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COVID-19 and Implications for Automation

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Abstract

COVID-19 may accelerate the automation of jobs as employers invest in technology to safeguard against pandemics. We identify occupations that have high automation potential and also exhibit a high risk of viral infection. We examine regional variation in terms of which U.S. local labor markets are most at risk. Next, we outline the differential impacts COVID-19 may have on different demographic groups. We find that the highest-risk occupations in the United States are those held by females with mid- to low wage and education levels. Using comparable data for 25 other countries, we also find that women in this demographic are at the highest risk internationally. We examine monthly employment data from the United States and find that women in high-risk occupations experienced a larger initial decline in employment and a weaker recovery during the pandemic.

Topics: Coronavirus disease (COVID-19), International topics, Labour markets

JEL codes: I14, I24, J15, J16, R12

1 Introduction

The COVID-19 crisis has caused severe economic loss along 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 have the potential to accelerate the process of automation as employers substitute workers with computers and robots, which 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 declines 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 database to construct indexes of automation and viral transmission risk. We identify U.S. local labor markets that may be most affected 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 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 between 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 find that U.S. females are about twice as likely as males to be in occupations that are at high risk of both COVID-19 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. stand out as being at highest risk of both transmission and automation. Although automation in response to the pandemic is likely an ongoing process, we look for early indications by examining monthly employment data from the U.S. Consistent with this hypothesis, women in high-risk occupations experienced a larger initial decline in employment and a weaker recovery during the pandemic.

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 skills 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 both low- to mid-level wages and educational attainment. Although we are examining the enhanced joint impact of automation and viral transmission risks, the groups that we find are most susceptible are generally consistent with Blanas et al. (2020) who find 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

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

incentivize firms to automate tasks that are generally completed by workers.[2] Autor and Reynolds (2020) refer to this phenomenon as "automation forcing" and argue that the technologies adopted by firms during the COVID-19 pandemic will likely result in leaner staffing in many industries post-pandemic. Leduc and Liu (2020) note that the uncertainty during a pandemic may lower aggregate demand and curb investment; yet, their quantitative general equilibrium analysis finds that a pandemic may nonetheless stimulate automation as firms replace workers with technologies that are not susceptible to the virus. Some research on COVID-19 has identified occupations with the highest risk of exposure,[3] while other research has 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. Our objective also differs in that we aim to characterize the joint relationship between COVID-19 transmission risk and automation potential across U.S. local labor markets and across 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 COVID-19 transmission risk and automation potential, 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 an occupation's risk of viral transmission as well as the degree to which it can be automated.[4] There are several important considerations when constructing a meaningful index. First, we need to decide which variables to include and how to aggregate the variables. Our index of an occupation's risk of viral trans-

[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.

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

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

mission 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 an individual works outside.[5]

For our main results, 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 follows:

$$RTI_i = RC_i + RM_i - NRA_i - NRI_i - NRM_i, \tag{1}$$

where RTI_i is the routine task intensity for the i^{th} occupation.[6] We add together the aggregate routine cognitive (*RC*) and routine manual (*RM*) variables. We also subtract the aggregate non-routine analytical (*NRA*), interpersonal (*NRI*) and manual variables (*NRM*). We standardize each of these five O*NET variables,[7] and provide a more detailed description of these variables in Appendix A.[8] We then construct Equation 1 and 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

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[5] *Physical proximity* is defined as the extent to which a job requires a 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)." The variable *face-to-face discussions* is defined as how often workers have to have face-to-face discussions with individuals/team on the job and the *exposed to disease or infections* variable is categorized by how often the job requires exposure to disease/infections. Finally, the two outdoor variables capture how often the job requires working outdoors and under cover (which could include a structure with a roof but no walls). Potential responses to these latter four variables are as follows: "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 provide a very useful "computerisable" index that we use to validate our automation index.

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

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

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

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 in the first approach. We present the results obtained using the first method, although our findings are not sensitive to this specification as the two approaches yield indexes that are highly correlated.

We match the risk of automation and the viral transmission risk indexes constructed with the O*NET to the 2013-2017 American Community Survey (ACS).[10] Unfortunately, there is no perfect mapping between the 6-digit ACS occupation variable and the O*NET, so we match the remaining occupations with fewer digits and average the variables over the matching O*NET occupations. We restrict our analysis to employed workers and exclude workers who are either in unpaid family businesses or in the military. We further restrict the sample to workers between ages 18 and 65. We use these same sample restrictions and conduct analysis with the January 2018 to February 2021 Current Population Survey (CPS) to examine the initial impact on trends in employment for high- and low-risk jobs by sex. For our international comparison, we use PIAAC which provides data that allows us 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

[10] Although the 2018 ACS is available, it uses the 2018 Standard Occupational Classification (SOC) whereas our O*NET indexes are based on the 2010 SOC. This limits our ability to merge our indexes to the 2018 data. In addition, using the 2013-2017 ACS provides a larger sample, which is beneficial for our analysis of local labor markets as several of the commuting zones we analyze are sparsely populated. However, we also completed our analysis using the 2018 ACS and obtained similar results to the findings presented below.

are occupations with high viral transmission risk but 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). Although each index has a larger fraction of occupations with values of 0.5 or higher (46.3% for automation potential and 34.3% for transmission risk), the fraction of occupations where both indexes are above this threshold is much smaller. Based on our ACS sample, workers in high-risk occupations represent around 17.9% of the employed U.S. population for the period 2013 to 2017. Roughly 34.7% of occupations are designated in the low-risk group (green triangles), representing a little less than 32% of the employed U.S. population during this period.

To get a feel for the indexes, Table 1 shows a sample of occupations with their associated automation potential and viral transmission index values. We also include the number of workers in each 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 the highest automation potential. Dental occupations are shown to be the two riskiest jobs for viral transmission, which is not surprising given that service providers in this profession are required to work at face-to-face proximity to their clients. Health-related occupations also make up the next two riskiest jobs.[11] 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 for these categories as were 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

[11] One potential critique of our approach is that we do not consider access to personal protective equipment used by essential workers, notably including medical and health care workers. However, even with additional precautions in terms of using protective equipment, there is still heightened risk for these professionals. The CDC reports that over 750 health care workers have lost their lives to COVID-19 and over 189,000 have been infected as of October 26, 2020 (Centers for Disease Control and Prevention, 2020). However, these statistics likely under-represent the actual number of infections and deaths, as the CDC notes that health care personnel status is not reported for all respondents.

