Lives and Livelihoods:

Potential Health and Economic Impacts of the COVID-19 Pandemic on the District's Workforce

by José Funes, Ph.D., Economic Geographer
DC Office of Planning

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ABSTRACT

By analyzing the occupational characteristics of DC residents—such as the feasibility of working from home and/or exposure to disease/infections—we provide preliminary insights into the magnitude of risk regarding job loss and exposure to COVID-19. Given the "social distancing" measures, approximately 58% of the DC workforce could perform their work from home, with the highest share (36%) of workers concentrated in four high-skilled occupations (management [11][3], business and financial operations [13], legal [23], and computer and mathematical sciences [15]. Moreover, through our exploratory spatial analysis captured vis-à-vis census tract, we observe a positive spatial correlation between the location of residents who are at a high risk of exposure to the virus and the location of surrounding residents who have a high risk of job loss—referred to as the **"double burden"** dilemma.

OBJECTIVE

In this brief, we aim to estimate the potential health and economic impacts of "social distancing" measures in the District of Columbia. By analyzing occupational characteristics of DC residents—such as the feasibility of working from home and exposure to disease/infections—we provide preliminary insights into the magnitude of risk regarding job loss and exposure to COVID-19 in DC.

BACKGROUND

Some preliminary work has been done in estimating the economic and health impacts of COVID-19 throughout the wider-US economy. For instance, Dingel and Neiman (2020) and Aaronson et al. 2020 looked at the potential economic impact by estimating: (i) the share of jobs that can be done via telework by industries at the national level; and (ii) the potential jobs impacted by COVID-19, respectively. On the health impact, Baker et al 2020 provides national health estimates on the burden of workers exposed to COVID-19 infection by occupations. We draw from these three studies to estimate the economic and health impacts on the DC workforce by occupations at two geographic levels: **DC (aggregate)** and **census tract.**

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[3]The number in brackets corresponds to the standard occupational classification system (SOC) code.

METHODS

Two sources of data were used in this analysis: American Community Survey (ACS-2014-2018) and the Occupational Information Network (O*NET). The ACS survey provides estimates and marginal errors of the number of workers in the District of Columbia by occupation, while O*NET provides contextual information by occupation. We acknowledge the existence of the longitudinal housing and economic dynamics (LEHD) program, which uses Origin-Destination Employment Statistics. For the purposes of this study, however, we found ACS (2014-2018) occupational data as a more effective resource as it provides also a high level of spatial granularity.

The risk of workplace exposure to an infectious disease was derived from the O*NET survey question: “How often does this job require exposure to disease/infections?” Within O*NET, these data are converted to a scale of 0-100—representing weighted-average frequency of the metric for each standard occupational classification system (SOC) code. The data for this study pulls from occupational data that had a score between 50-100, representing exposure to a disease/infection for more than one month. As such, we estimate the total number of workers with exposure to infectious diseases per the census tract data.

