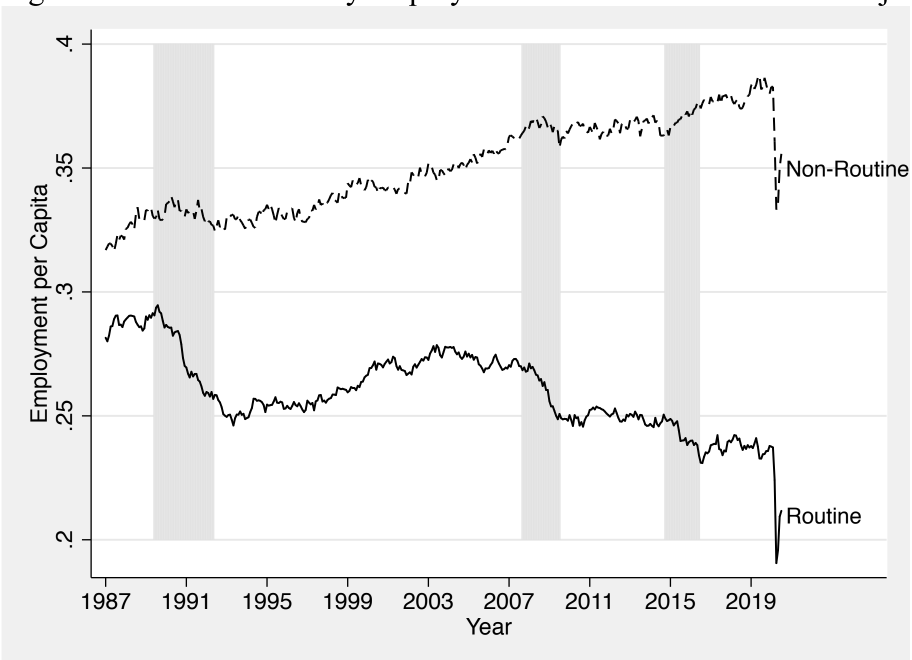
Saint-Paul, G., 1993. "Productivity growth and the structure of the business cycle." *European Economic Review*, *37*(4):861-83.

Schumpeter, J.A., 1934, "Depressions: Can we learn from past experience?" *The economics of the recovery program*, New York, New York London: McGraw-Hill, OCLC 1555914

Zhang, M.B., 2019. "Labor-Technology Substitution: Implications for Asset Pricing." *The Journal of Finance*, *74*(4):1793-839.