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 cutoff. For a number of occupations, it might be argued that the automation index values in Table 1 seemingly belie the automation potential as being 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 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 the 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 these teachers have with their students.

An issue noted in Blinder's (2009) related research on the risk of occupations being offshored is that the threshold used to define "jobs at risk" is subjective. This point, and the fact that a high percentage 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.[12] This robustness check is further motivated by the observation 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.[13] We also provide estimates where we characterize the occupations that are 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 least at risk.

3 Results

Figure 2 (a) shows the fraction of individuals whose automation potential index is over 0.5 for each commuting zone (CZ) in the U.S.[14] Similar to Muro et al. (2019), we find a concentration of CZs with high automation potential in the American Heartland.[15] 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 in high-risk occupations in the Midwest, 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

[12] In another robustness check we considered a higher threshold of 0.6 for defining high-risk occupations. Our findings are qualitatively 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.

[13] 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.

[14] 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`).

[15] We follow Muro et al. (2019) in using DeVol's (2019) definition of 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.

males and further disaggregate by additional demographic characteristics. We also show corresponding maps for both indexes ≥ 0.5 by sex in Figure 4, and then for both indexes ≥ 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-19 transmission and automation. This result cannot be explained by the preponderance of females in medical professions. The row titled "Non-Medical" in Table 2 removes medical professions[16] and shows that females remain over twice as likely as males to have high occupational risk of both COVID-19 transmission and automation.

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 percentage 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 the disparity between men and women to using a lower threshold. It also addresses the critique that a lower threshold may be justified due to the 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 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.[17] 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

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

[17] 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.

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.[18] 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, for each racial group females are more likely to be at high risk of both automation and transmission 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 cutoff for lower pay is two-thirds of median state-level earnings and the lower threshold for high pay is one and a half times the median state-level earnings. Medium-pay occupations are defined as those paying between the low- and high-pay cutoffs. We find that the occupations held by low- and mid-income earning individuals entail the 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.[19] 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 a 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-

[18] In the remainder of this section we mainly focus on the results for our baseline definition of "high risk," which is defined as an occupation having both indexes greater than 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.

[19] 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 a bachelor's includes individuals with some college to those with an associate's degree. Bachelor or higher includes a bachelor's, master's, and doctoral degrees, and professional degrees beyond a bachelor's.

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; this is particularly so for females. Further, low- and mid-level-educated males are more concentrated in low-risk occupations than females with higher levels of education. Adjusting the high-risk threshold from 0.5 to 0.4, the low- and mid-level-educated females, in particular, are much more concentrated in “high-risk” occupations. Together, the columns labelled “Both < 0.5” and “Both ≥ 0.4” highlight that low- and mid-level-educated females are the demographic group with the 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.

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 that suggests 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 greater for women than for men. Our results also indicate that the occupations held by women with low- to mid-level wages and educational attainment 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 explains the employment and wage growth in the lower tail of the skills 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 the pandemic risk may spur technological changes that result in at least the partial automation of some of the tasks in these occupations.

3.1 Trend in Employment is Worse for High-Risk Females in the U.S. during the COVID-19 Crisis

The results in the preceding sections do not address whether the jobs we define as high risk have actually been automated. The data required to answer this question are not yet available. It may take time for jobs to be automated as forward-looking firms take into consideration both the current risks and those associated with the possibility of future pandemics. Yet, we can get early insights by looking at recent CPS employment data during the COVID-19 pandemic.

Figure 6 plots the percentage change in monthly employment relative to its pre-pandemic 2018–19 average values for females and males. For each sex, we differentiate between high-risk occupations and those with at least one index below 0.5. For males, employment in high-risk occupations largely followed a similar trend to other occupations throughout the pandemic to date. In contrast, female employment in high-risk occupations incurred a larger initial drop and experienced a weaker recovery. Although automation is one of many possible factors that explains this trend, it is nonetheless consistent with our finding that females are more likely than males to experience job losses from automation during the COVID-19 pandemic.

4 International Comparisons

Our analysis highlights 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 that face these risks in other countries, using data from PIAAC.

PIAAC is a survey of adult cognitive and workplace skills, with approximately 5,000 adults being surveyed in each of the programme's 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 Bureau of Labor Statistics' (BLS) 2010 SOC to ISCO-08 crosswalk to convert our O*NET automation potential and transmission risk indexes to the ISCO-08 (4-digit) unit groups classification.[20] We use the PIAAC Public Use File, which unfortunately does not include ISCO-08 unit groups for a number of countries, notably the U.S. We therefore present the ACS-based demographic group averages alongside the PIAAC-based means for the same groups.[21]

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 younger than 18 or older than 65 years of age. We also drop the PIAAC observations that do not report ISCO-08 unit groups as well as the 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.[22]

Figure 7 plots country-specific fractions of populations that work in occupations with automation potential and transmission risk indexes both greater than or equal to 0.5. The country-specifics fraction of the population in these high-risk occupations range from 18% in Ecuador to 29% in Japan.[23] Figure 7 also shows that our findings regarding the higher risk U.S. female workers face 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 with our U.S. ACS specifications, to the greatest extent possible.

We measure wages by using PIAAC's purchasing power parity (PPP) adjusted measure of hourly earnings excluding bonuses.[24] Mirroring our ACS specification, we follow the

[20]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.

[21]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 7–10 indicate that our U.S. mean group estimates are of a comparable magnitude to the corresponding estimates for other countries.

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

[23]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.