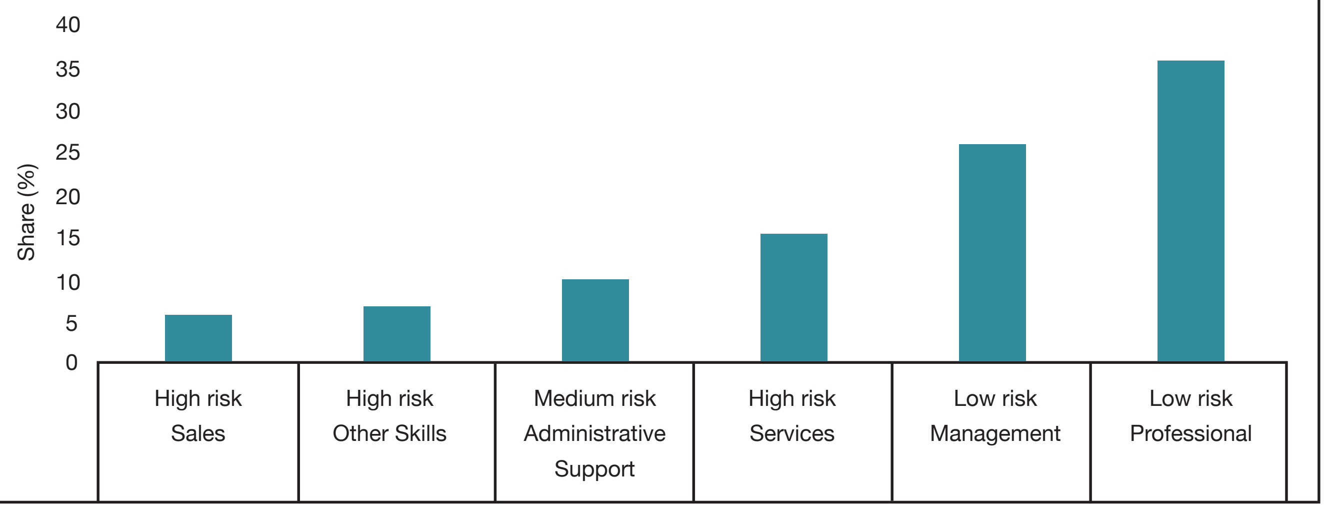
The second index that we estimate is the total number of workers that can perform their work from home. This feasibility measure is based on responses to two O*NET surveys covering “work context” and “generalized work activities” (Dingel and Neiman 2020). This index is used as a proxy for risk of unemployment; a high value indicates increased ability to perform their work at home and a lower risk of job loss. Likewise, the opposite scenario holds true. In the appendix section, Table B.1 shows the share of jobs that can be done from home and section B.2 shows the equations to estimate the total number of potential telecommuters per census tract.

RESULTS AND DISCUSSION

Pre-COVID-19

This section provides a baseline snapshot of the DC workforce ex-ante COVID-19 pandemic[4]. Figure 1 shows a bar chart with the share of occupations in six categories and risk of unemployment. As of 2004-2018 5 years ACS estimate, 374,067 workers were employed in six broad occupations. The highest share of DC residents' occupations falls within the professional and management categories (36%, 26%, respectively). The other 38% of the workforce occupations include services 15%, administrative support 9%, other skills labor 7%, and sales 6%.

Figure 1. Share (percentage) of workers clustered by occupations[5] and risk of unemployment based on "social distancing" measures:



Source: Own calculations based on ACS (2014-2018). Other skills include within contact-intensive sectors: transportation, construction, material moving, production occupations, installation and farming occupations.

Tables A.1 and A.2 [Appendix] present disaggregate results of this analysis. The tables provide summary statistics on the number of workers, shares, median incomes, and the vulnerability of job loss for each of the 22 SOC occupations. Adhering to "social

[4]We acknowledge the outdated statistics, but we would not expect the share of occupations to have changed before the Covid-19 pandemic.

[5]Clusters of occupations by SOC codes: Professional [15,17,19,21,23,25,27,29]; Services [31,33,35,37,39]; Other skills [45,47,49,51,53]; Management [11,13] and Sales [41].