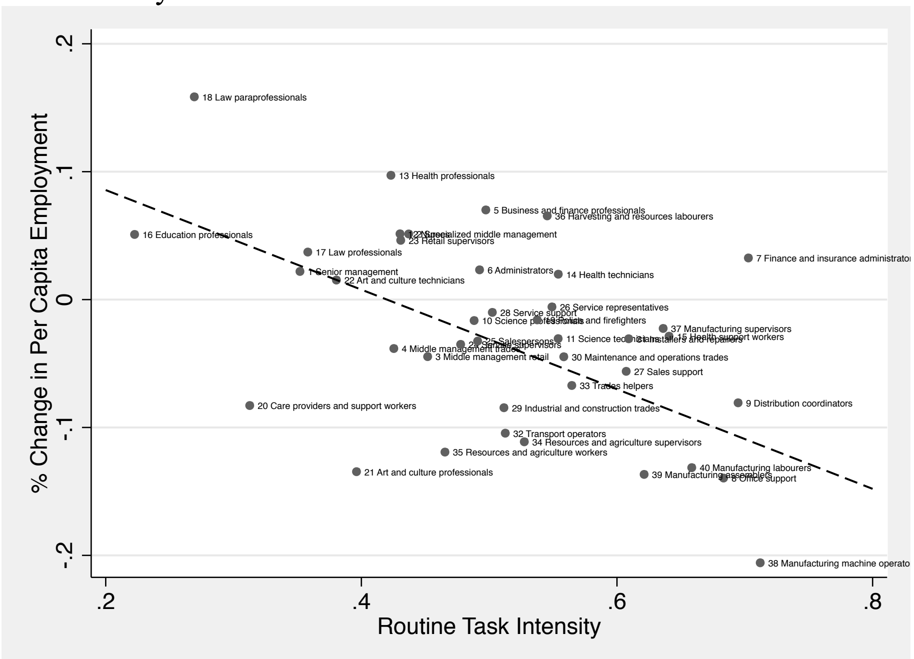
Figures

Figure 1: Canadian monthly employment in routine and non-routine jobs



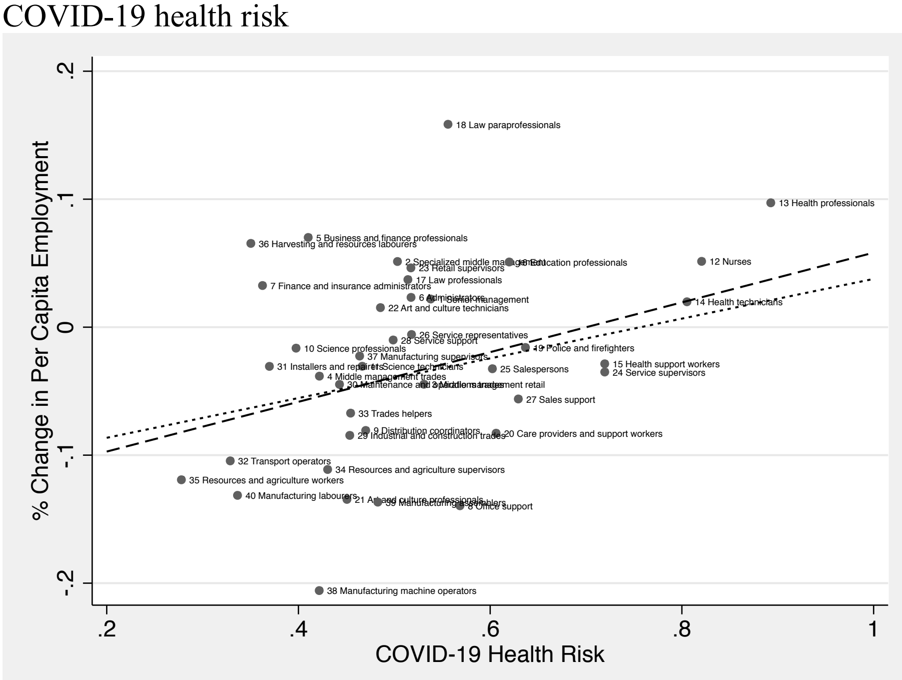
Notes: Time range is January 1987 to July 2020. Shaded periods represent the three most significant economic downturns. LFS 40 occupations are classified as routine/non-routine following Blit (2020).

Figure 2: Average percent change in employment per capita over the three recessions and routine task intensity



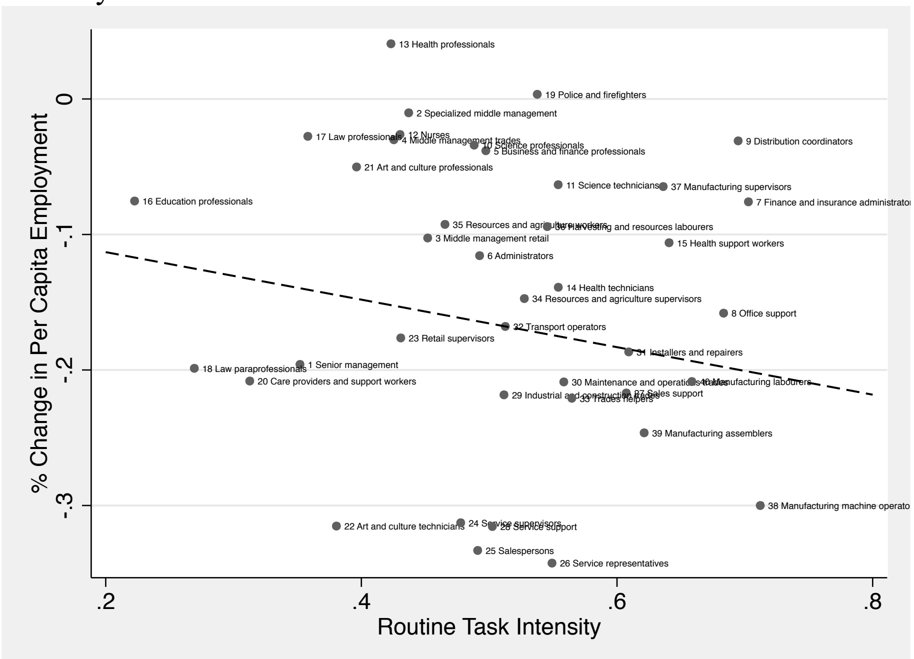
Notes: Average percent peak to trough change in per capita employment for the three recessions. Descriptions of the 40 LFS occupations have been shortened for ease of illustration. WLS fit line with employment as weights.

Figure 3: Average percent change in employment per capita over the three recessions and COVID-19 health risk



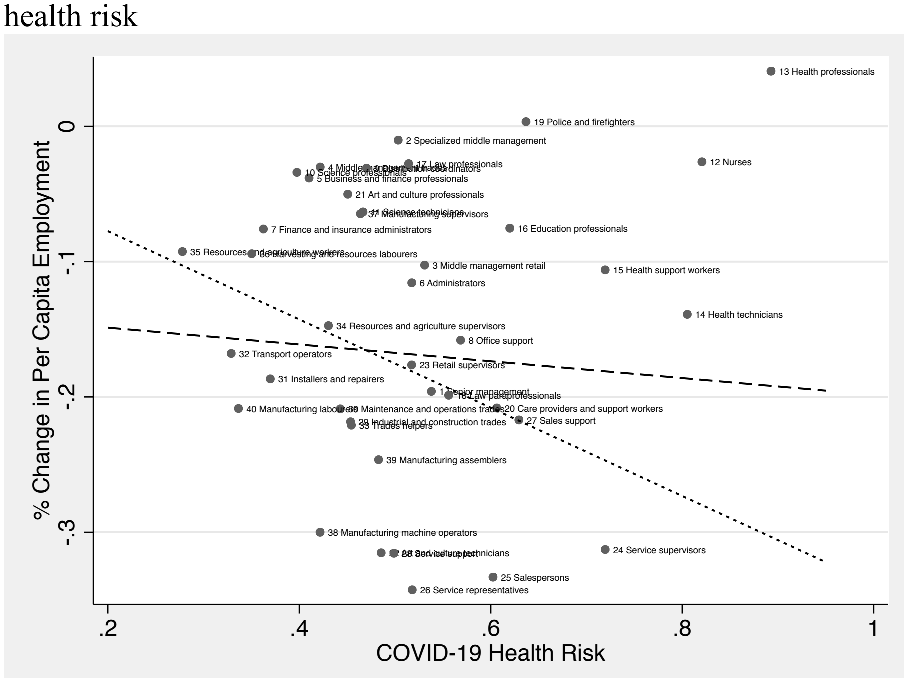
Notes: Average percent peak to trough change in per capita employment for the three recessions. Descriptions of the 40 LFS occupations have been shortened for ease of illustration. Dashed line represents WLS fit line with employment as weights for the full sample. Dotted line is WLS fit line without health (12-15) occupations.

