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COVID-19 AND IMPLICATIONS FOR AUTOMATION

Alex W. Chernoff
Casey Warman

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The American Community Survey data comes from the IPUMS-USA, University of Minnesota, www.ipums.org (Ruggles et al., 2020). The O*NET data is available at https://www.onetonline.org/. The automation potential and viral transmission risk variables used in this paper constructed from the O*NET are available at Download Data. The views in this paper are those of the authors and do not necessarily reflect those of the Bank of Canada or the National Bureau of Economic Research. All errors are our own.

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ABSTRACT

COVID-19 may accelerate the automation of jobs, as employers invest in technology to adapt the production process to safeguard against current and potential future pandemics. We identify occupations that have high automation potential and also exhibit a high degree of risk of viral infection. We then examine regional variation in terms of which U.S. local labor markets are most at risk. Next, we outline the differential impact that COVID-19 may have on automatable jobs for different demographic groups. We find that occupations held by U.S. females with mid to low levels of wages and education are at highest risk. Using comparable data for 25 other countries, we find women in this demographic are also at highest risk internationally.

Alex W. Chernoff
234 Laurier Ave W
Ottawa, ON
K1A 0G9
Canada
achernoff@bankofcanada.ca

Casey Warman
Department of Economics
Dalhousie University
6214 University Avenue, Room A23
Halifax, NS B3H 4R2
CANADA
and NBER
warmanc@dal.ca

1 Introduction

The COVID-19 crisis has caused severe economic loss with record unemployment rates. While some sectors will recover quickly, for other sectors, COVID-19 will have long lasting effects. Specifically, COVID-19 and the threat of future pandemics has the potential to accelerate the process of automation, as employers substitute workers with computers and robots that are unaffected by pandemics. Autor (2015) notes that many forms of automation are complimentary to labor, and Bessen (2019) argues that automation may lead to employment growth in some industries and a decline in others. Therefore, it is likely that COVID-19 induced technological change will increase productivity and wages in some occupations. However, workers in other occupations may be displaced and face large lifetime earnings losses. It is therefore important to identify which jobs are at risk from the heightened push to automate jobs in response to the COVID-19 pandemic and the possibility of future pandemics.

We use information from the O*NET to construct indexes of automation and viral transmission risk. We identify the U.S. local labor markets that may be most impacted by the potential push to automate jobs due to an overlap in viral transmission risk and automation potential. We also examine the demographic groups in the U.S. and across 25 other countries that may be vulnerable to automation due to infection transmission risk.

Similar to previous research, we find that the American Heartland region has a high concentration of jobs with automation potential. We also find isolated local labor markets with elevated risk across the South and along the West Coast. In contrast, viral transmission risk is highest on the East Coast, although there is some overlap of transmission and automation in the Heartland. Due to the lack of collocation of transmission risk and automation potential, there does not appear to be a well-defined spatial pattern in terms of regions that are highest in the potential risk of COVID-19 induced automation. Instead, we find important demographic differences. We uncover that U.S. females are about twice as likely as males to be in occupations that are at high risk of both COVID transmission and automation. When we further disaggregate by earnings, race, and education, we find that this risk is always higher for females relative to males in the same group. Women with low to mid-level wages and educational attainment in the U.S. standout as being at highest risk of both transmission and automation.

We also use data from the Programme for the International Assessment of Adult Competencies (PIAAC) to estimate the joint risk of automation and viral transmission faced by workers in 25 other countries. Women are again disproportionately represented in occupations with high automation potential and viral transmission risk. In all 26 countries in our analysis, we find a greater fraction of females than males in these high-risk occupations. As with the U.S., we find that occupations held by females with mid to low-level wages and education face the highest risk.

The main contribution of our paper is the development and analysis of occupation-specific indexes of automation and COVID-19 transmission risk. Studying these indexes in tandem provides the first characterization of the demographic groups and local labor markets that face joint-risks from COVID-19 and automation. Our paper is related to a well-established literature on automation.[1] An important finding in this literature is that automation is most pervasive in the middle of the skill distribution in jobs featuring routine tasks. Consistent with this literature, we find that the joint risk of automation and COVID-19 transmission is highest for occupations held by females with low to mid-level wages and educational attainment. Although we are examining the enhanced impact of the joint automation and viral transmission risks, the groups that we find are most susceptible is generally consistent with Blanas et al. (2020) who finds that the fall in demand resulting from automation is felt strongest by low and medium-skill workers as well as females.

Our work also contributes to the rapidly growing economic research on COVID-19. Bridging the research on automation and COVID-19 is the idea that pandemic risk may incentivize firms to automate tasks previously completed by workers.[2] Leduc and Liu (2020) note that this investment incentive may be partially offset by lower aggregate demand result-

[1]See Autor (2015) for a review of the literature on workplace automation.

[2]While COVID-19 and the threat of future pandemics may accelerate automation, the economic recession caused by COVID-19 may also increase automation. Hershbein and Kahn (2018) argue that the Great Recession accelerated the routine-biased technological change, while Jaimovich and Siu (2020) find that over the past 35 years, almost all the losses in routine occupations occurred during economic downturns.

ing from elevated uncertainty, however their quantitative general equilibrium analysis finds that job uncertainty can nonetheless stimulate automation. Some research on COVID-19 has identified occupations with the highest risk of exposure,[3] while others have estimated the fraction of jobs that can be completed without putting workers at risk (Boeri et al., 2020), and the fraction that can be carried out from home (Dingel and Neiman, 2020). Caselli et al. (2020) study the relationship between robots and COVID-19 risk in Italy. They find that industries that make greater use of robots (pre-COVID-19) face lower risk from COVID-19 contagion. We focus more broadly on automation, and our objective also differs in that we aim to characterize the joint-relationship between automation potential and COVID-19 transmission risk across U.S. local labor markets and demographic groups in the U.S. and internationally. As noted by Caselli et al. (2020), this relationship is inherently endogenous and our objective is to characterize the correlations between automation potential and COVID-19 transmission risk using carefully constructed indexes, which we hope will be useful for future work on this topic.

2 Data and Viral Transmission Risk and Automation Indexes

We use the O*NET Database to create measures of the viral transmission risk of an occupation, as well as the degree to which an occupation can be automated.[4] There are several important considerations when constructing a meaningful index. First, we need to decide which variables to include, as well as how to aggregate the variables. The viral transmission risk of an occupation is constructed using the three O*NET variables *physical proximity*, *face-to-face discussions*, and *exposed to disease or infections* as well as the average of the two O*NET variables *outdoors, exposed to weather* and *outdoors, under cover*, which capture how often the individual works outside.[5]

[3]For Canada, Baylis et al. (2020) have developed a tool to determine the degree to which each occupation is at risk of viral transmission. They consider the characteristics of the occupation using the O*NET as well as the observed characteristics of the workers in each occupation from Census data.

[4]We use version 24.3 of the O*NET.

[5]*Physical proximity* is defined as the extent to which the job require the worker to perform job tasks in close physical proximity to other people. It includes the following values: “1. I don’t work near other people (beyond 100 ft.)”, “2. I work with others but not closely (e.g., private office)”, “3. Slightly close (e.g., shared office)”, “4. Moderately close (at arm’s length)”, “5. Very close (near touching)”. *Face-to-face discussions* is defined as how often do you have to have face-to-face discussions individuals/team in the job and the *exposed to disease or infections* variable is categorized by how often the job requires exposure to disease/infections. Finally,

For the main results we present, we follow a large literature such as Autor et al. (2003), Acemoglu and Autor (2011) and others that use the O*NET to classify routine and non-routine variables. We construct the commonly used routine task-intensity measure to capture automation, which is estimated as:

$$RTI_j = RC_j + RM_j – NRA_j – NRI_j – NRM_j \tag{1}$$

where RTI_j is the routine task-intensity for the k^{th} occupation.[6] We add together the aggregate routine cognitive (*RC*) and routine manual (*RM*) variables. We also subtract off the aggregate non-routine analytical (*NRA*), interpersonal (*NRI*) and manual variables (*NRM*). Appendix A provides a brief description of the O*NET variables used to construct the five indices used to create the RTI measure.[7] We aggregate the O*NET for each of the five indices after standardizing the variables.[8] We then construct Equation 1 and then normalize the resulting RTI index to be between zero and one and use this as our measure of how automatable an occupation is.[9]

To aggregate the variables used to create the viral transmission risk index, we pursue two popular methods in the literature. For our main results, we average the standardized O*NET questions and then normalize the index to be between zero and one, as we did with our RTI index. Our second method involves performing factor analysis using the U.S. population from the pooled 2013-2017 ACS data as weights, and then normalizing the index in the same manner as with the first approach. We present the results using the first method, although our findings are not sensitive to this specification as the two approaches yield indexes that

the two outdoor variables capture how often does the job requires working outdoors and under cover (which could include a structure with roof but no walls). These latter four variables have the following categories: "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", or "5. Every day". For the two outdoor variables, we reverse the order of these categories to capture the increasing risk of infection of working indoors. See https://www.onetonline.org/ for more details.

[6] Frey and Osborne (2017) also have a very useful "computerisable" index which we used to validate our automation index.

[7] See Mihaylov and Tijdens (2019) for an excellent discussion of the routine task-intensity measure and the relevant literature.

[8] For standardizing, we readjust the given variable as follows: *standardized variable* = (X_i - mean(X))/std(X).

[9] We normalize the index using the following equation: *normalized index* = (index$_i$ - min(index))/(max(index) - min(index)).

are highly correlated.