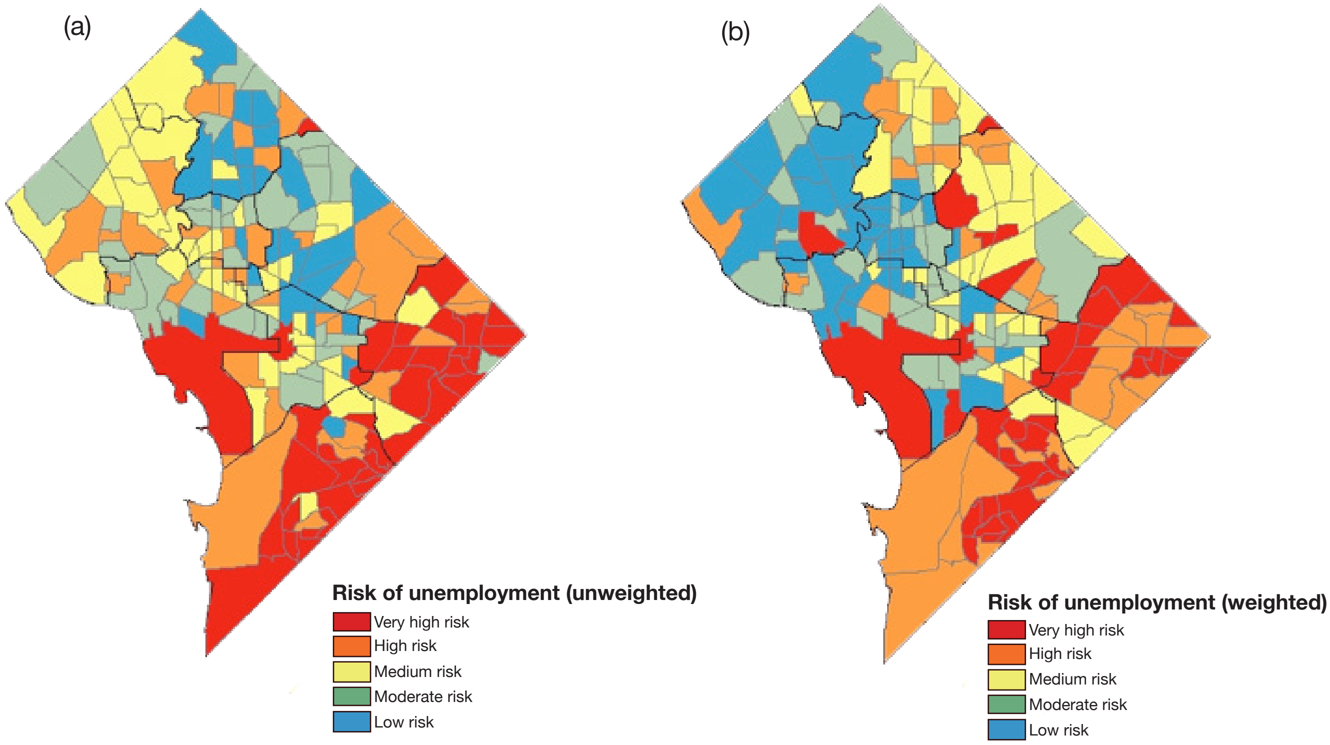
distancing" measures, approximately 58% of this workforce could perform their work from home, with the highest share (36%) of workers concentrated in four high-skilled occupations. These top occupations include: management [11], business and financial operations [13], legal [23], and computer and mathematical sciences [15], with annual incomes ranging from $80,000 to $130,000. We expect workers employed in these occupations to have a low risk of job loss. In contrast, workers with the highest risk of job loss, reduced income or furloughs represent about 35% of the workforce with incomes ranging from $27,000 to $54,000. These occupations include: food preparation [35], personal care and service occupations [39], building and ground and cleaning occupations [37], and protective services [33]. This analysis shows that the coronavirus more likely affected disproportionally the less educated people.

COVID-19 Period

To identify neighborhood local conditions, such as housing and food needs affected by "social distancing" measures, we employed geographic indices to show the risk of unemployment to DC residents. To do this, we present two geographic composite indices by census tract. These indices provide summary statistics on risk levels of job loss. Figure 2 shows two maps—an unweighted index and a weighted index of the risk of job loss. The unweighted version shows at-risk jobs for each occupation ability to telework. The weighted version factors in by each occupation labor participation and ability to telework.

Figure 2 (a) maps out the total number of occupations at risk by census tract; in this figure Ward 7 and Ward 8 show a high risk of job loss denoted by the following categories: very high risk and high risk. Once we control by the number of workers per occupation and their ability to telework, the effective number of jobs at risk becomes more concentrated in Wards 4, 5, 7, and 8 as is illustrated in Figure 2 (b). Given the likelihood of income loss throughout these Wards, we would expect rental and mortgage forbearance to increase, purchasing of food for households to decrease, and the risk of food insecurity to become more prominent throughout the area. Food insecurity could potentially rise along with poverty levels. In this scenario, the most vulnerable populations—those who are very close to the poverty line—are at a high risk of falling into poverty. Furthermore, other studies have shown evidence of worsen housing affordability for service, retail and transportation workers.