Figure 4: COVID-19 peak to trough percent change in employment per capita and routine task intensity



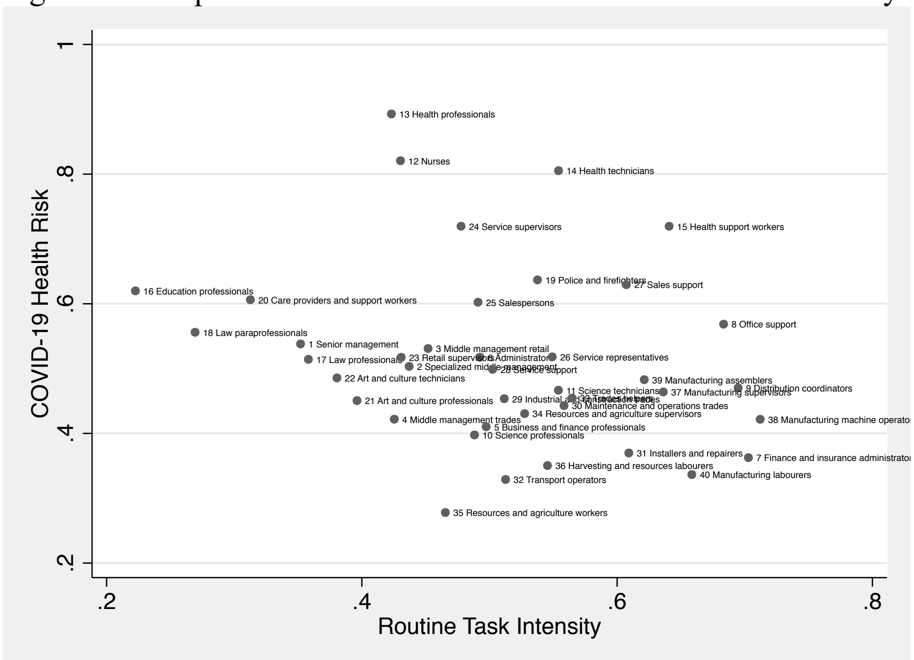
Notes: Percent peak to trough (February to April 2020) change in per capita employment by occupation. Descriptions of the 40 LFS occupations have been shortened for ease of illustration. WLS fit line with employment as weights.

Figure 5: COVID-19 peak to trough percent change in employment per capita and COVID-19 health risk



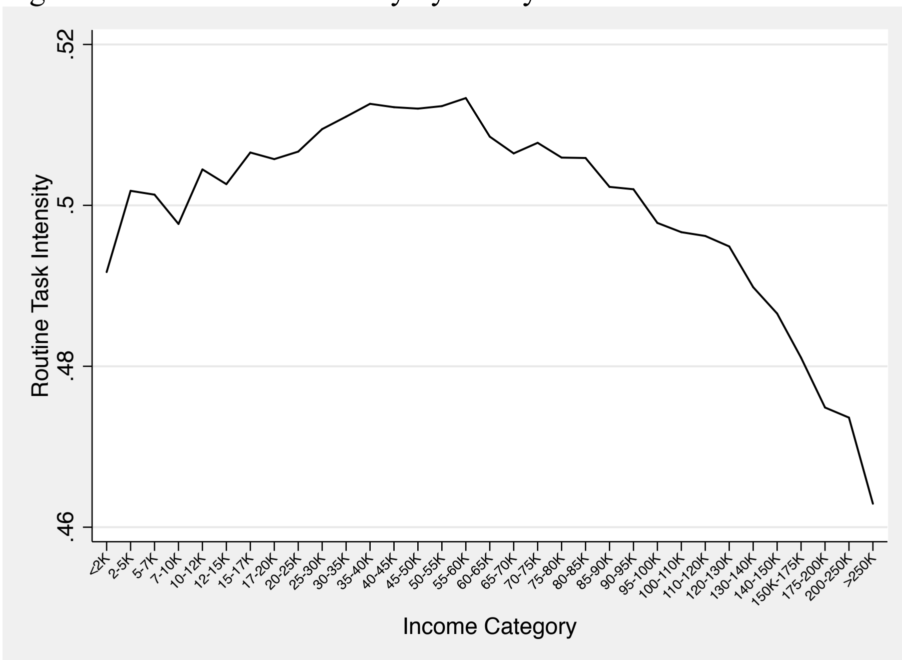
Notes: Percent peak to trough (February to April 2020) change in per capita employment by occupation. Descriptions of the 40 LFS occupations have been shortened for ease of illustration. Dashed line represents WLS fit line with employment as weights for the full sample. Dotted line is WLS fit line without health (12-15) occupations.