We match the risk of automation and viral transmission risk indexes constructed with the O*NET to the 2013-2017 American Community Survey (ACS). Unfortunately, there is not a perfect mapping between the 6-digit ACS occupation variable and the O*NET so we also match the remaining occupation with fewer digits and average the variables over the matching O*NET occupations. We restrict our analysis to employed workers, and exclude workers in unpaid family businesses or in the military. We further restrict the sample to workers that are between ages 18 and 65. For our international comparison, we use the Programme for the International Assessment of Adult Competencies (PIAAC) which provides data to make comparable estimates for 25 other countries. We introduce the PIAAC data in greater detail in Section 4 prior to discussing these estimates.

In Figure 1 we plot our indexes of viral transmission risk and automation potential. The high-risk occupations are defined as those with both indexes being greater than or equal to 0.5 and are indicated by red squares. We further differentiate between low-risk occupations (green triangles) if they are below 0.5 on both indexes, and medium-risk occupations (orange circles) if they have an index value greater than or equal to 0.5 for only one of the two indexes. The medium-risk occupations can be thought of as containing two categories. First, are occupations with high viral transmission risk but have a low degree of automation potential. The second category are occupations with low viral transmission risk but high automation potential.

From the scatter plot we see that only 15.3% of the (unweighted) occupations are categorized as high risk (red squares), even though automation potential is greater than or equal to 0.5 for 46.3% of the occupations and in terms transmission risk, 34.3% of occupations are greater than or equal to 0.5. Based on our ACS sample, workers in high-risk occupations represent around 17.9% of the 2013 to 2017 employed U.S. population. Roughly 34.7% of occupations are designated in the low-risk group (green triangles), representing a little less than 32% of the 2013 to 2017 employed U.S. population.

Table 1 shows a sample of occupations with their associated automation and viral transmission index value to get a feel for the indexes. We also include the number of workers in the occupation to understand how important a given job is for the U.S. labor force. The top half of the table includes the four highest and lowest ranked occupations for each index. According to our automation index, 'tire builders' is the occupation with highest automation potential. Dental occupations occupy the two riskiest jobs of viral transmission, which is not surprising given that service providers are required to work at face-to-face proximity to clients in this profession. Health related occupations also make up the next two riskiest jobs.[10] At the low end of the index are solitary professions (meter readers), and professions that have very minimal exposure to diseases or infections (tire builders). At the bottom of Table 1 we show 'high', 'medium', and 'low-risk' occupations using the same definitions of these categories as was used in Figure 1. Specifically, we show examples of the largest occupations in each of these three risk categories. The largest high-risk occupations are in service-related industries, including retail salespersons, secretaries and cashiers, which are jobs involving close contact with clients and co-workers.

Some of the high-risk occupations are only marginally classified as such on both indexes. However, we present several robustness checks below that demonstrate that our results are not dependent on the precise location of the high-risk cut-off. For a number of occupations, it might be argued that the automation index values in Table 1 seemingly belie automation potential as too high (e.g. dental hygienists). While we acknowledge that it is unlikely that these occupations will be fully automated, it is conceivable that partial automation of some of the tasks associated with these jobs could occur and may be accelerated because of COVID-19.

The medium-risk category provides a few interesting cases of professions that are either high in automation potential and low in transmission risk (janitors and building cleaners), or vice versa (elementary and middle school teachers and registered nurses).

Despite there being several jobs with very low index scores in the low-risk category, the

[10]One potential critique of our approach is that we do not take into consider access to personal protective equipment used by essential workers, notably including medical and healthcare workers. However, even with additional precautions in terms of using protective equipment, there is still heightened risk of these professionals. The CDC reports that over 750 health care workers have lost their lives to COVID-19 and over 189 thousand have been infected as of October 26rd, 2020 (Centers for Disease Control and Prevention, 2020). However, these statistics likely underrepresent the actual number of infections and death, as the CDC notes that healthcare personnel status is not reported for all respondents.

largest occupations in terms of number of workers still have non-negligible index values across both measures. The medium-risk occupations are similarly large and the minimum index values are also only moderately low. This shows that most of the large occupations in the U.S. entail at least some degree of automation potential and viral transmission risk. If one considers the possibility of at least partial automation of these jobs, a large fraction of the U.S. labor force could be affected. Note also that the index distinguishes between 'elementary and middle school teachers' and 'post-secondary teachers'. While both have similar automation potential, the elementary and middle school teachers experience much higher transmission risk, likely due to the higher degree of physical proximity that elementary teachers have with their students.

An issue noted in Blinder's (2009) related research on occupational risk of offshoring, is that the threshold used to define "jobs at risk" in Figure 1 is subjective. This point, and the fact that a high fraction of the U.S. population is employed in low-risk occupations under our baseline specification, motivates us to also consider a lower threshold of 0.4 for the high-risk cutoff.[11] This robustness check is further motivated by the observations that COVID-19 may lower the threshold at which an employer may decide to automate a job, as firms invest in technology to replace workers that are forced to stay at home due to shelter-in-place policies or illness.[12] We also provide estimates where we characterize the occupations at *low* risk of pandemic-induced automation. We define occupations as low risk if both indexes are below a threshold of 0.5. This also allows us to look at this issue in terms of jobs that are at least risk.

[11] In another robustness check we considered a higher threshold of 0.6 for defining high-risk occupations. Our findings are qualitative similar under this alternative specification. As can be seen from Figure 1, it is difficult to consider thresholds above 0.6 as there are very few occupations with both automation and transmission risk above this value.

[12] Some of these investments may involve partially automating jobs, while other occupations may be fully replaced by computers and robots. This also motivates the use of a lower threshold, as jobs that have potential for partial automation will have a lower index value yet may nonetheless experience pandemic-induced automation.

3 Results

Figure 2(a) shows the fraction of individuals whose automation potential index is over 0.5 for each Commuting Zone (CZ).[13] Similar to Muro et al. (2019), we find a concentration of CZs with high automation potential in the American Heartland.[14] However there is also a scattering of CZs with high automation potential across the South and along the West Coast. In contrast, Figure 2(b) shows that CZs with high transmission risk are more concentrated on the East Coast.

In Figure 3, we map the fraction of individuals with occupational automation potential and transmission risk both greater than 0.5. The CZs with a relatively large fraction of individuals in high-risk occupations are evenly distributed across the U.S., which reflects the lack of collocation in the joint distribution of viral transmission risk and automation potential. However, there is a relative void of high-risk occupations in the mid-west, where automation potential and transmission risk are both relatively low for most CZs.

In Table 2 we report the mean automation and transmission risk indexes for females and males, and further disaggregate by additional demographic characteristics. We also show corresponding maps for both ≥ 0.5 and under 0.5 by sex in Figure 4 and then for ≥ 0.5 by sex and education level in Figure 5.

Overall, the columns titled 'Both ≥ 0.5' indicate that females are about twice as likely as males to be in occupations that are at high risk of both COVID transmission and automation. This result cannot be explained by the preponderance of females in medical professions. The row 'Non-Medical' in Table 2 removes medical professions,[15] and shows that females remain over twice as likely as males to have high occupational risk of both COVID transmission and automation.

[13] We reweight the Public Use Microdata Area (PUMA) to get Commuting Zones using the weights provided by Peter McHenry (see `https://wmpeople.wm.edu/site/page/pmchenry/crosswalksbetweenpumasandczs`).

[14] We follow Muro et al. (2019) in using DeVol's (2019) definition the American Heartland as including the following states: ND, MN, WI, MI, SD, IA, IL, IN, OH, NE, KS, MO, KY, OK, AR, TN, MS, AL, LA.

[15] Medical professions are defined as occupations in the "healthcare practitioners and technical occupations" and "healthcare support occupations" SOC major groups. These healthcare occupations have a transmission risk of around 0.85 but only make up around 8.47% of our weighted sample so do not have much impact on the overall transmission risk.

The columns titled 'Both ≥ 0.4' show the fraction of females and males whose automation and transmission risk indexes are both above 0.4. Using this lower threshold implies classifying a much larger fraction of the U.S. population as high risk, and we again see that females are approximately 31% more likely than males to be in high-risk occupations. This shows the robustness of this disparity between men and women to using a lower threshold, and also addresses the critique that a lower threshold may be justified due to heightened incentive to automate resulting from the pandemic-risk currently facing the U.S. workforce.

Another way to examine this issue is to look for corroborating evidence when we flip the analysis and look at workers in jobs least at risk. The columns titled 'Both < 0.5' show the fraction of females and males that are in occupations that are at low risk of both automation and COVID-19 transmission. Males are much more likely than females to be in these low-risk occupations. Together with the high-risk results, this indicates that females are also more concentrated in medium-risk occupations. [16] The relative concentration of males in low-risk occupations partially explains why using alternative values for the high-risk threshold does not change our main finding, which is that women are more likely than men to be employed in high-risk occupations.

To better understand our main result, we further disaggregate the average index values for women and men across other demographic characteristics.[17] We begin by showing differences in automation and transmission risk by sex and race. Some differences are apparent, including that occupations held by non-white individuals are at a slightly higher risk of both automation and transmission. However, the racial differences are smaller than the differences based on sex. Interestingly, females in each racial group are more likely to be at high risk of both automation and transmission as compared with males of the same race.

Next, we consider differences based on sex across low, medium, and high paying occupations. We follow the OECD's (2019) definition of low and high pay. Specifically, the upper cut-off for lower pay is two-thirds of median state-level earnings, and the lower thresh-

[16] Recall from Figure 1 that medium-risk occupations (orange circles) are defined as having only one of the index values greater than or equal to 0.5.