Figure 2. Risk of unemployment by census tract (a) unweighted and (b) weighted



Source: Own calculations based on ACS (2014-2018)

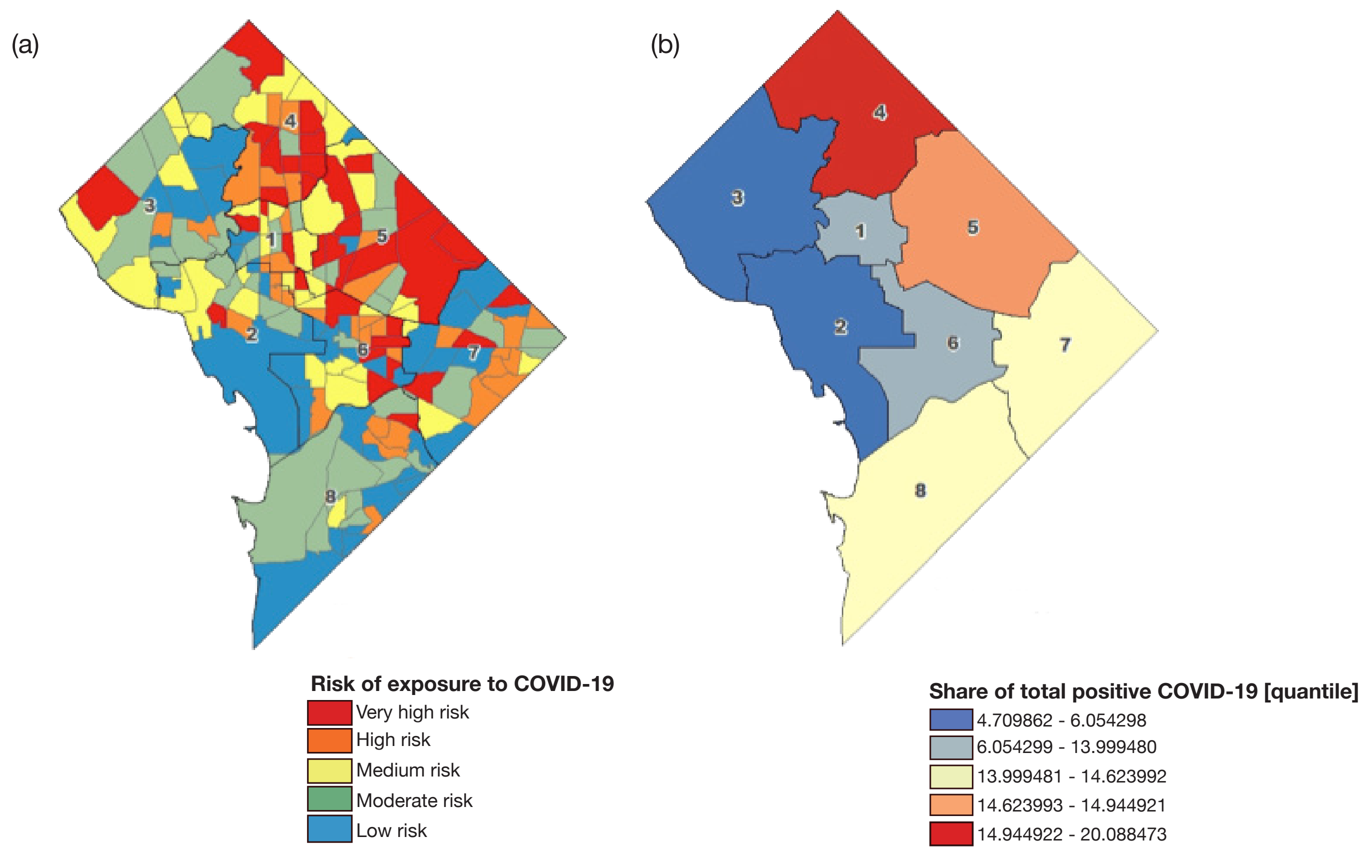
Risk to infectious diseases

Table A.3 [Appendix] summarizes the top 5 occupational sectors (two-digit SOC) representing the highest share of workers potentially exposed to a disease/infection for more than one month. Occupations in the health sector, which represent about 7% of the DC workforce, have the highest exposure to infectious diseases in a month's time. The data for this study pulls from occupational data that had a score between 50-100, representing exposure to a disease/infection for more than one month. The full list includes: healthcare support [31], healthcare practitioners/technical occupations [29], and health diagnosing/treating practitioners [29]. Other groups with high risk of exposure to infectious diseases include: production occupations [51], protective services [33], and personal care/service occupations [39], which represent about 5% of DC workforce. Medium risk of exposure includes three occupations: community and social service and education/training/library occupations. Due to confidentiality issues, the latest ACS samples such as 2014-2018 contain less details, which combine codes from earlier ACS versions (Ruggles et al. 2020).