Figure 6: Occupation COVID-19 health risk and routine task intensity



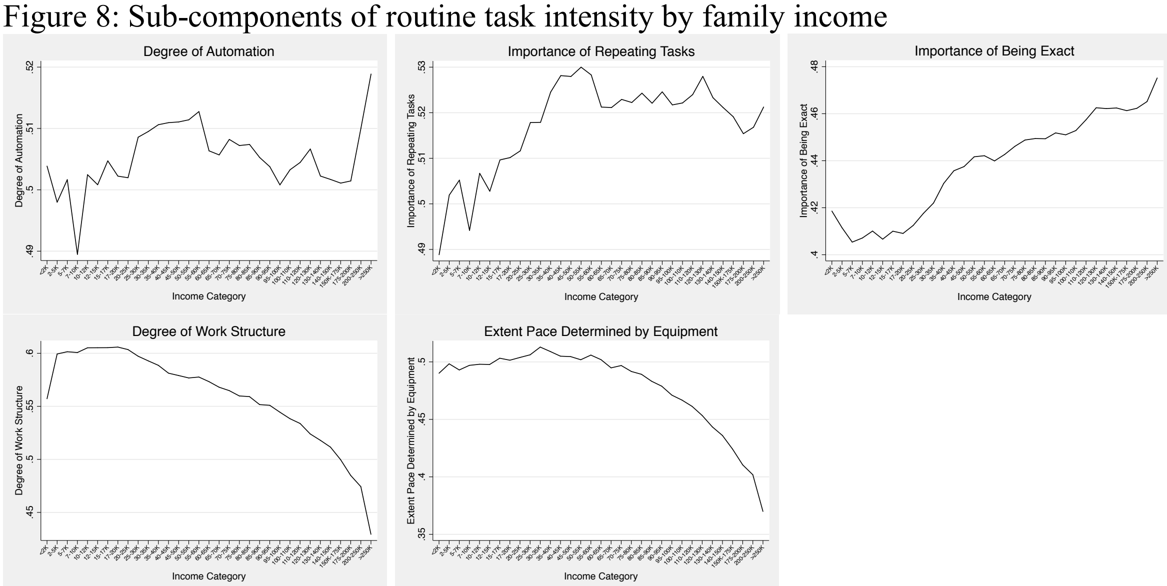
Notes: Indices of COVID-19 health risk and routine task intensity for each of 40 LFS occupation groups

Figure 7: Routine task intensity by family income



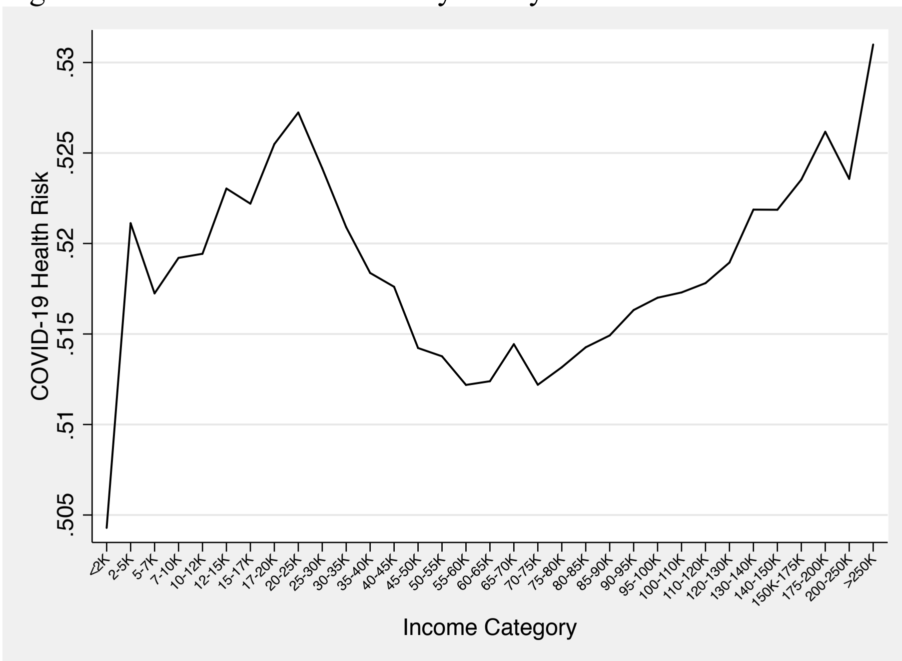
Notes: Income is total income of Census family.

Figure 8: Sub-components of routine task intensity by family income



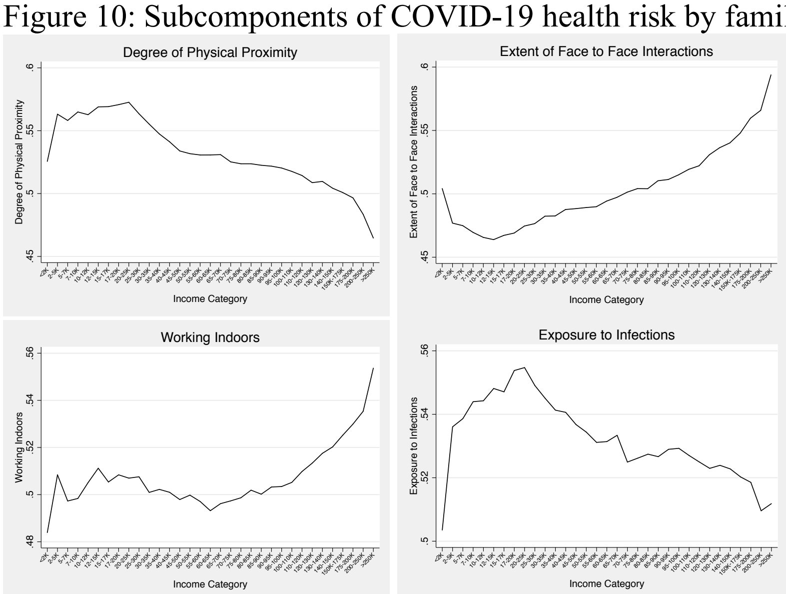
Notes: Income is total income of Census family.