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

OECD (2019) in defining the three wage levels (low, medium and high), based on the low- and high-wage cutoffs. Specifically, the upper cutoff for the lower wage is two-thirds of the median PPP adjusted earnings, and the lower threshold for the high wage is one and a half times the median PPP adjusted earnings.[25] As is the case for the U.S., the high-wage earners in our sample of PIAAC countries are the least likely to be in high-risk occupations. Averaging across our PIAAC sample, low- and mid-wage earners are more likely to be in high-risk occupations by 11 and 9 percentage points, respectively, compared to high-wage earners. Figure 8 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 obtained an upper secondary level of 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 more likely to be in high-risk occupations, by a margin of 6 and 7 percentage points, respectively, compared to workers with high-level educational attainment. Figure 9 also shows that the differential between workers with high- and low-to-mid-level education is more stark for females than for males.

Finally, we consider differences between younger and older workers' likelihoods of being in high-risk occupations.[26] For our sample of PIAAC countries, the likelihood is higher for younger workers by approximately 4 percentage points. As can be seen in Figure 10, the risk differential between younger and older workers is greater for females relative to males, on average, across our sample of PIAAC countries.

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

[26] As with the ACS, we define younger workers as those between the ages of 18 and 49, and older workers as being from 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-19 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 among women in this demographic 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 potential and 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. The sample is restricted to individuals aged between age 18 and 65 years.

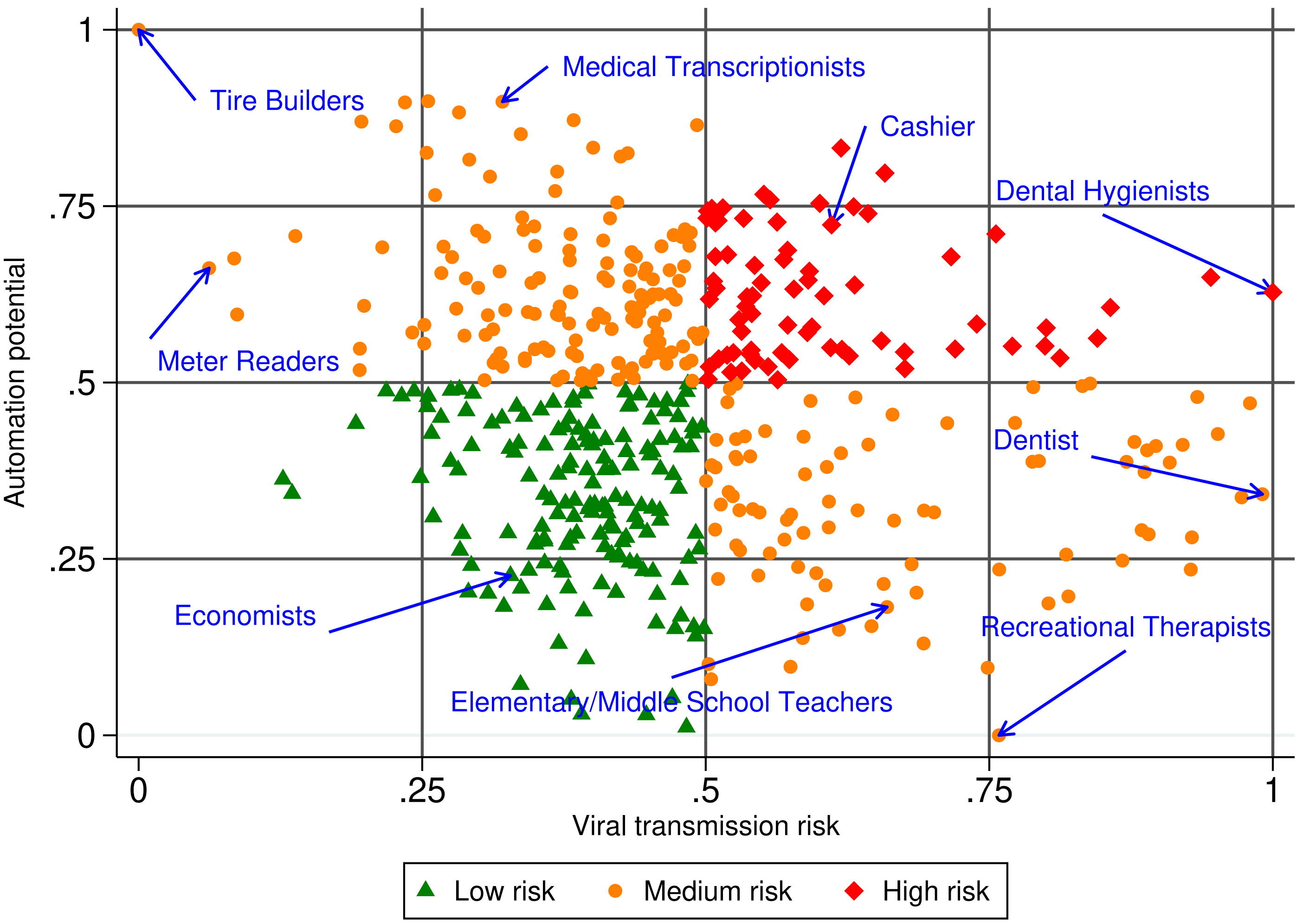
Table 2: Mean automation potential and transmission risk indexes by demographic characteristics

	Females					Males				
	Automation	Transmission Risk	Both $\geq$0.5	Both $\geq$0.4	Both <0.5	Automation	Transmission Risk	Both $\geq$0.5	Both $\geq$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. The sample is restricted to individuals aged between 18 and 65 years.