As DC prepares to re-open the economy, the workplace and where people live play an important role in helping to prevent and contain the spread of the virus. Knowledge about the workplace by occupation and where people live, more specifically, is relevant for risk management and communication to workers about their increased risk of potential exposure to a disease. As such, we employed a geographic index to identify neighborhoods that show the risk of exposure to infectious diseases. Figure 3 shows two maps—an index of the risk of exposure to infectious diseases by census tract and a map of the total positive cases of COVID-19 by Ward.

Figure 3 (a) and 3 (b) displays the risk of COVID-19 exposure and share of COVID-19 cases, respectively. Figure 3a highlights census tracts for Ward 4, Ward, 5, Ward 6 and Ward 7 with high risk of exposure to infectious diseases denoted by the following categories: very high risk and high risk. In contrast, Figure 3.b reports the number of total positive COVID-19 by Ward as of May 13th. We can observe a positive spatial correlation between the risk of exposure to infectious diseases and the number of COVID-19 cases.

Figure 3. (a) Risk of exposure to COVID-19 by census tract and (b) share of COVID-19 cases by Ward



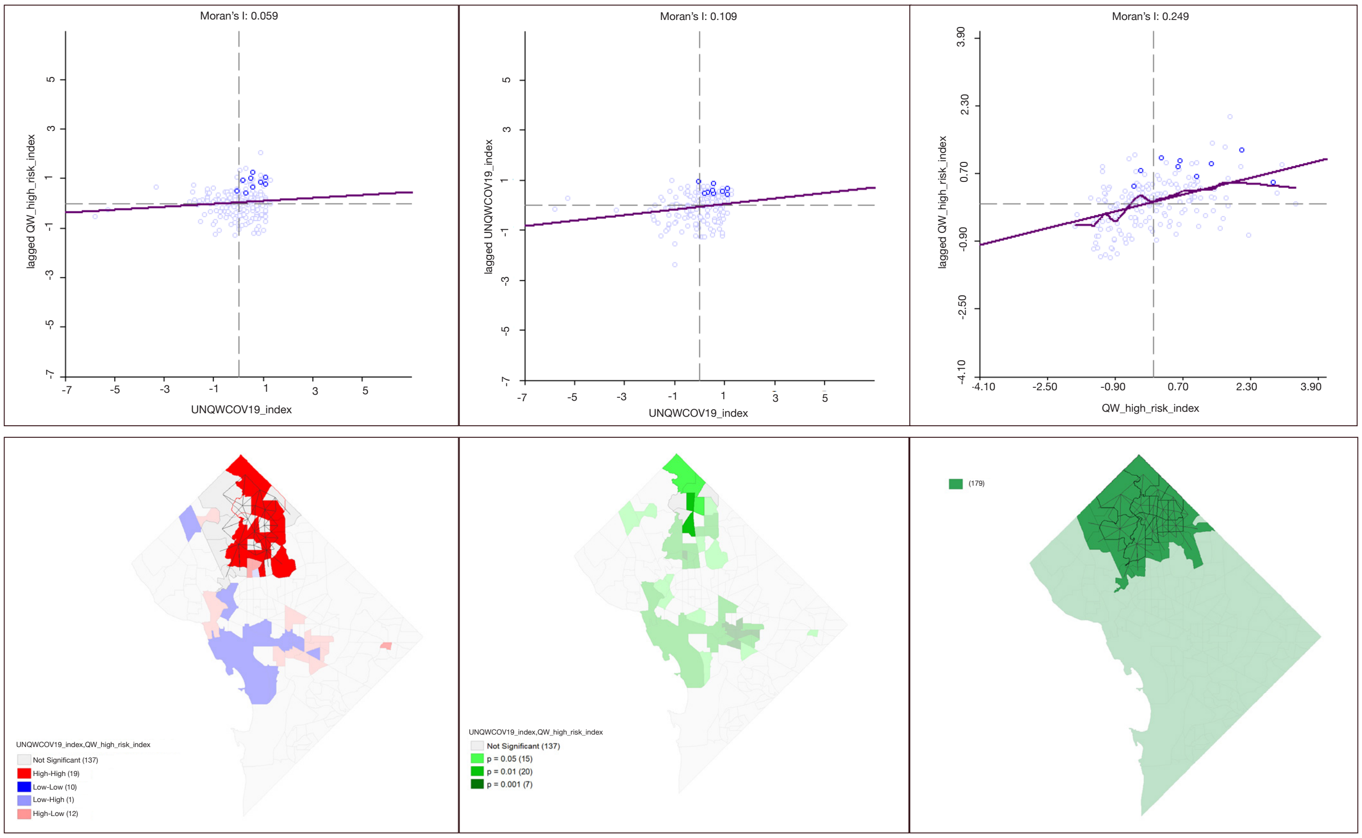
Source: Own estimations based on ACS 2014-2018, O*NET 2018, and DC coronavirus-data [07/22/2020].