Figure 9: COVID-19 health risk by family income



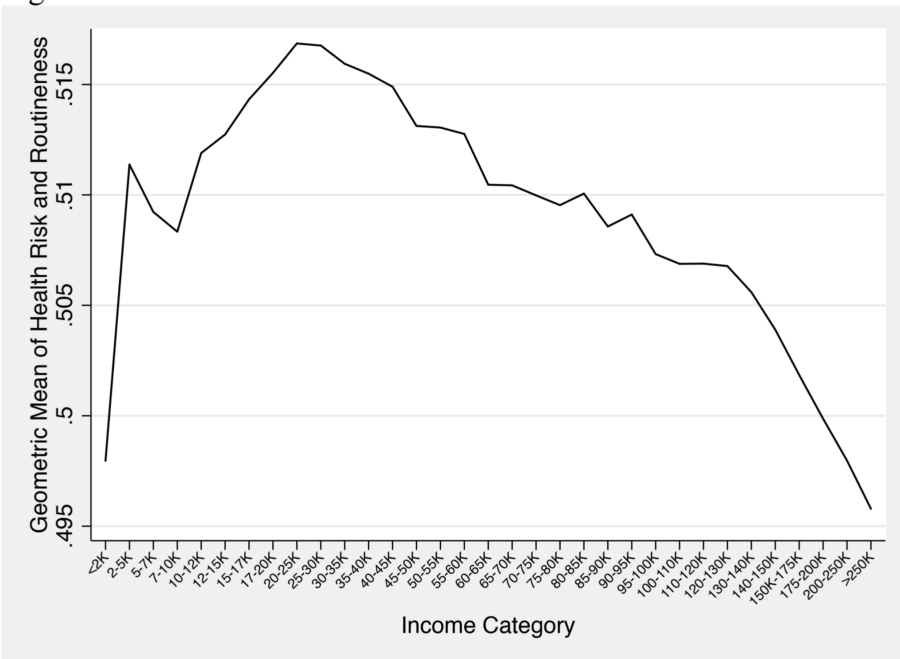
Notes: Income is total income of Census family.

Figure 10: Subcomponents of COVID-19 health risk by family income



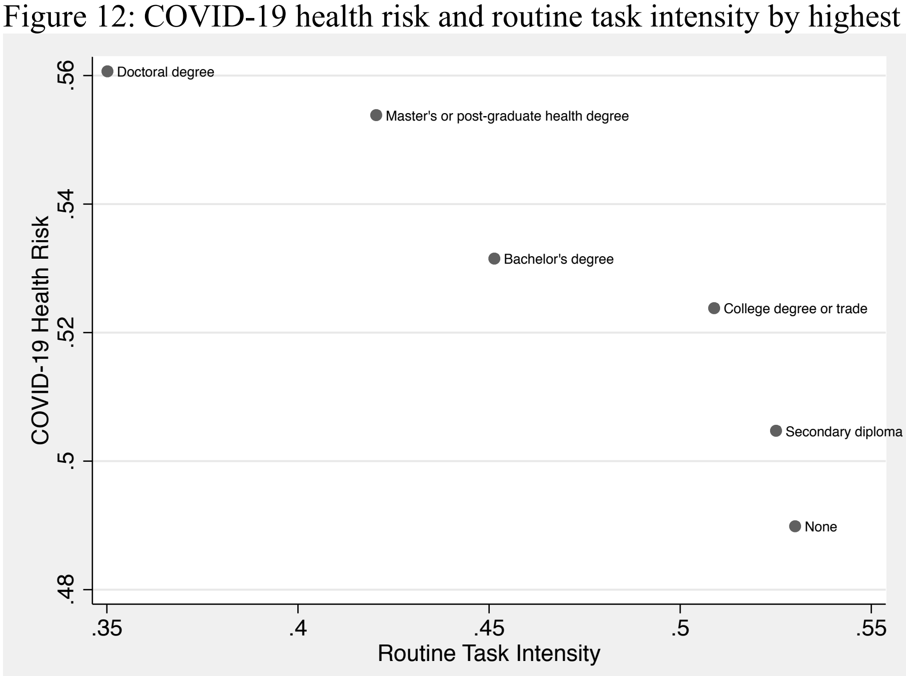
Notes: Income is total income of Census family.

Figure 11: Geometric mean of COVID-19 health risk and routine task intensity by family income



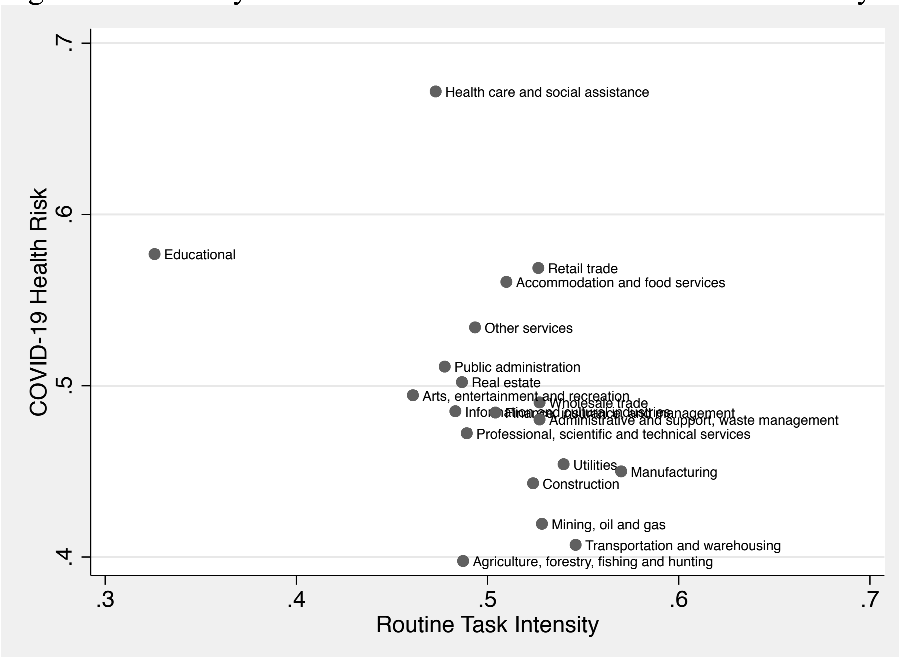
Notes: Income is total income of Census family.