[17] In the remainder of this section we mainly focus on the results for our baseline definition of 'high risk', which is defined by an occupation having both indexes greater or equal to 0.5. However, as can be seen from Table 2, we find qualitatively similar results using the lower threshold of 0.4.

old for high-pay is one and a half times median state-level earnings. We use the remainder to classify the medium pay occupations. We find that the occupations held by low and mid-income earning individuals entail highest risk. This result holds for both sexes, although the differences are more stark for females than males. Females at each income level are also more likely to be at high risk of both automation and transmission as compared with males with the same average income level.

Table 2 also considers the risk associated with the occupations of males and females across different educational attainment levels.[18] For each level of educational attainment, females are again at a higher risk of both transmission and automation. However, females with low and mid-level educational attainment (some post-secondary but less than bachelor's) stand out as the highest risk sub-group. Figure 5 shows this geographically, and illustrates that the higher risk occupations held by females with low and mid-level education are evenly distributed across CZs in the U.S.

We also see some notable differences along sex and education demographics for the low-risk category (i.e. columns titled 'Both indexes < 0.5' in Table 2). Low and mid-level educated workers are the least likely to be in the low-risk category, particularly for females. Further, low and mid-level educated males are more concentrated in low-risk occupations than high-educated females. Adjusting the high-risk threshold from 0.5 to 0.4 the low and mid-level educated females are particularly much more concentrated in "high-risk" occupations. Together, the 'Both indexes < 0.5' and the estimates with the lower high-risk threshold at 0.4 highlight that low and mid-level educated females are the demographic group with highest risk of pandemic-induced automation.

Finally, we consider differences in automation and transmission risk by sex and age in the final rows of Table 2. While there is relatively little variation across age groups, for each age group we find that women are more likely than men to be in occupations that have a high risk of both automation and transmission.

[18] High School or less is defined as individuals with a High school diploma or GED, or an education level below this. Some post-secondary but less than bachelor's includes individuals with between some college to those with an Associate's degree. Bachelor or higher includes, bachelor's degree, master's degree, professional degree beyond a bachelor and doctoral degree.

To summarize, our main finding is that women are more likely than men to be in occupations that are at high risk of both COVID-19 transmission and automation. This finding adds to an emerging literature suggesting that women are more exposed to loss of employment as a result of the COVID-19 pandemic. While not related to automation per se, recent work by Bartik et al. (2020) and Cajner et al. (2020) finds that the drop in employment at the onset of the COVID-19 pandemic recession has been larger for women than for men. Our results also indicate that the occupations held by women with low to mid-level wages and education face the highest risk of pandemic-induced automation, which links our paper to the job polarization literature. Autor and Dorn (2013) argue that the growth of in-person service occupations largely explain the employment and wage growth in the lower tail of the skill distribution. Our analysis indicates that some of these service occupations now face a confluence of automation and viral transmission risk. While these jobs often require physical dexterity and interpersonal skills that are difficult to codify, the growing pressure on employers to adapt the production process in response to pandemic risk may spur technological change that results in at least partial automation of some of the tasks in these occupations.

4 International Comparisons

Our analysis has highlighted the U.S. occupations and demographic groups at greatest risk of viral transmission and automation. In this section we broaden our focus to examine the demographic profile of workers facing these risks in other countries using data from the Programme for the International Assessment of Adult Competencies (PIAAC).

PIAAC is a survey of adult cognitive and workplace skills, with approximately 5,000 adults being surveyed in each of the 40 participating countries. PIAAC is designed to be valid for cross-cultural and international comparisons, with occupations classified using the International Standard Classification of Occupations 2008 (ISCO-08).

Our methodological approach involves using the BLS's 2010 SOC to ISCO-08 crosswalk to convert our O*NET automation potential and transmission risk indexes to ISCO-08 (4-

digit) unit groups classification.[19] We use the PIAAC Public Use File, which unfortunately does not include ISCO-08 unit groups for a number of countries, notably including the U.S. We therefore present the ACS-based demographic group averages alongside the PIAAC based means for the same groups.[20]

We use several filters to match our PIAAC sample as closely as possible to the ACS sample. Specifically, we include only employed workers, and exclude workers in unpaid family businesses and workers that are younger than 18 or older than 65. We also drop PIAAC observation that do not report an ISCO-08 unit group, as well as ISCO-08 occupations that cannot be merged to the 2010 SOC. Applying these filters leaves us with a sample of 86,740 adults from 25 different countries.[21]

Figure 6 plots the fraction of the population that work in occupations with automation potential and transmission risk indexes both greater or equal to 0.5. The country-specific fraction of the population in these high-risk occupations ranges from 18% in Ecuador to 29% in Japan.[22] Figure 6 also shows that our findings regarding the higher risk facing U.S. female workers is also apparent internationally. In all 26 countries in our analysis, we find a greater fraction of females than males in high-risk occupations.

Next, we further analyze demographic differences across different levels of wages and educational attainment, as well as different age cohorts. We specify these demographic groups for our PIAAC sample in parallel to our U.S. ACS specifications to the greatest extent possible.

We measure wages using PIAAC's purchasing power parity (PPP) adjusted measure of hourly earnings excluding bonuses.[23] Mirroring our ACS specification, we follow the

[19]The BLS's 2010 SOC to ISCO-08 crosswalk was downloaded from the url: https://www.bls.gov/soc/soccrosswalks.htm. ISCO-08 has 436 unit groups, whereas 2010 SOC has 840 (6-digit) detailed occupations. For many-to-one mappings, we average the indexes across the SOC 2010 codes corresponding to each ISCO code.

[20]We acknowledge that differences in the level of aggregation between the 2010 SOC and ISCO-08 may confound comparisons between the U.S. and PIAAC countries. Nevertheless, our results in Figures 6–9 indicate that our U.S. mean group estimates are of a comparable magnitude to the corresponding estimates for other countries.

[21]For the countries used in the analysis, the sample sizes range from 1,690 (Russia) to 4,955 (Peru) observations.

[22]For this figure and all bar graphs in this section, we order by ranking the countries by the fraction of the overall population in high-risk occupations.

[23]PIAAC converts earnings into constant U.S. dollars using an OECD PPP measure.

OECD (2019) in defining three wage levels (low, medium and high) based on a low and high wage cut-offs. Specifically, the upper cut-off for lower wage is two-thirds of median PPP adjusted earnings, and the lower threshold for high-wage is one and a half times median PPP adjusted earnings.[24] As is the case for the U.S., high wage earners are the least likely to be in high-risk occupations in our sample of PIAAC countries. Averaging across our PIAAC sample, low and mid-wage earners are 11 and 9 percentage points more likely to be in high-risk occupations, respectively. Figure 7 shows that for males and females alike, low and mid-wage workers typically face higher risk than their high-wage counterparts across the 26 countries in our analysis.

Educational attainment levels are defined using the International Standard Classification of Education (ISCED) classifications codes that are provided in PIAAC. We follow the same approach in defining low, medium and high-level educational attainment levels as we did with our ACS specification. Adults are classified as having low educational attainment if they have an upper secondary education or lower, mid-level educational attainment if they have some post-secondary but less than a bachelor's degree, and high-level educational attainment if they have a bachelor's degree or higher. In our PIAAC sample, workers with low and medium-level education are 6 and 7 percentage points more likely to be in high-risk occupations, respectively, as compared with workers with high-level educational attainment. Figure 8 also shows that the differential between workers with high and low/mid-level education is starker for females than males.

Finally, we consider differences between younger and older workers' likelihood of being in high-risk occupations.[25] For our sample of PIAAC countries, younger workers are more likely to be in high risk occupations by approximately 4 percentage points. As can be seen in Figure 9, the risk differential between younger and older workers is larger for females relative to males on average across our sample of PIAAC countries.

[24] In calculating median wage earnings, we exclude self-employed individuals and those working fewer than 30 hours per week.

[25] As with the ACS, we define younger workers as those between the ages of 18 and 49, and older workers as being 50 to 65 years of age.

5 Conclusion

We provide the first analysis of the demographic groups and U.S. local labor markets that face joint-risks from COVID-19 and automation. Geographically, with few exceptions we find that regions with high automation potential largely do not overlap with areas of high viral transmission risk. As a result, commuting zones where both automation potential and transmission risk are high are diffusely distributed across the U.S. In contrast, we find a concentration of risk among certain demographic groups. In particular, we find that females are about twice as likely as males to be in occupations that are at high risk of both COVID transmission and automation. Females with low to mid-level wages and educational attainment face the highest joint risk from COVID-19 transmission and automation. Internationally our analysis shows that the higher risk facing women with lower wages and educational attainment is pervasive across the 25 PIAAC countries in our sample.

The COVID-19 pandemic is forcing firms and workers to re-imagine the potential of information technology in the workplace. More generally, Frey and Osborne (2017) point out that automation is no longer limited to routine tasks, and Brynjolfsson and McAfee's (2014) observations regarding the remarkable pace of technological change highlight the challenges of predicting the occupations that may be automated in the near future. These observations motivate future research on the evolving relationship between automation and viral transmission risk in response to COVID-19 and future pandemics.