In addition, we observe a potential double burden dilemma by location – a census tract with high risk of exposure to COVID-19 surrounded by census tracts with high risk of job loss. SOC's occupations with medium and high risks of job loss include twelve occupations as shown in Figure 1. To illustrate this, figure 4 shows three scatter plots and three maps. The scatter plots show a bivariate Moran's I and two univariate Moran's I plots. The bivariate Local Moran measures the degree of spatial association between one variable and the lag variable of another variable. The univariate Local Moran, on the other hand, measures local spatial association of one variable.

From left to right, Figure 4 shows 1) a bivariate Moran's I plot depicting on the Y axis the lag values of the ability of no teleworking and on the x-axis the values of the risk of being exposed to COVID-19; 2) a univariate Moran's I plot showing on the x-axis the risk of exposure to COVID-19 and on the y-axis the lag variable of the risk of exposure to COVID-19; and 3) a univariate Moran's I showing on the x-axis the risk of job loss and on the y-axis the lag variable of the risk of job loss. The maps, from left to right, show 1) the bivariate cluster map depicting the spatial relationship between the value of the risk of exposure to COVID-19 at each census tract i and the average of the neighboring values (spatial lag $\sum_j w_{ij} y_j$) of the risk of job loss, 2) the bivariate significance map demonstrating the clustering and significance levels of the clusters in 1; and 3) the connectivity map displaying the connectivity of the spatial matrix.

Taking a closer look into the bivariate cluster map (button-left), we can observe four clusters. These are high-high or hot spots (red) which represent high values of the risk of exposure to COVID-19 surrounded by census tracts with high values of the lag variable of the risk of job loss (18 census tracts). This is what we labeled as a double burden observed in census tracts of Wards 1, 4, and 5. For illustration purposes, highlighted points in the scatter plots and highlighted census tracts in the maps help to visualize the spatial linkage between the risk of job loss and the risk of exposure to COVID-19. There are low-low (10 census tracts) or cold spots (blue) which are low values of the risk of exposure to COVID-19 surrounded by census tracts with low values of the lag variable of the risk of job loss. The third cluster denotes low-high (light blue), which are low values of the risk of exposure to COVID-19 surrounded by census tracts with high values of the risk of job loss (1 census tract). And finally, the fourth cluster (11 census tracts) is high-low (pink) which represents high values of the risk of exposure to COVID-19 surrounded by census tracts with low values of the risk of job loss. These last two clusters are known as spatial outliers.

Figure 4. Top row [left to right]: a bivariate Moran's I scatter plot and two univariate Moran's I. Bottom row [left to right]: a bivariate cluster map, a bivariate significant map and a connectivity graph map



Source: Own estimations based on ACS 2014-2018, O*NET 2018, and DC coronavirus-data [07/22/2020].

Tables A.1, A.2 and A.3 [Appendix] present the aggregate results of this analysis.