7 Figures

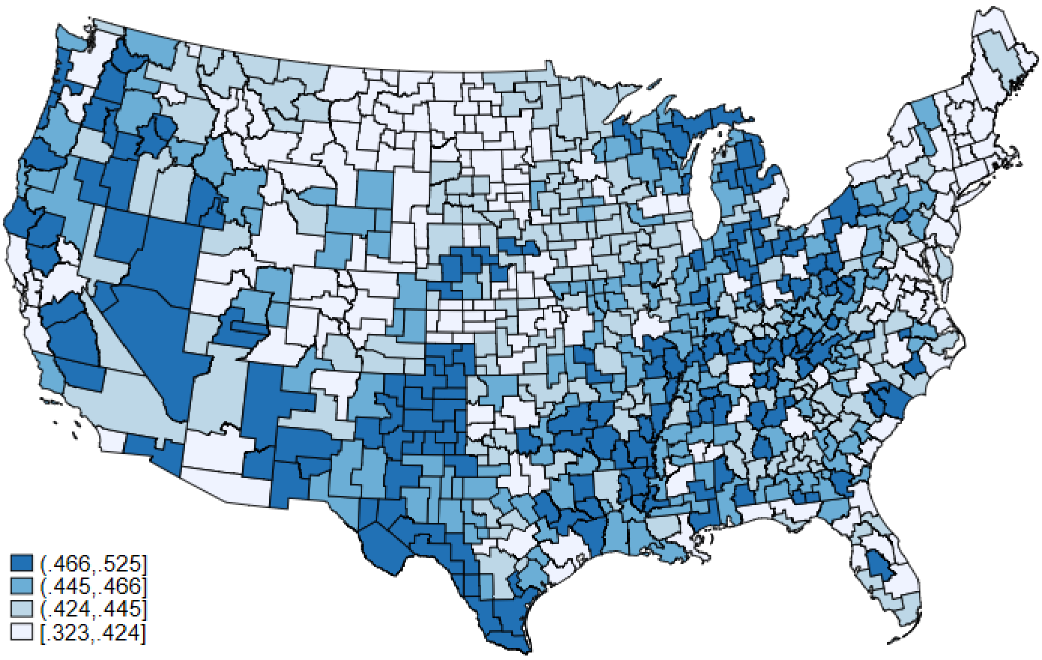
Figure 1: Automation potential versus transmission risk of occupation



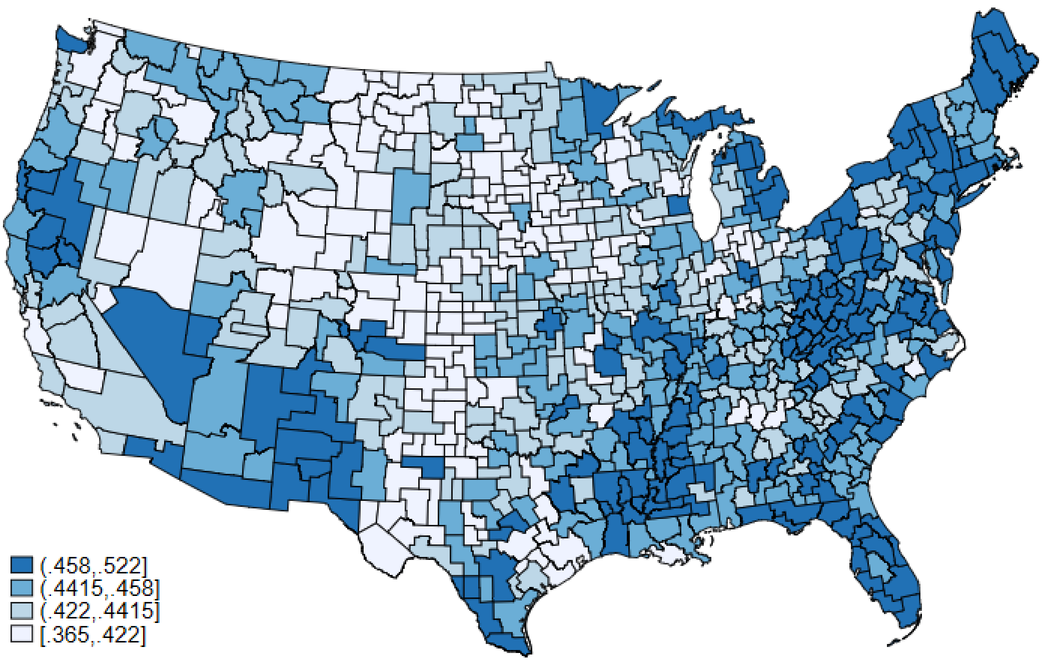
Notes: Automation potential and transmission risk indexes are created from the O*NET Database and are normalized to range between zero and one. High-risk occupations are defined as those with both indexes being greater than or equal to 0.5 and are indicated by the red squares. Low-risk occupations are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

Figure 2: Index ≥ 0.5 by commuting zone

(a) Automation potential ≥ 0.5

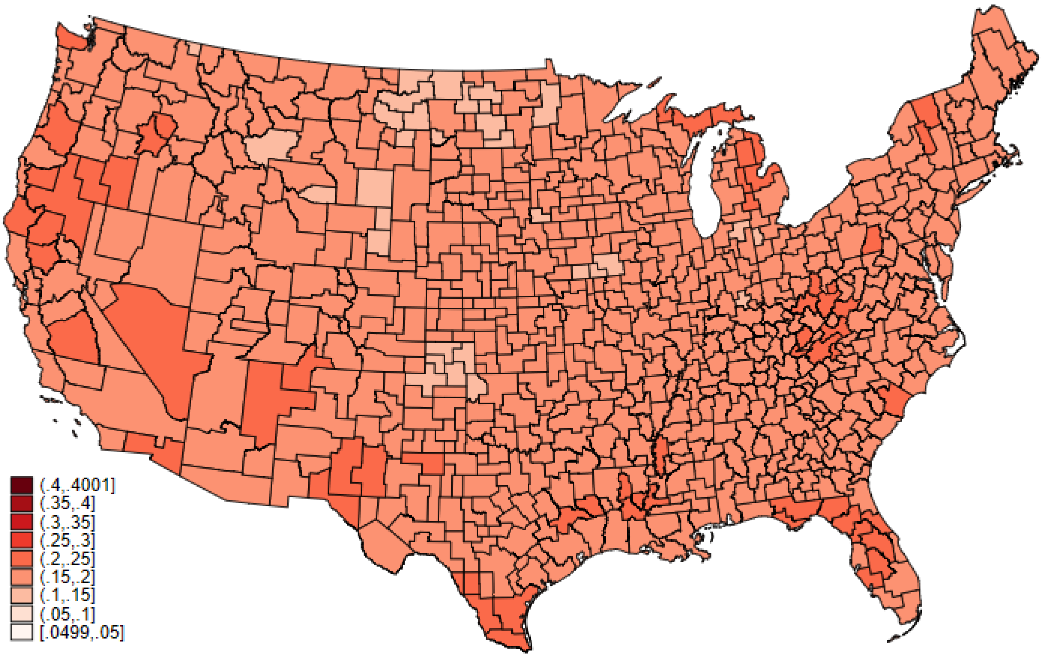


(b) Transmission risk ≥ 0.5



Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates use weighted counts from the 2013 to 2017 ACS. The sample is restricted to individuals aged between 18 and 65 years.