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6 Tables

Table 1: Four highest and lowest automation viral transmission risk occupations, and five largest occupations by low, medium and high-risk categories

Occupation	Automation potential	Viral transmission risk	Number of workers
Automation potential			
Four highest index values			
Tire builders	1.000	0.000	14,534
Motion picture projectionists	0.899	0.255	3,168
Medical transcriptionists	0.898	0.321	41,737
Telephone operators	0.897	0.235	36,585
Four lowest index values			
Recreational therapists	0.000	0.759	11,396
Directors, religious activities and education	0.011	0.483	62,656
First-line supervisors of non-retail sales	0.029	0.448	1,150,933
Emergency management directors	0.030	0.390	9,370
Viral transmission risk			
Four highest index values			
Dental hygienists	0.628	1.000	174,532
Dentists	0.342	0.991	147,945
Respiratory therapists	0.471	0.980	107,360
Nurse anesthetists	0.337	0.972	28,517
Four lowest index values			
Tire builders	1.000	0.000	14,534
Meter readers, utilities	0.662	0.062	26,820
Refuse and recyclable material collectors	0.676	0.084	92,911
Logging workers	0.596	0.087	60,294
Joint risk of viral transmission and automation potential			
Five largest high-risk occupations			
Retail salespersons	0.533	0.574	3,160,827
Secretaries and administrative assistants	0.589	0.529	3,024,309
Cashiers	0.724	0.611	2,979,325
Stock clerks and order fillers	0.658	0.591	1,544,194
Personal care aides	0.547	0.620	1,255,453
Five largest medium-risk occupations			
Elementary and middle school teachers	0.182	0.660	3,479,855
Registered nurses	0.281	0.929	2,980,075
First-Line supervisors of retail sales workers	0.370	0.588	2,975,820
Customer service representatives	0.412	0.643	2,600,696
Janitors and building cleaners	0.592	0.411	2,343,953
Five largest low-risk occupations			
Driver/sales workers and truck drivers	0.489	0.275	3,279,329
Accountants and auditors	0.402	0.453	1,864,126
Post-secondary teachers	0.151	0.473	1,366,250
Sales representatives, wholesale and manufacturing	0.412	0.382	1,302,196
Grounds maintenance workers	0.480	0.255	1,245,202

Notes: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. The number of workers in each occupation is estimated from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

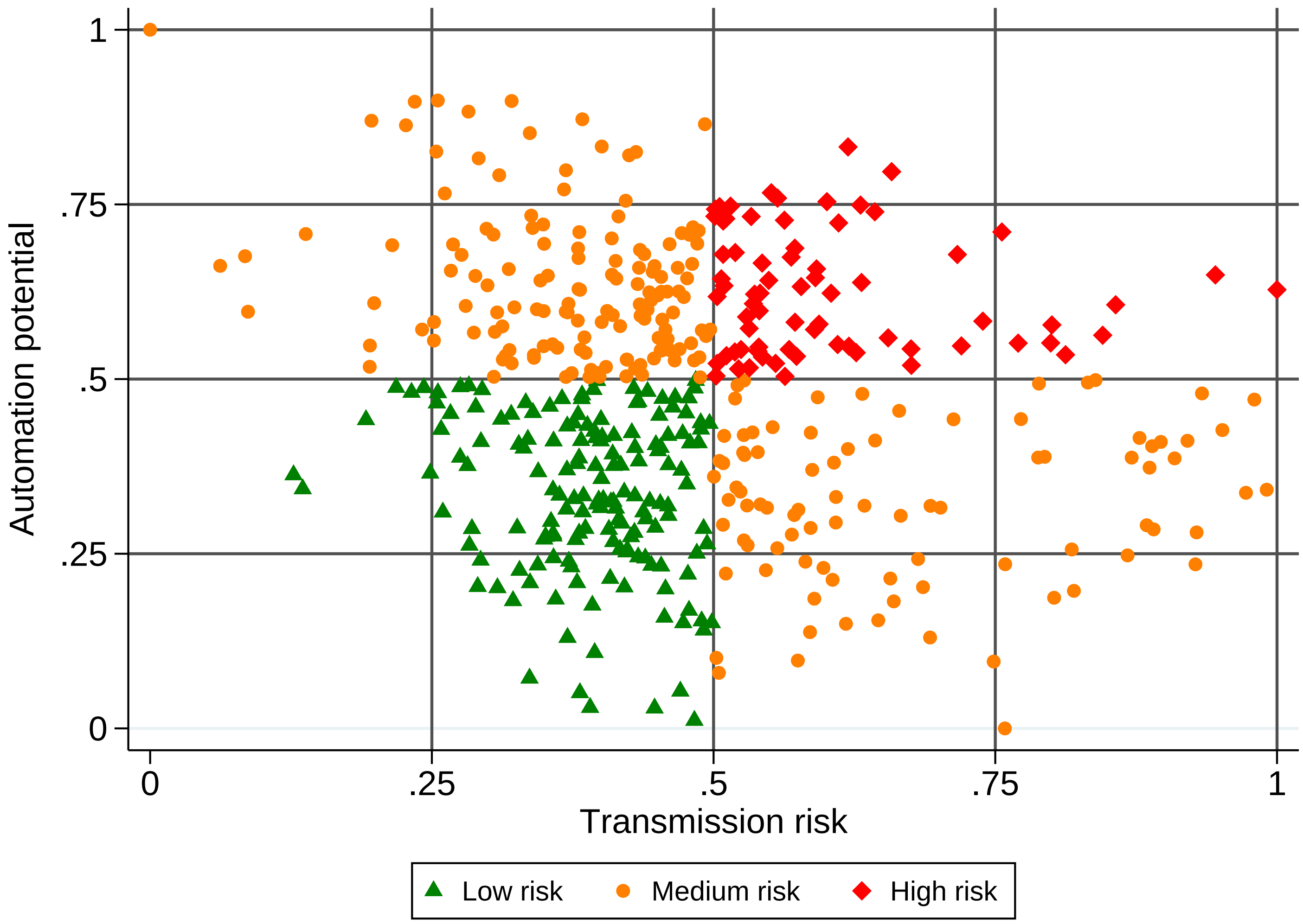
Table 2: Mean automation potential and transmission risk indexes by demographic characteristics

	Females					Males				
	Automation	Transmission Risk	Both ≥0.5	Both ≥0.4	Both <0.5	Automation	Transmission Risk	Both ≥0.5	Both ≥0.4	Both <0.5
Overall	0.451	0.562	0.243	0.551	0.191	0.444	0.456	0.120	0.422	0.434
	(0.187)	(0.159)	(0.429)	(0.497)	(0.393)	(0.167)	(0.132)	(0.325)	(0.494)	(0.496)
Non-medical	0.458	0.514	0.252	0.551	0.223	0.446	0.442	0.119	0.422	0.450
	(0.193)	(0.108)	(0.434)	(0.497)	(0.416)	(0.167)	(0.110)	(0.323)	(0.494)	(0.497)
White	0.434	0.564	0.232	0.508	0.212	0.425	0.458	0.113	0.393	0.467
	(0.190)	(0.161)	(0.422)	(0.500)	(0.409)	(0.169)	(0.129)	(0.316)	(0.488)	(0.499)
Black	0.475	0.577	0.259	0.627	0.135	0.484	0.468	0.155	0.518	0.324
	(0.177)	(0.159)	(0.438)	(0.484)	(0.342)	(0.160)	(0.138)	(0.362)	(0.500)	(0.468)
Latino or Hispanic	0.500	0.539	0.272	0.661	0.124	0.491	0.432	0.119	0.452	0.376
	(0.172)	(0.146)	(0.445)	(0.474)	(0.330)	(0.147)	(0.129)	(0.323)	(0.498)	(0.484)
Asian American	0.446	0.563	0.245	0.547	0.263	0.428	0.490	0.140	0.473	0.461
	(0.182)	(0.170)	(0.430)	(0.498)	(0.440)	(0.170)	(0.143)	(0.347)	(0.499)	(0.498)
All other races	0.460	0.559	0.262	0.578	0.192	0.455	0.467	0.144	0.465	0.392
	(0.185)	(0.154)	(0.440)	(0.494)	(0.394)	(0.167)	(0.134)	(0.351)	(0.499)	(0.488)
Low pay	0.508	0.551	0.298	0.685	0.109	0.495	0.441	0.149	0.502	0.359
	(0.164)	(0.143)	(0.457)	(0.465)	(0.312)	(0.149)	(0.131)	(0.356)	(0.500)	(0.480)
Medium pay	0.443	0.565	0.233	0.525	0.187	0.462	0.450	0.118	0.428	0.397
	(0.191)	(0.161)	(0.423)	(0.499)	(0.390)	(0.161)	(0.131)	(0.323)	(0.495)	(0.489)
High pay	0.334	0.572	0.091	0.278	0.389	0.365	0.470	0.068	0.301	0.578
	(0.161)	(0.188)	(0.288)	(0.448)	(0.487)	(0.156)	(0.132)	(0.251)	(0.459)	(0.494)
High school or less	0.541	0.532	0.315	0.740	0.093	0.508	0.419	0.118	0.469	0.383
	(0.149)	(0.137)	(0.464)	(0.439)	(0.290)	(0.139)	(0.119)	(0.322)	(0.499)	(0.486)
Post-secondary < BA	0.493	0.575	0.316	0.650	0.140	0.464	0.464	0.161	0.477	0.388
	(0.171)	(0.164)	(0.465)	(0.477)	(0.347)	(0.161)	(0.128)	(0.368)	(0.499)	(0.487)
BA or higher	0.339	0.572	0.119	0.308	0.317	0.346	0.493	0.083	0.313	0.541
	(0.172)	(0.167)	(0.323)	(0.462)	(0.465)	(0.157)	(0.139)	(0.276)	(0.464)	(0.498)
Age 18 to 49	0.452	0.565	0.248	0.556	0.187	0.452	0.459	0.131	0.441	0.412
	(0.186)	(0.159)	(0.432)	(0.497)	(0.390)	(0.165)	(0.132)	(0.337)	(0.496)	(0.492)
Age 50 to 65	0.449	0.555	0.234	0.539	0.200	0.424	0.451	0.096	0.379	0.487
	(0.190)	(0.160)	(0.423)	(0.498)	(0.400)	(0.170)	(0.132)	(0.295)	(0.485)	(0.500)