Figure 12: COVID-19 health risk and routine task intensity by highest degree



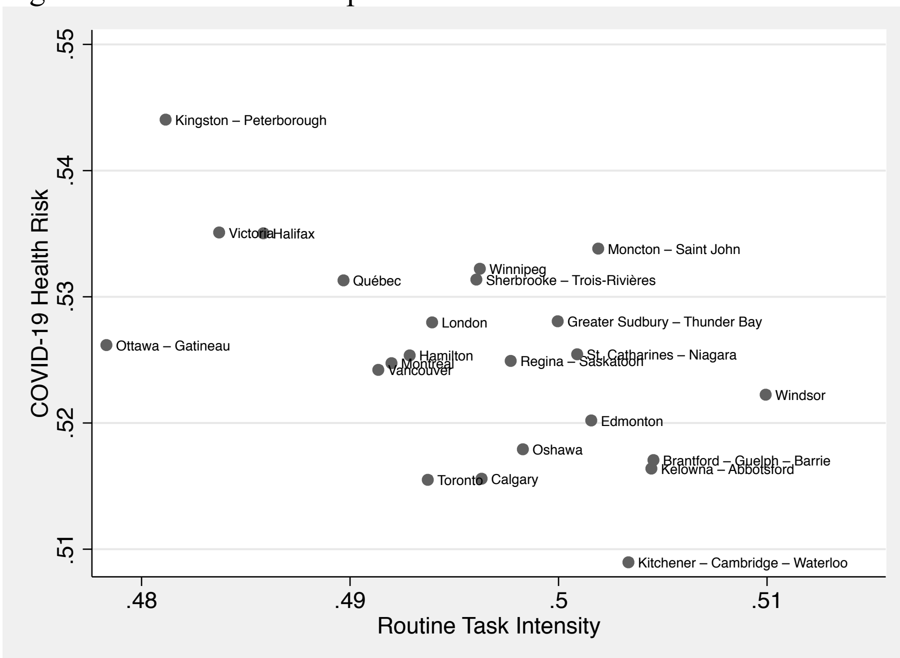
Notes: Highest certificate, diploma, or degree attained. Some categories have been combined. College degree or trade category combines codes 3-8. Master’s or post-graduate health degree combines codes 10-12.

Figure 13: Industry COVID-19 health risk and routine task intensity



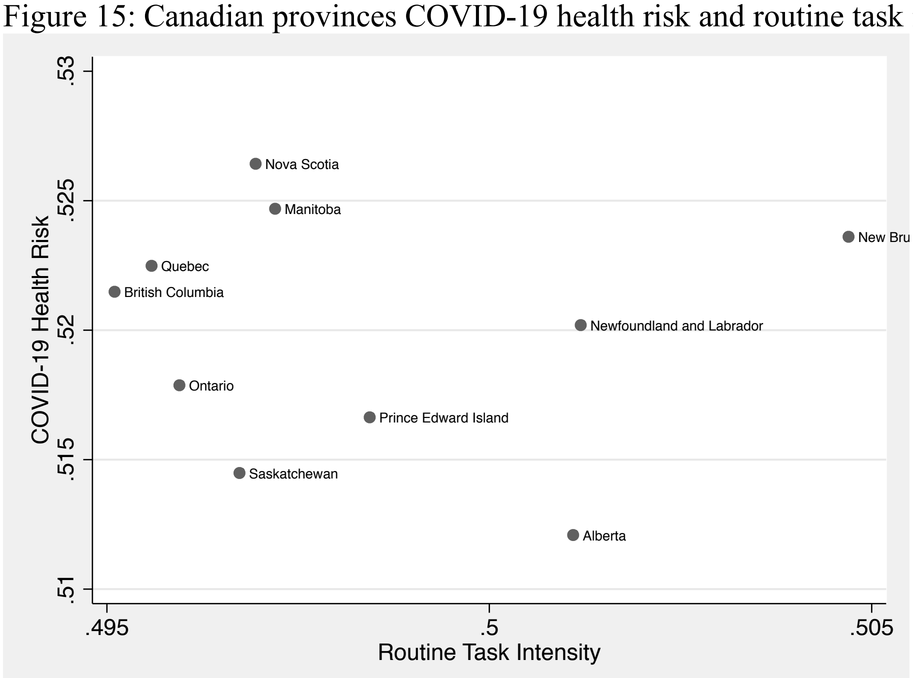
Notes: 19 Census PUMF industry sectors (based on NAICS 2012)

Figure 14: Canadian metropolitan areas COVID-19 health risk and routine task intensity



Notes: Census PUMF 23 Census Metropolitan Areas or Census agglomerations based on current residence. Some agglomerations have been combined.

Figure 15: Canadian provinces COVID-19 health risk and routine task intensity



Notes: Province based on current residence.