Policy Implications

This analysis provides multiple useful applications for policymakers and planners. Potential applications include:

- Providing a baseline snapshot of the DC workforce ex-ante COVID-19 pandemic and ex-post the economic shock;
- Estimating potential forgone salary aggregates as input for potential tax base losses;
- Detailing the share of jobs that could be performed at home to serve as an important input to predict District and neighborhood economic performance;
- Identifying geographic areas with a potential double burden dilemma or with a positive spatial correlation between the risk of job loss and the risk of exposure to infectious diseases;
- Identifying geographic areas with a high risk of unemployment and high risk of exposure to infectious disease to use as a proxy for identifying local conditions on housing, food needs, and health;

Limitations of this Study

- O*NET data is based on a self-reported subjective questionnaire and therefore subject to bias and misclassification
- O*NET occupation-level does not account for within-job exposure
- O*NET occupation-level does not account for within-job ability to work from home
- Our estimates of teleworking are based on one scenario. As new surveys and real COVID-19 data at finer resolution become available, these new datasets in combination with simulations of various policy scenarios could generate new estimates by occupation and industry.

CONCLUSION

This analysis provided a granular view of the occupations and number of workers at risk of job loss due to the spread of the pandemic and thus could inform key stakeholders and policymakers of: (1) the re-skilling needed to help boost employment; and (2) the level of effort needed to mitigate the negative outcomes associated with loss of income, such as, increasing levels of food insecurity and decreasing rental affordability. Proxied by occupation, this analysis shows that DC residents with occupations categorized as essential (such as, grocery store workers, healthcare providers, etc.) are at high risk of exposure to COVID-19. Additionally, it is important to note that many workers with essential jobs are among the less paid. The spatial disaggregate analysis shows the concentration of risk of job loss and of exposure to infectious diseases by location. Already, this analysis indicates that locations with the highest share of black and Hispanic populations are disproportionally affected. We foresee the need to develop a detailed heat map or matrix displaying the relationship of the number of jobs lost by industry and by occupation. This analysis could be combined with strategies to open the economy by phases. These estimates will need to be updated frequently to capture the dynamic nature of both the labor market and the pandemic.

APPENDIX

Table A.1 Top 10 Occupations at Risk of Job Loss

Occupations - SOC	Number of Workers	**Percent of Workers Affected/No Telework Policy**	Median Annual Income
Food Preparation and Serving	17,818	100%	$21,987
Building and Grounds Cleaning & Maintenance	12,914	100%	$25,943
Construction and extraction	7,282	100%	$38,588
Production	2,577	99%	$45,335
Installation, Maintenance and Repair	2,440	99%	$42,600
Farming	103	99%	$11,544
Transportation	7,680	97%	$38,993
Material moving	5,730	97%	$30,512
Protective Service	8,806	94%	$41,186
Personal care and service	9,805	74%	$23,750

Source: Own calculations based on: ACS (2014-2018) and O*NET 2018; Dingel and Neiman (2020)

Table A.2 Occupations at Risk of Job Loss Ranked by Number of Workers

SOC	Occupations – SOC	Number of Workers	**Number of Workers/No Telework Policy**	Median Income
35	Food Preparation and Serving	17,818	17,818	$21,987
41	Sales and related occupations	22,562	16,245	$34,489
37	Building and Grounds Cleaning & Maintenance	12,914	12,914	$25,943
43	Offices and Administrative support	35,522	12,433	$42,404
33	Protective Service	8,806	8,278	$41,186
11	Management	59,037	7,675	$93,601
53	Transportation	7,680	7,450	$38,993
47	Construction and extraction	7,282	7,282	$38,588

Table A.2 Occupations at Risk of Job loss Ranked by Number of Workers (cont.)

SOC	Occupations – SOC	Number of Workers	**Number of Workers/No Telework Policy**	Median Income
39	Personal care and service	9,805	7,256	$23,750
19	Life, Physical, and Social Science	12,492	5,746	$80,088
53	Material moving	5,730	5,558	$30,512
21	Community and Social Service	8,810	5,550	$58,913
13	Business and Financial Operations	40,005	4,801	$80,561
27	Art, design, entertainment, sports & media	16,704	4,009	$26,791
51	Production	2,577	2,551	$45,335
49	Installation, Maintenance, and Repair	2,440	2,416	$42,600
17	Architecture and Engineering	5,120	1,997	$84,937
23	Legal	25,982	779	$126,769
25	Education, Training, and Library	22,422	448	$52,541
45	Farming	103	102	$11,544
15	Computer and Mathematical	22,770	0	$84,026

Source: Own calculations based on: ACS (2014-2018). This list excludes health-related occupations as the demand for their skills increases as the number of COVID-19 patients rises.