Notes: Standard deviations are in parenthesis under the mean estimates. Automation potential and transmission risk indexes are normalized to range between zero and one. The number of workers in each occupation is estimated from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

7 Figures

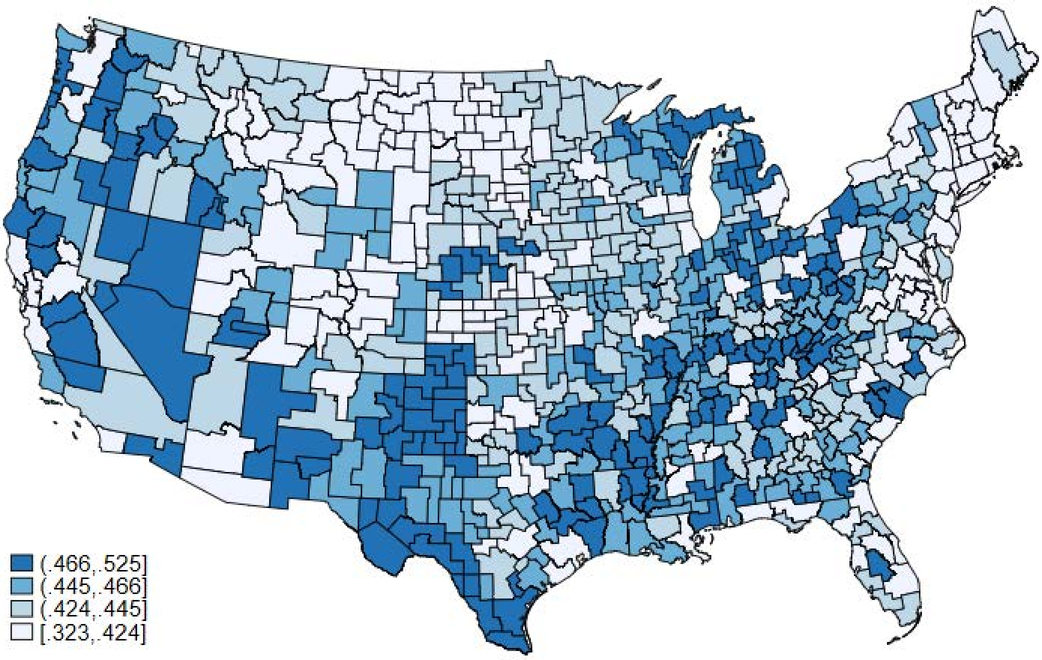
Figure 1: Automation potential versus transmission risk of occupation



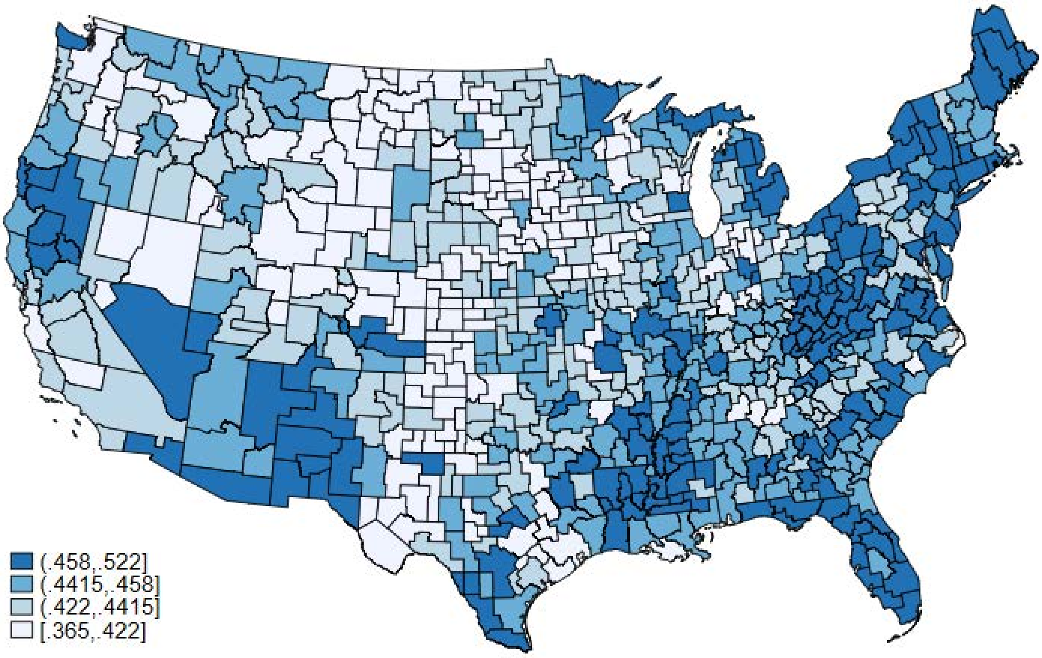
Notes: Automation potential and transmission risk indexes are created from the O*NET and are normalized to range between zero and one. High-risk occupations are defined as those with both indexes being greater than or equal to 0.5 and are indicated by red squares. Low-risk occupations are defined as those with both indexes below 0.5 and are indicated by green triangles. Medium-risk occupations are defined as those with an index value greater than or equal to 0.5 for only one of the two indexes and are indicated by orange circles.

Figure 2: Index ≥ 0.5 by commuting zone

(a) Automation potential ≥ 0.5

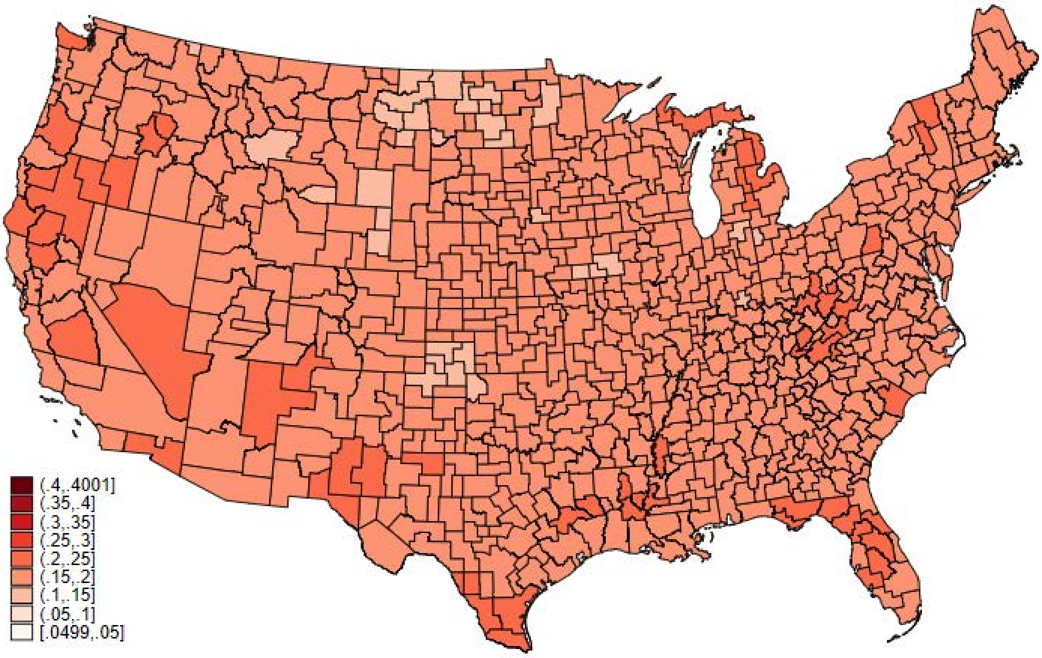


(b) Transmission risk ≥ 0.5



Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

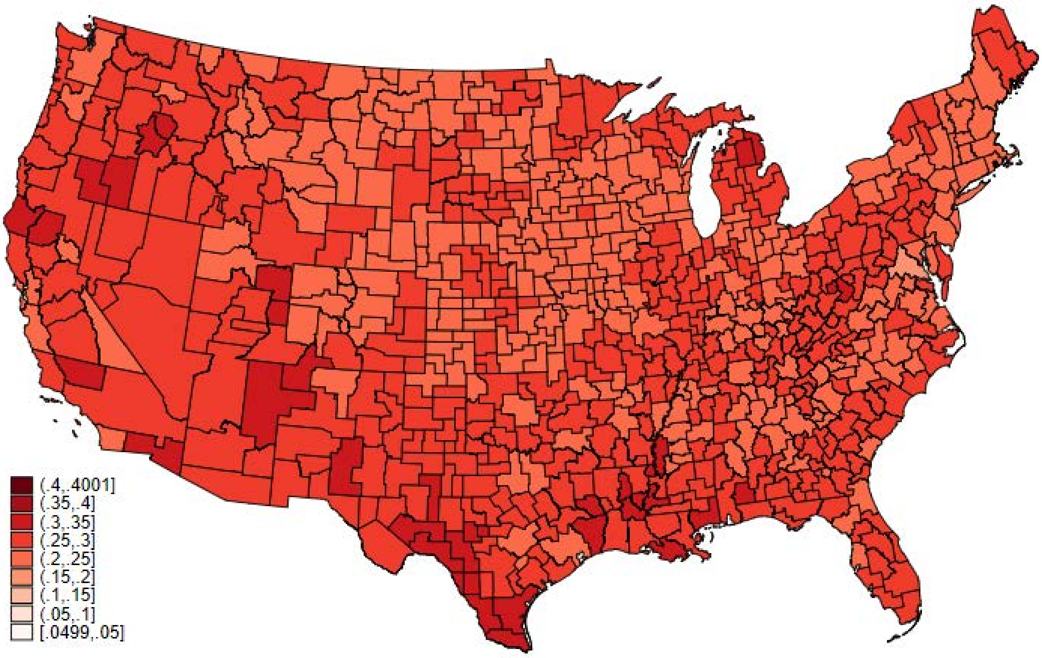
Figure 3: Automation potential and transmission risk both ≥ 0.5