Tables

Table 1: Index of routine task intensity and subcomponents for each of 40 LFS occupation categories

Occupation	Automation	Repetitive	Exact	Structured	Pace	Routine index
38 Processing and manufacturing machine operators and related production workers	0.78	0.57	0.47	0.81	0.92	0.71
7 Finance, insurance and related business administrative occupations	0.74	0.95	0.84	0.65	0.35	0.70
9 Distribution, tracking and scheduling coordination occupations	0.80	0.87	0.65	0.49	0.67	0.69
8 Office support occupations	0.71	0.94	0.75	0.64	0.38	0.68
40 Labourers in processing, manufacturing and utilities	0.71	0.53	0.21	0.92	0.93	0.66
15 Assisting occupations in support of health services	0.54	0.77	0.63	0.72	0.55	0.64
37 Processing, manufacturing and utilities supervisors and central control operators	0.75	0.64	0.46	0.44	0.90	0.64
39 Assemblers in manufacturing	0.44	0.52	0.62	0.71	0.82	0.62
31 Other installers, repairers and servicers and material handlers	0.55	0.48	0.56	0.64	0.82	0.61
27 Sales support occupations	0.48	0.63	0.56	0.84	0.53	0.61
33 Trades helpers, construction labourers and related occupations	0.40	0.44	0.42	0.72	0.84	0.56
30 Maintenance and equipment operation trades	0.36	0.48	0.64	0.60	0.73	0.56
14 Technical occupations in health	0.40	0.69	0.70	0.48	0.51	0.55
11 Technical occupations related to natural and applied sciences	0.65	0.55	0.56	0.50	0.51	0.55
26 Service representatives and other customer and personal services occupations	0.59	0.64	0.44	0.68	0.39	0.55
36 Harvesting, landscaping and natural resources labourers	0.71	0.12	0.06	0.89	0.94	0.55
19 Occupations in frontline public protection services	0.41	0.72	0.69	0.43	0.44	0.54
34 Supervisors and technical occupations in natural resources, agriculture and related production	0.53	0.49	0.29	0.48	0.84	0.53
32 Transport and heavy equipment operation and related maintenance occupations	0.41	0.35	0.28	0.77	0.76	0.51
29 Industrial, electrical and construction trades	0.40	0.34	0.48	0.64	0.71	0.51
28 Service support and other service occupations, n.e.c.	0.56	0.35	0.19	0.79	0.63	0.50
5 Professional occupations in business and finance	0.71	0.57	0.67	0.38	0.16	0.50
6 Administrative and financial supervisors and administrative occupations	0.47	0.81	0.53	0.36	0.30	0.49
25 Sales representatives and salespersons wholesale and retail trade	0.56	0.69	0.33	0.58	0.30	0.49
10 Professional occupations in natural and applied sciences	0.60	0.47	0.50	0.55	0.32	0.49
24 Service supervisors and specialized service occupations	0.41	0.41	0.37	0.54	0.65	0.48
35 Workers in natural resources, agriculture and related production	0.55	0.27	0.14	0.64	0.74	0.47
3 Middle management occupations in retail and wholesale trade and customer services	0.63	0.58	0.38	0.25	0.42	0.45
2 Specialized middle management occupations	0.58	0.53	0.52	0.28	0.27	0.44
23 Retail sales supervisors and specialized sales occupations	0.63	0.54	0.55	0.22	0.22	0.43
12 Professional occupations in nursing	0.32	0.62	0.76	0.24	0.20	0.43
4 Middle management occupations in trades, transportation, production and utilities	0.64	0.33	0.26	0.29	0.61	0.43
13 Professional occupations in health (except nursing)	0.45	0.50	0.69	0.19	0.28	0.42
21 Professional occupations in art and culture	0.20	0.47	0.51	0.51	0.29	0.40
22 Technical occupations in art, culture, recreation and sport	0.31	0.33	0.33	0.50	0.43	0.38
17 Professional occupations in law and social, community and government services	0.41	0.38	0.47	0.38	0.16	0.36
1 Senior management occupations	0.55	0.43	0.29	0.11	0.38	0.35
20 Care providers and educational, legal and public protection support occupations	0.20	0.26	0.21	0.65	0.25	0.31
18 Paraprofessional occupations in legal, social, community and education services	0.22	0.24	0.17	0.61	0.11	0.27
16 Professional occupations in education services	0.16	0.23	0.14	0.37	0.21	0.22

Table 2: Index of COVID-19 health risk and subcomponents for each of 40 LFS occupation categories