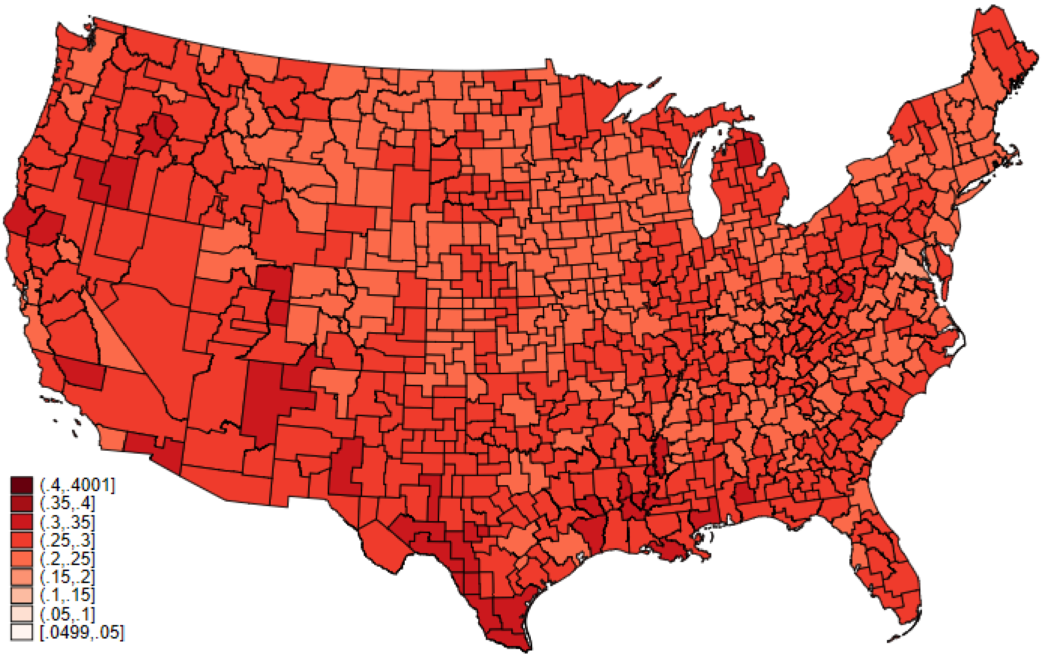
Figure 3: Automation potential and transmission risk both ≥ 0.5



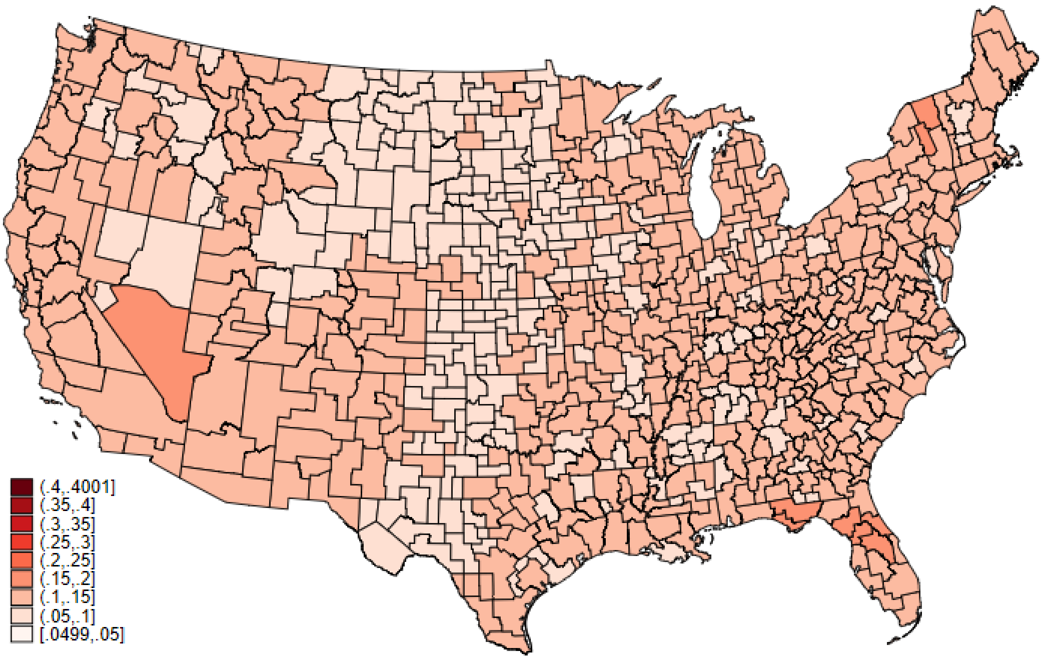
Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates use weighted counts from the 2013 to 2017 ACS. The sample is restricted to individuals aged between 18 and 65 years.