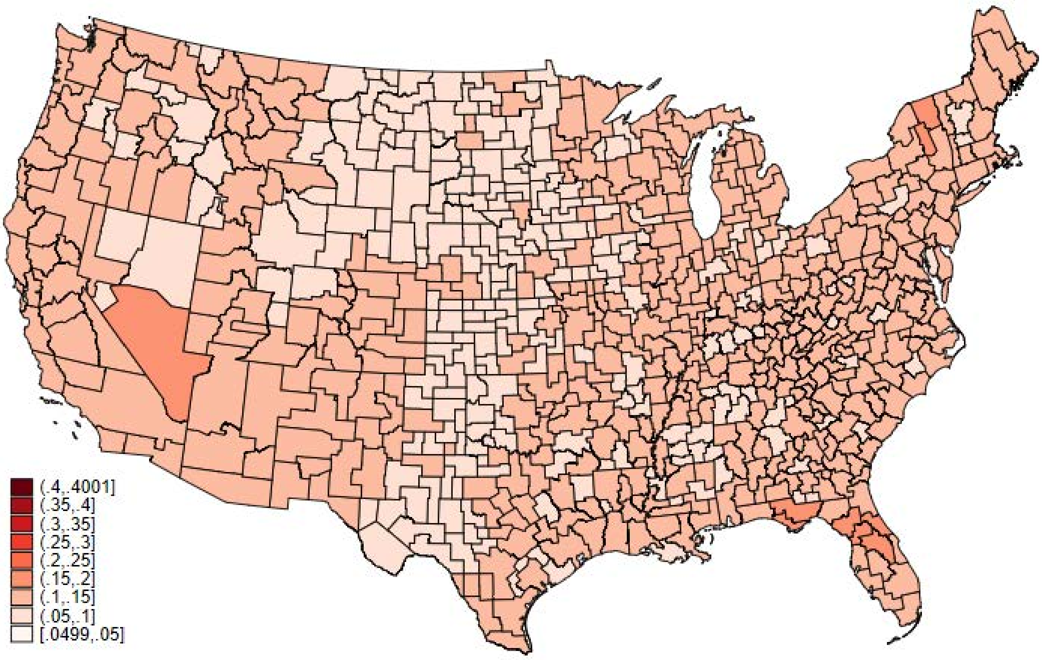
Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

Figure 4: Automation potential and transmission risk both ≥ 0.5 by commuting zone, by sex

(a) Females



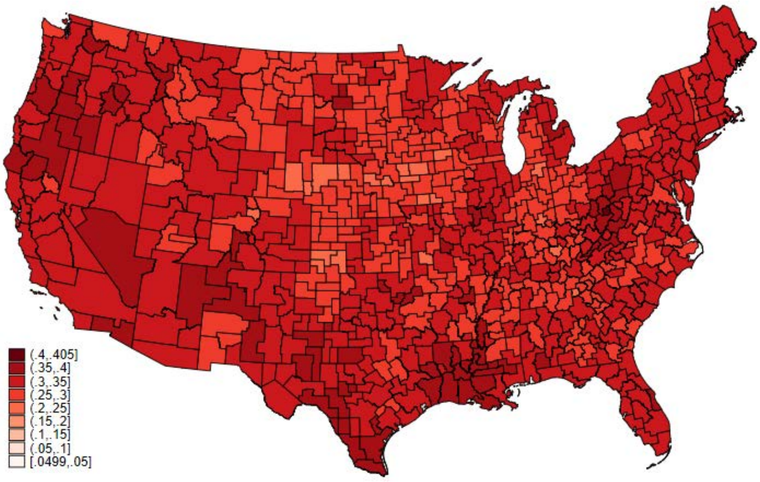
(b) Males



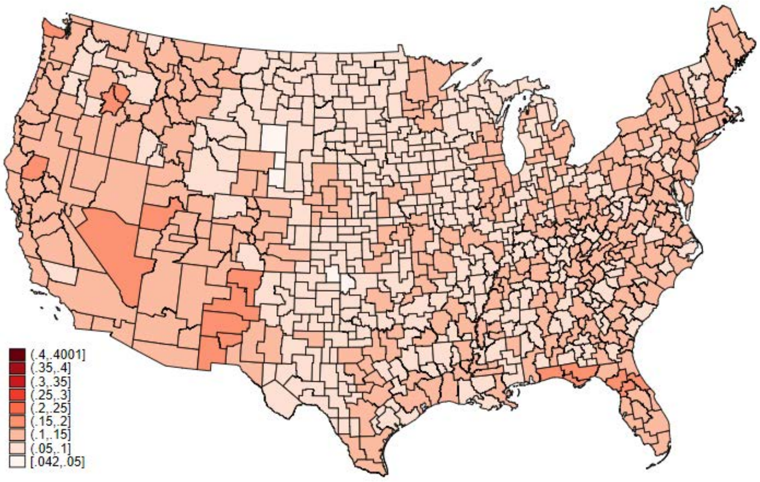
Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

Figure 5: Automation potential and transmission risk both ≥ 0.5 by commuting zone, by education and sex