Occupation	Proximity	Facetoface	Indoor	Exposure	Health index
13 Professional occupations in health (except nursing)	0.90	0.88	0.85	0.94	0.89
12 Professional occupations in nursing	0.89	0.80	0.64	0.96	0.82
14 Technical occupations in health	0.88	0.63	0.78	0.93	0.81
24 Service supervisors and specialized service occupations	0.77	0.62	0.78	0.71	0.72
15 Assisting occupations in support of health services	0.91	0.37	0.66	0.94	0.72
19 Occupations in frontline public protection services	0.82	0.75	0.10	0.88	0.64
27 Sales support occupations	0.74	0.44	0.69	0.65	0.63
16 Professional occupations in education services	0.64	0.60	0.57	0.67	0.62
20 Care providers and educational, legal and public protection support occupations	0.87	0.35	0.37	0.84	0.61
25 Sales representatives and salespersons wholesale and retail trade	0.65	0.87	0.33	0.57	0.60
8 Office support occupations	0.40	0.47	0.81	0.61	0.57
18 Paraprofessional occupations in legal, social, community and education services	0.64	0.43	0.39	0.76	0.56
1 Senior management occupations	0.32	0.82	0.47	0.54	0.54
3 Middle management occupations in retail and wholesale trade and customer services	0.46	0.69	0.50	0.47	0.53
26 Service representatives and other customer and personal services occupations	0.68	0.25	0.62	0.52	0.52
6 Administrative and financial supervisors and administrative occupations	0.21	0.56	0.69	0.60	0.52
23 Retail sales supervisors and specialized sales occupations	0.51	0.70	0.44	0.42	0.52
17 Professional occupations in law and social, community and government services	0.28	0.62	0.61	0.54	0.51
2 Specialized middle management occupations	0.26	0.74	0.62	0.40	0.50
28 Service support and other service occupations, n.e.c.	0.52	0.25	0.59	0.64	0.50
22 Technical occupations in art, culture, recreation and sport	0.59	0.42	0.47	0.46	0.49
39 Assemblers in manufacturing	0.59	0.61	0.51	0.22	0.48
9 Distribution, tracking and scheduling coordination occupations	0.38	0.56	0.47	0.47	0.47
11 Technical occupations related to natural and applied sciences	0.47	0.59	0.41	0.39	0.47
37 Processing, manufacturing and utilities supervisors and central control operators	0.51	0.56	0.31	0.48	0.46
33 Trades helpers, construction labourers and related occupations	0.62	0.56	0.05	0.59	0.45
29 Industrial, electrical and construction trades	0.58	0.55	0.34	0.34	0.45
21 Professional occupations in art and culture	0.53	0.32	0.56	0.39	0.45
30 Maintenance and equipment operation trades	0.51	0.58	0.25	0.43	0.44
34 Supervisors and technical occupations in natural resources, agriculture and related production	0.56	0.57	0.11	0.49	0.43
4 Middle management occupations in trades, transportation, production and utilities	0.35	0.75	0.20	0.39	0.42
38 Processing and manufacturing machine operators and related production workers	0.46	0.30	0.63	0.29	0.42
5 Professional occupations in business and finance	0.25	0.51	0.72	0.17	0.41
10 Professional occupations in natural and applied sciences	0.24	0.49	0.64	0.22	0.40
31 Other installers, repairers and servicers and material handlers	0.50	0.47	0.16	0.35	0.37
7 Finance, insurance and related business administrative occupations	0.19	0.33	0.65	0.29	0.36
36 Harvesting, landscaping and natural resources labourers	0.77	0.14	0.02	0.47	0.35
40 Labourers in processing, manufacturing and utilities	0.51	0.23	0.46	0.14	0.34
32 Transport and heavy equipment operation and related maintenance occupations	0.42	0.20	0.13	0.56	0.33
35 Workers in natural resources, agriculture and related production	0.35	0.23	0.09	0.44	0.28

Table 3: Peak to trough employment drop during three recessions and occupation characteristics

Dependent Variable: Peak to trough percentage change in employment per capita

	(1) OLS	(2) OLS	(3) WLS
Routine Task Intensity	-0.28**	-0.16*	-0.20**
	(0.11)	(0.09)	(0.09)
COVID-19 Health Risk	0.14**	0.13**	0.14**
	(0.06)	(0.06)	(0.05)
Trend		5.99***	5.16***
		(1.51)	(1.27)
Recession Fixed Effects	No	Yes	Yes
R-squared	0.1629	0.3009	0.3424
Observations	120	120	120

Notes: Columns (1) and (2) estimated using ordinary least squares while (3) uses weighted least squares with employment per capita as weights. Robust standard errors clustered by occupation. Dependent variable is the peak to trough percentage change in employment per capita. Peak to trough for the three recessions are June 1989 to May 1992, September 2007 to July 2009, and October 2014 to June 2016. Observations are recession-occupation pairs. Occupations are the 40 LFS occupation categories. Asterisks indicate statistical significance: * = $p<0.1$, ** = $p<0.05$, *** = $p<0.01$.

Table 4: Peak to trough COVID-19 employment drop and occupation characteristics

Dependent Variable: February-April 2020 percentage change in employment per capita

	(1) OLS	(2) OLS	(3) WLS
Routine Task Intensity	-0.16	-0.06	-0.18
	(0.15)	(0.16)	(0.18)
COVID-19 Health Risk	-0.31*	-0.27	-0.37**
	(0.18)	(0.19)	(0.17)
Trend		3.87*	1.61
		(2.18)	(2.94)
R-squared	0.0841	0.1294	0.1521
Observations	36	36	36

Notes: Columns (1) and (2) estimated using ordinary least squares while (3) uses weighted least squares with employment per capita as weights. Robust standard errors. Dependent variable is the February to April 2020 percentage change in employment per capita. Observations are LFS occupation categories. Health related occupations (categories 12, 13, 14, 15) are excluded from the analysis. Asterisks indicate statistical significance: * = $p<0.1$, ** = $p<0.05$, *** = $p<0.01$.

Table 5: Relationship between COVID-19 health index and routine task intensity across occupations, income groups, industries, and cities

Dependent Variable: COVID-19 health index

	(1) Occupations	(2) Incomes	(3) Industries	(4) Cities
Routine Task Intensity	-0.22*	-0.27***	-0.59**	-0.46***
	(0.12)	(0.04)	(0.26)	(0.16)
R-squared	0.0381	0.5450	0.1909	0.1788
Observations	40	33	19	23

Notes: Weighted least squares regressions with robust standard errors. Column (1) examines relationship across the 40 LFS occupation categories, (2) across 33 Census family income groups, (3) across 19 NAICS industries, and (4) across 23 MSAs and agglomerations. Asterisks indicate statistical significance: * = p<0.1, ** = p<0.05, *** = p<0.01.