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

(a) Females



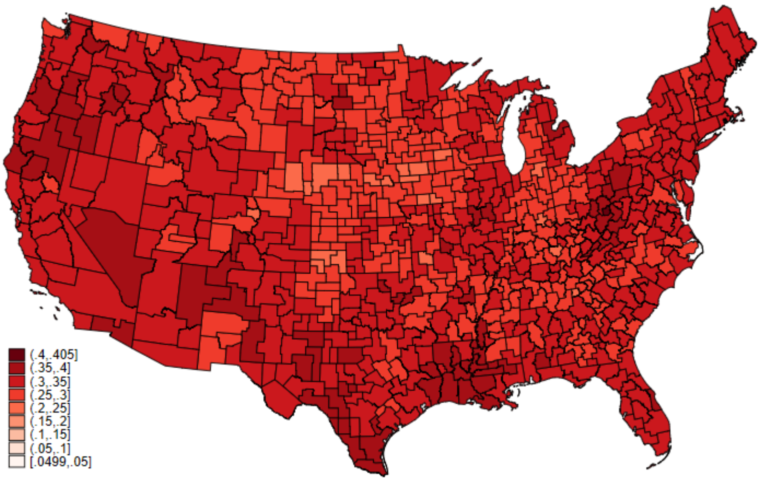
(b) Males



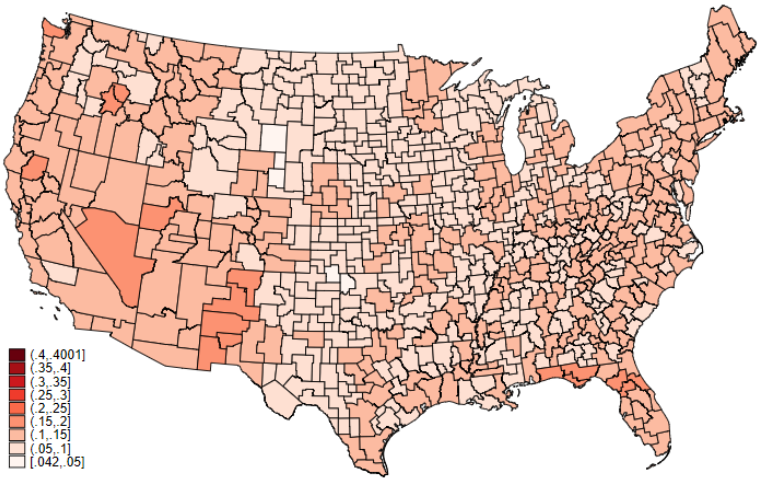
Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates use weighted counts from the 2013 to 2017 ACS. The sample is restricted to individuals aged between 18 and 65 years.