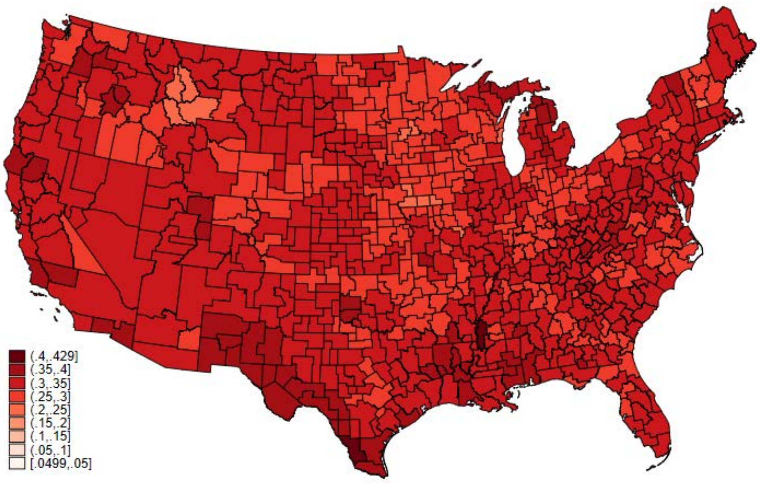
(a) High school or less, females



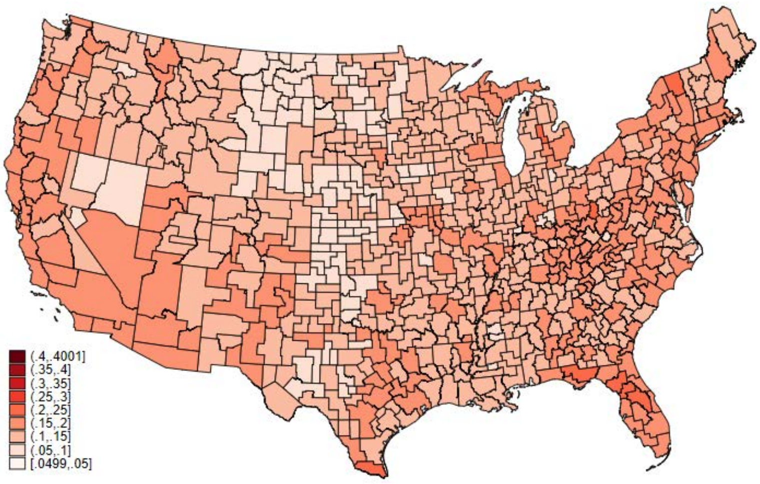
(b) High school or less, males



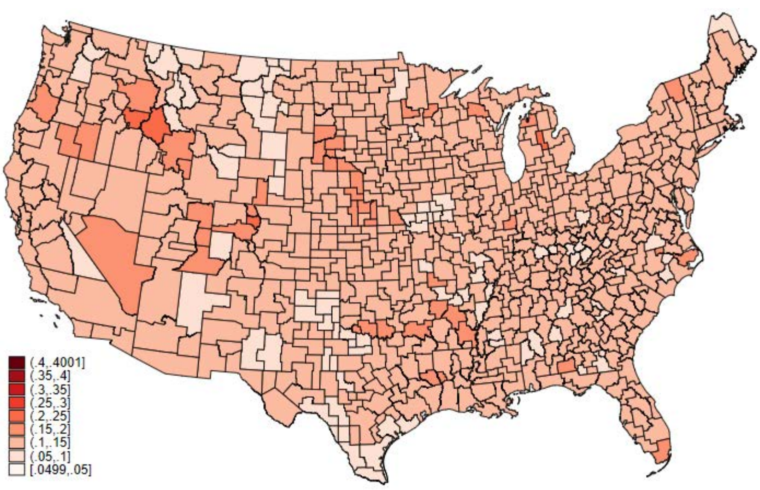
(c) Post secondary < BA, females



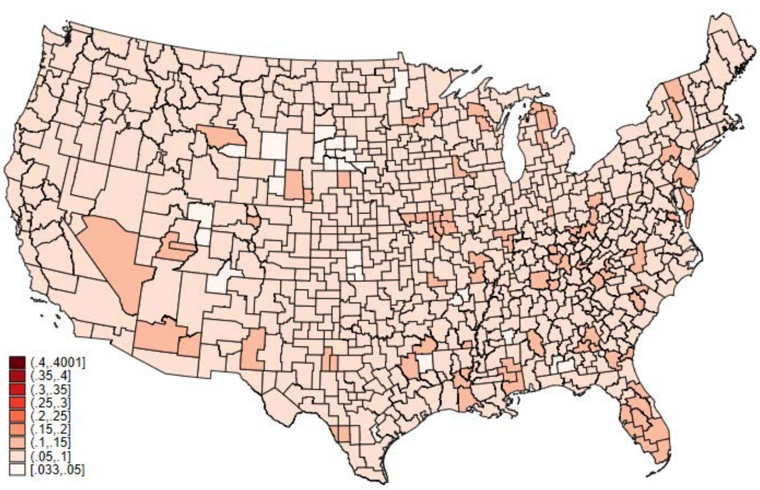
(d) Post secondary < BA, males



(e) BA or higher, females

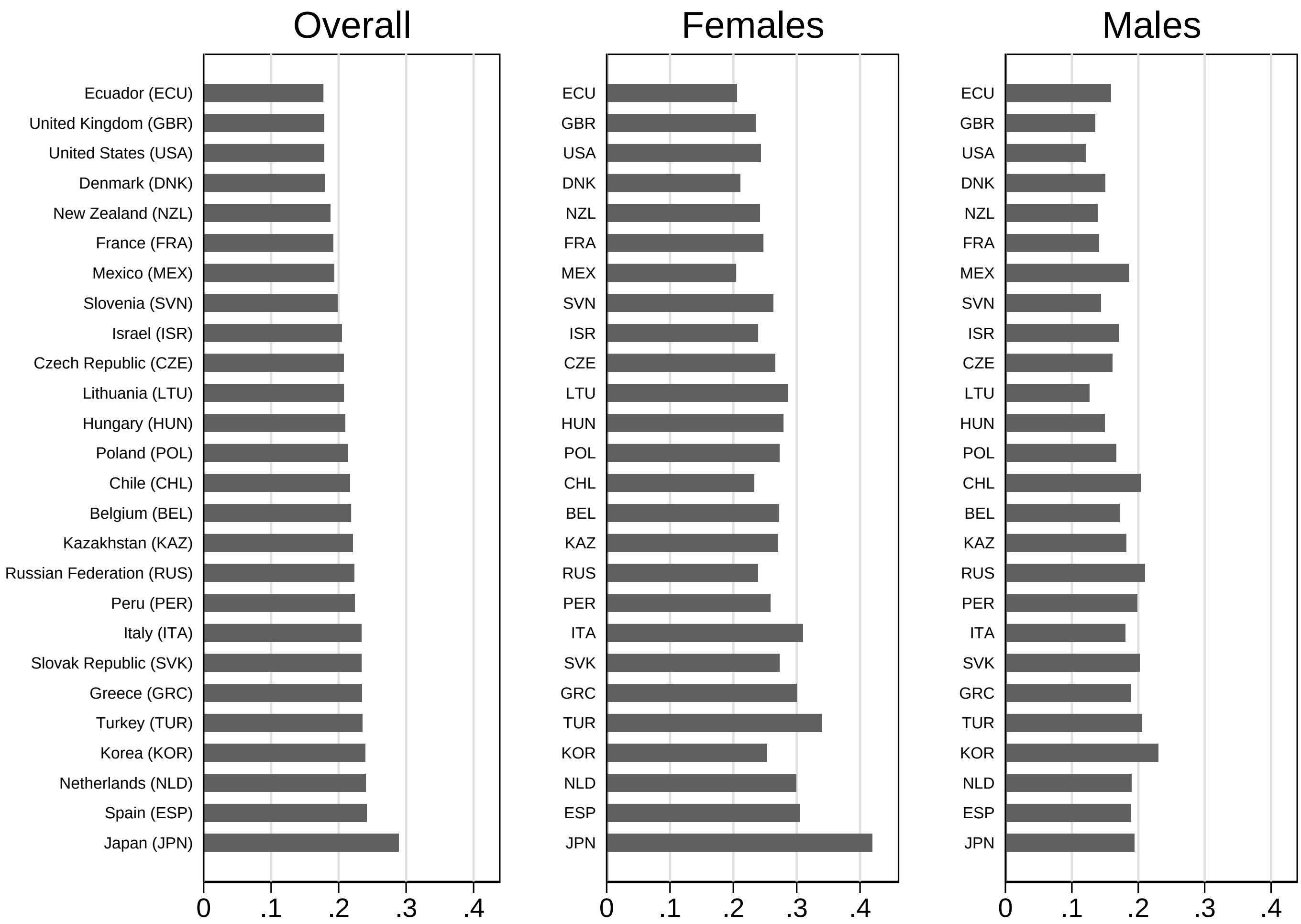


(f) BA or higher, males



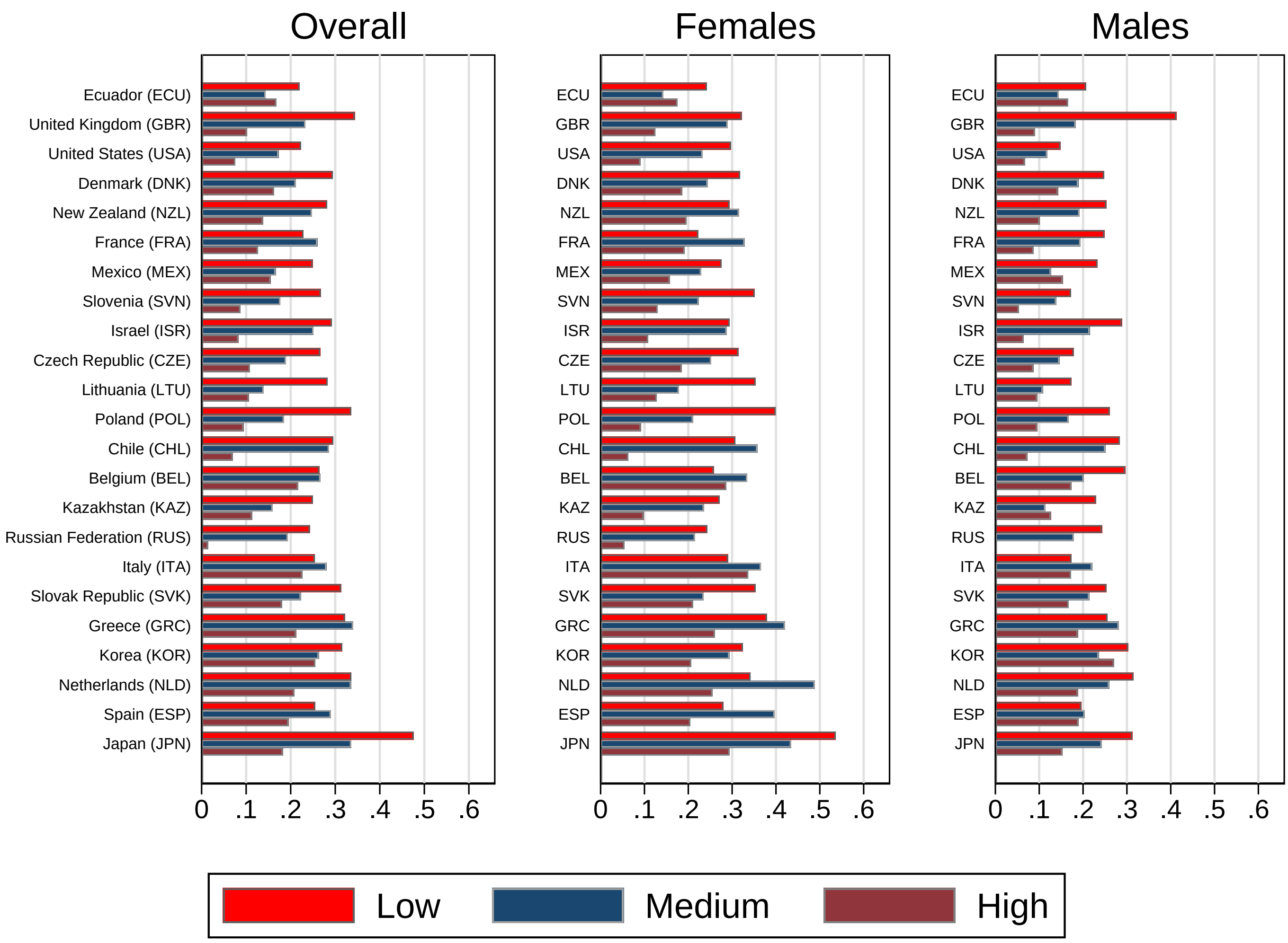
Note: Darker red: More at risk. Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates from the weighted counts from the 2013 to 2017 ACS. Sample restricted to individuals who were between age 18 and 65.