Table A.3 Top 10 Occupations at Risk of Disease/Infection Exposure

Occupations – SOC	Number of workers	**Number of Workers at Risk of Exposure**	Median Annual Income
Healthcare practitioners and technical	12,081	11,054	$69,651
Health diagnosing and treating practitioners	9,511	8,703	$77,915
Offices and administrative support	35,522	5,755	$42,404
Health care support	5,894	5,664	$28,130
Education, Training, and Library	22,422	5,224	$52,541

Table A.3 Top 10 Occupations at Risk of Disease/Infection Exposure (cont.)

Occupations – SOC	Number of Workers	**Number of Workers at Risk of Exposure**	Median Annual Income
Personal care and service	9,805	5,108	$23,750
Legal	25,982	4,781	$126,769
Protective Service	8,806	4,588	$41,186
Sales	22,562	4,151	$34,489
Personal care and service	9,805	74	$23,750

Source: Own calculations based on: ACS (2014-2018) and O*NET 2018; Baker et al. 2020

Table B.1 Share of jobs by SOC's occupations that could potentially work from home

SOC	Occupation	**O*NET-derived baseline**
15	Computer and Mathematical	1
25	Education, Training, and Library	0.98
23	Legal	0.97
13	Business and Financial Operations	0.88
11	Management	0.87
27	Arts, Design, Entertainment, Sports, and Media	0.76
43	Office and Administrative Support	0.65
17	Architecture and Engineering	0.61
19	Life, Physical, and Social Science	0.54
21	Community and Social Service	0.37
41	Sales and Related	0.28
39	Personal Care and Service	0.26
33	Protective Service	0.06
29	Healthcare Practitioners and Technical	0.05
53	Transportation and Material Moving	0.03
31	Healthcare Support	0.02
45	Farming, Fishing, and Forestry	0.01
51	Production	0.01
49	Installation, Maintenance, and Repair	0.01

Table B.1 Share of jobs by SOC's occupations that could potentially work from home

SOC	Occupation	**O*NET-derived baseline**
47	Construction and Extraction	0
35	Food Preparation and Serving Related	0
37	Building and Grounds Cleaning and Maintenance	0

Source: Dingel and Neiman 2020 based on O*NET survey

B.2 Indices Estimation

Index of exposure to $- COV19_i = \sum_{Oj=1,\dots,24}^{i}$ *proportion of workers exposed to infection diseases by occupation*$_{Oji}$ where QW – $COV19_i$ is occupations at risk of COVID-19 by census tract i. This total number is equal to the summation of occupations at risk of exposure to infectious diseases for more than one month. Occupation$_{Oj}$ is indexed from 1 to 24 SOC-designated occupations.

Index of telework $- TELE_i = \sum_{Oj=1,\dots,22}^{i} QW_{Oji}$ **proportion of workers telecommute*$_{Oji}$ where $QW - TELE_i$ is the total number of workers that can perform their work from home by census tract i. This total number of telecommuters is equal to the summation of the number of workers per occupation multiplied by the proportion of workers that can perform their work from home. We removed health-related occupations as the demand for their skills increases as the number of COVID-19 patients rises. The unweighted version drops the QW_{Oji} variable and just factors in the proportion of workers by occupation likely to telecommute. These variables are rescaled to a range between 0 and 1 by applying the following formula:

$$\text{Rescaled value (r)} = \frac{\text{actual value - minimum value}}{\text{maximum value - minimum value}}$$

Risk Indices

Rescaled indices were classified into five quantiles. For the index on risk of job loss, the first quantile corresponds to “very high risk” while the fifth quantile corresponds to “low Risk”. As for the index on the risk of exposure to infectious diseases, the first quantile corresponds to “low risk” while the fifth quantile is “very high risk”.

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