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

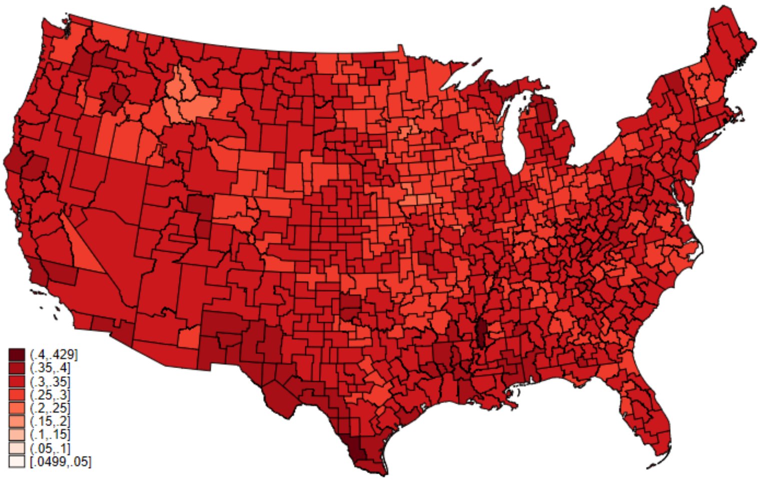
(a) High school or less, females



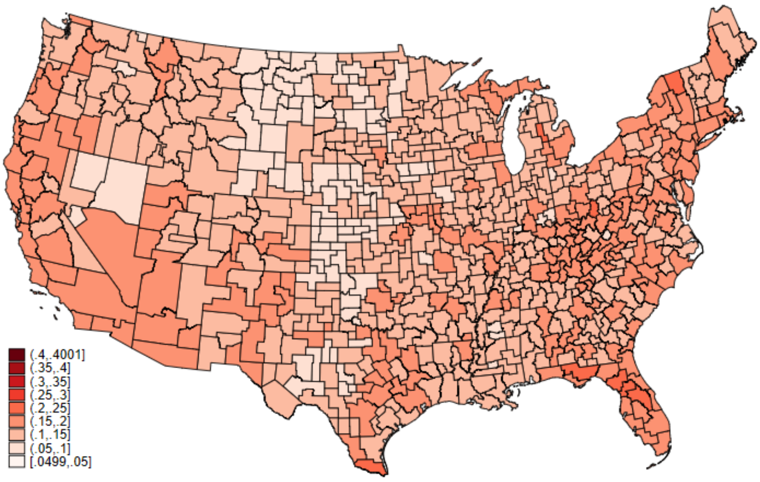
(b) High school or less, males



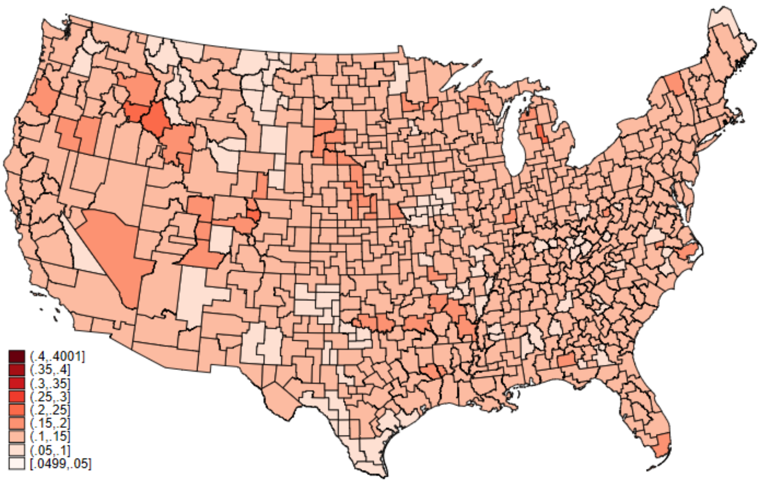
(c) Post secondary $<$ BA, females



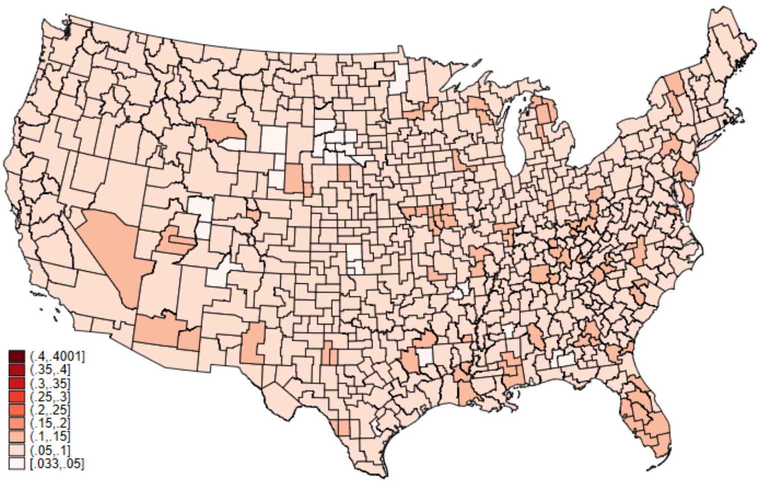
(d) Post secondary $<$ BA, males



(e) BA or higher, females

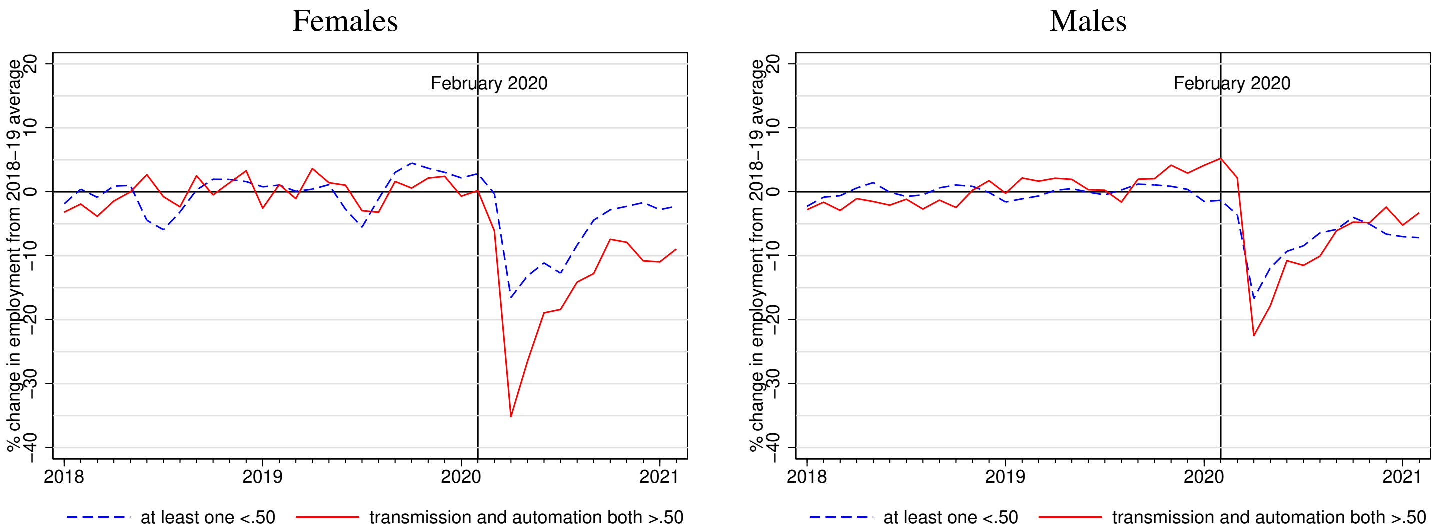


(f) BA or higher, males



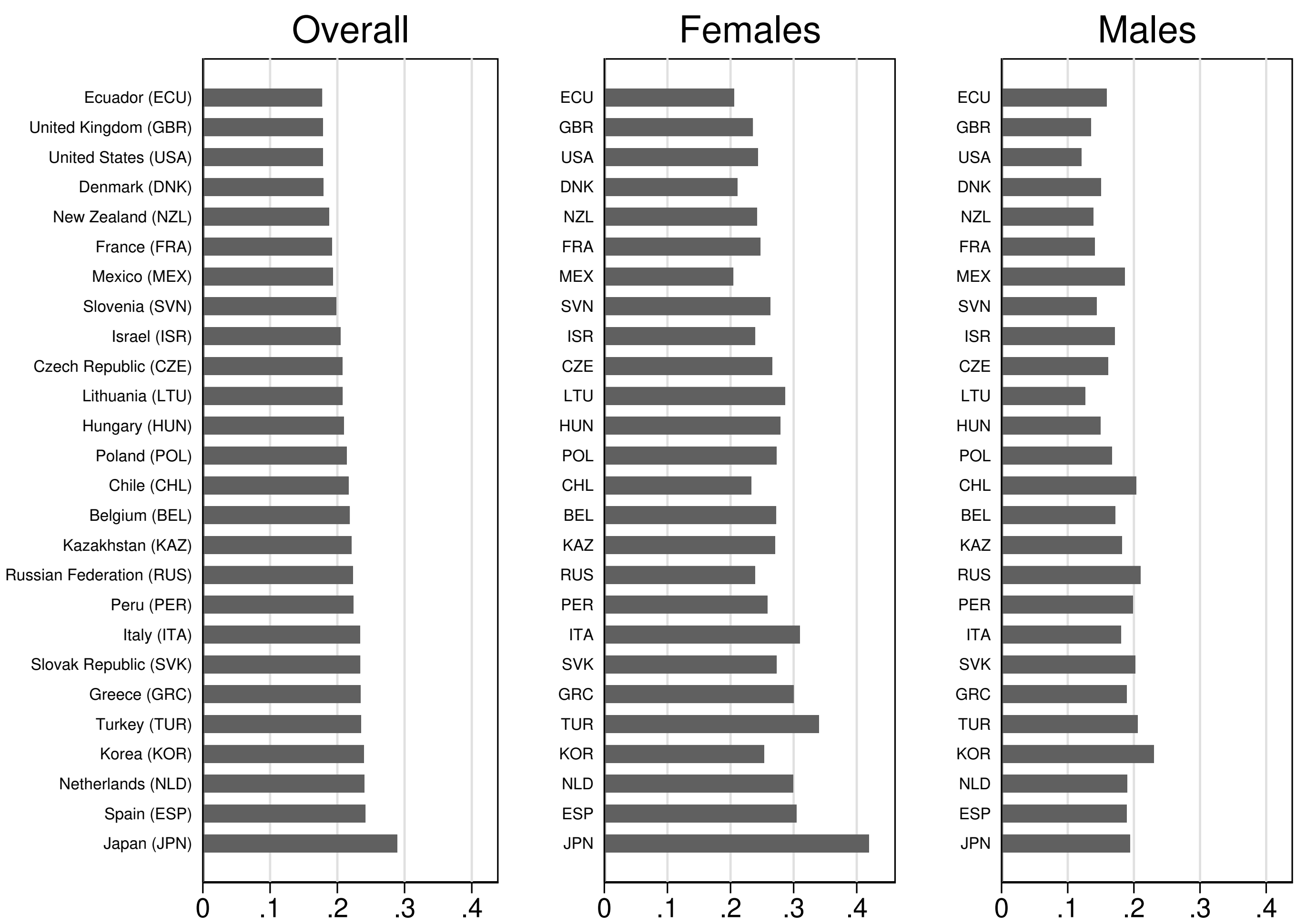
Note: Darker red: more at risk. Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one. Estimates use weighted counts from the 2013 to 2017 ACS. The sample is restricted to individuals aged between 18 and 65 years.