Figure 6: Fraction of population with both indexes $\geq$0.5



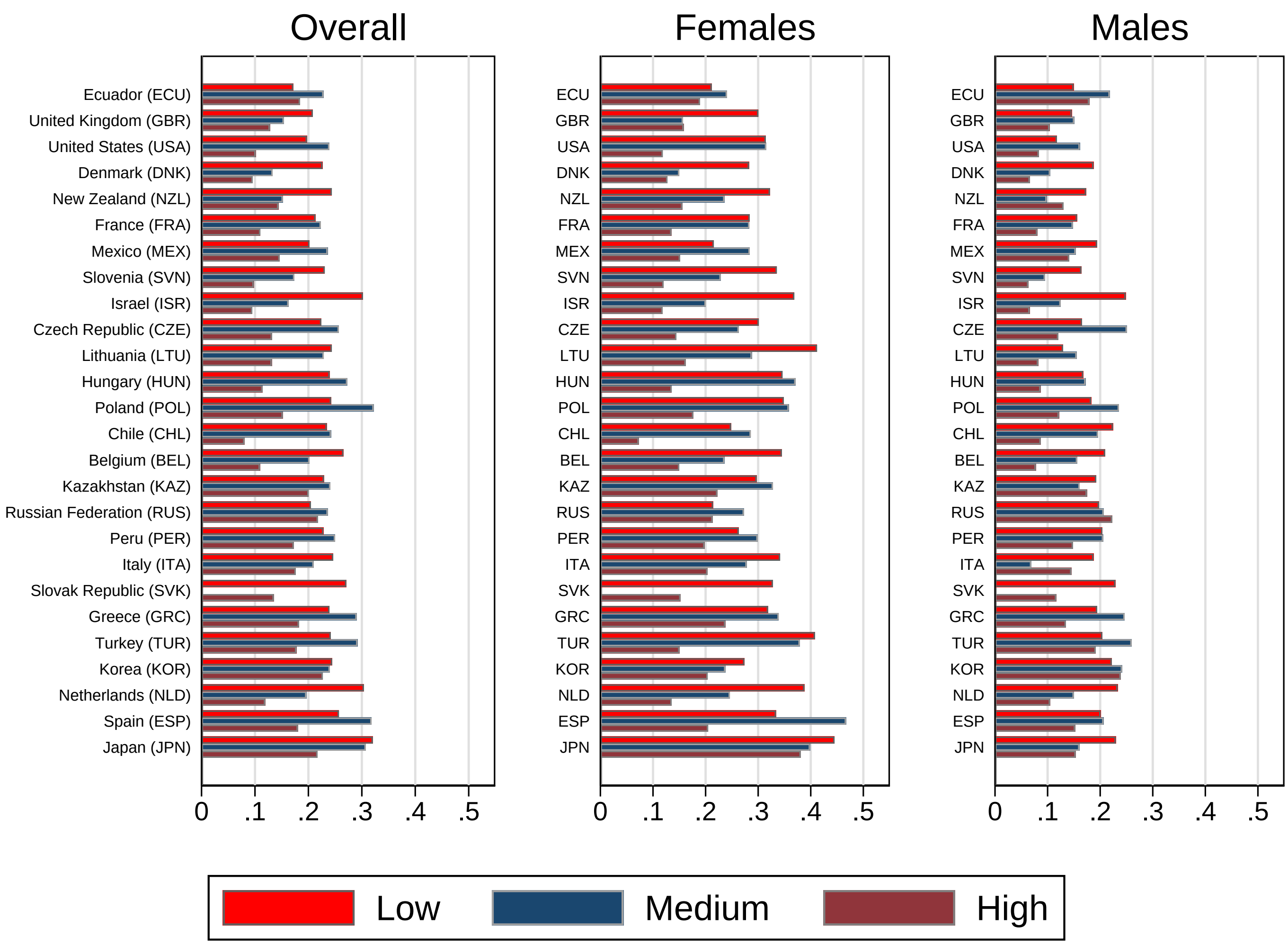
Notes: In this figure and all subsequent bar charts the horizontal bars measure the fraction of the population that work in occupations with automation potential and transmission risk indexes both $\geq$ 0.5. U.S. values are identical to the corresponding mean values reported in Table 2. Values for all other countries are country and demographic group-specific mean values, calculated after using the BLS's 2010 SOC to ISCO-08 crosswalk to convert our O*NET automation potential and transmission risk indexes to ISCO-08 classification.

Figure 7: Fraction of population with both indexes >0.5, by wage level



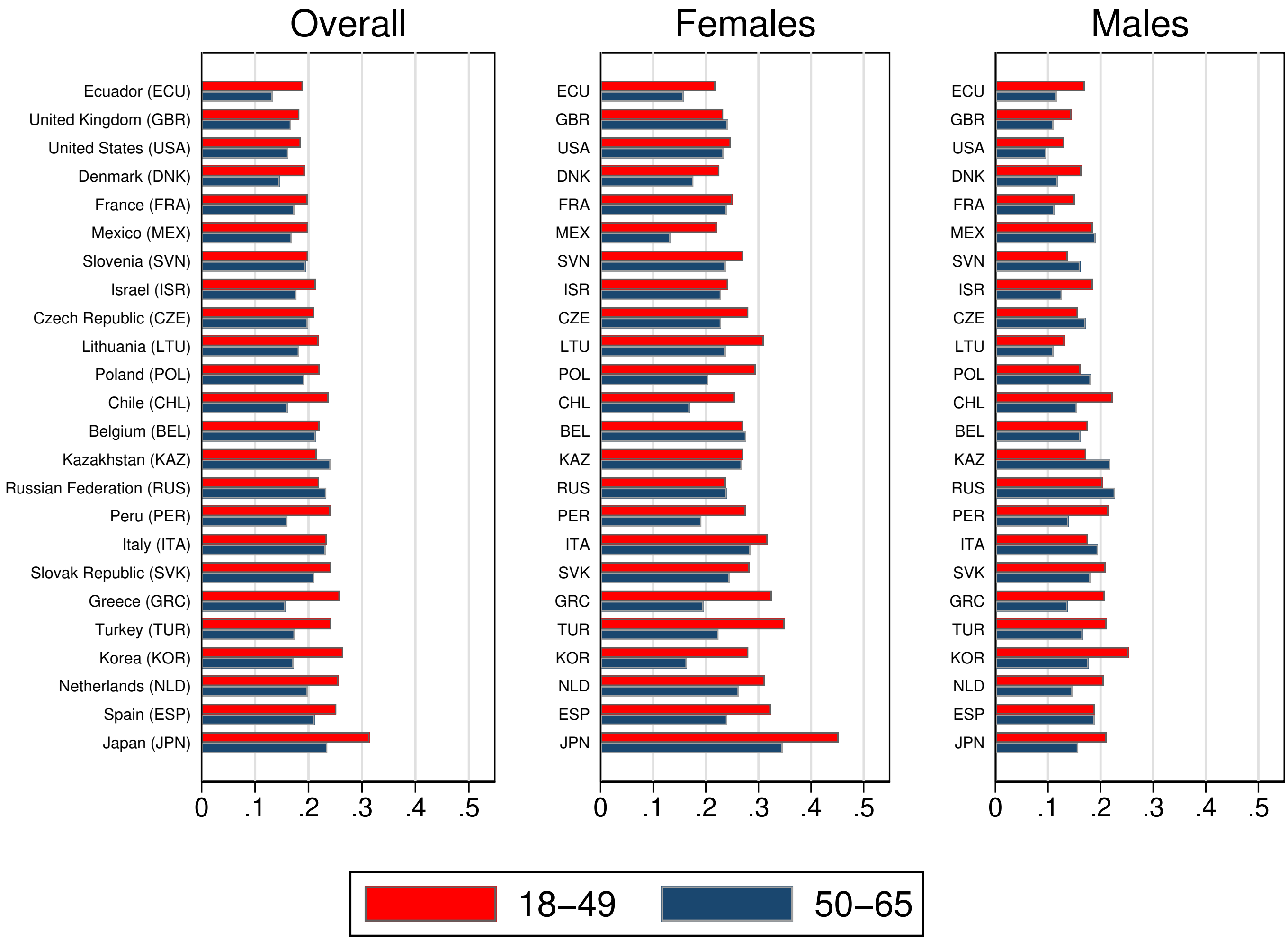
Notes: The upper cut-off for lower wage is two-thirds of median earnings, and the lower threshold for high-wage is one and a half times median earnings. Medium wage earners are defined as those with earnings between the low and high wage cut-offs. U.S. values are identical to the corresponding mean values reported in Table 2. For all other countries wage earnings data are from PIAAC.

Figure 8: Fraction of population with both indexes $\geq$0.5, by educational attainment level



Notes: Low educational attainment is defined as high-school or less, medium-level educational attainment includes individuals with some post-secondary, but less than a bachelor's degree, high educational attainment includes individuals with a bachelor's degree or higher. U.S. values are identical to the corresponding mean values reported in Table 2. For all other countries educational attainment levels are from PIAAC.

Figure 9: Fraction of population with both indexes ≥0.5, by age group



Notes: U.S. values are identical to the corresponding mean values reported in Table 2. For all other countries data are from PIAAC.

Appendices

A Routine task-intensity O*NET variables

1. ***Routine cognitive:***importance of repeating the same tasks; importance of being exact or accurate; (reverse of) structured versus unstructured work.

2. ***Routine manual:*** pace determined by speed of equipment; controlling machines and processes; spend time making repetitive motions.

3. ***Non-routine analytical:*** analyzing data or information; thinking creatively; interpreting the meaning of information for others.

4. ***Non-routine cognitive:*** establishing and maintaining interpersonal relationships, guiding, directing and motivating subordinates, coaching and developing others.

5. ***Non-routine manual:*** operating vehicles, mechanized devices, or equipment; spend time using hands to handle, control or feel objects, tools or controls; manual dexterity and spatial orientation.