Figure 6: Females in High-Risk Occupations: Larger Initial Decline in Employment and Weaker Recovery



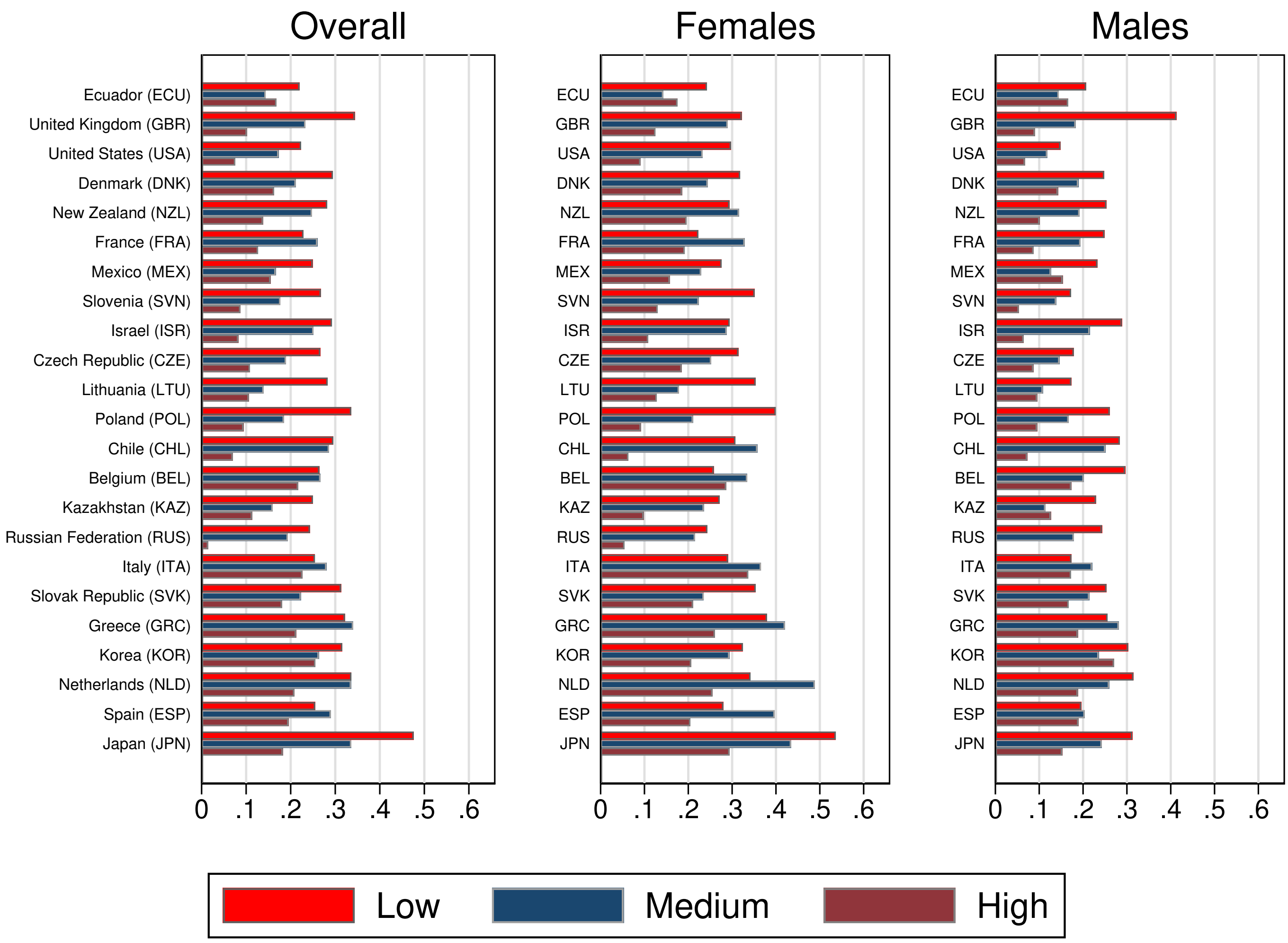
Note: Employment counts are calculated from the CPS.

Figure 7: Fractions of population with both indexes ≥0.5



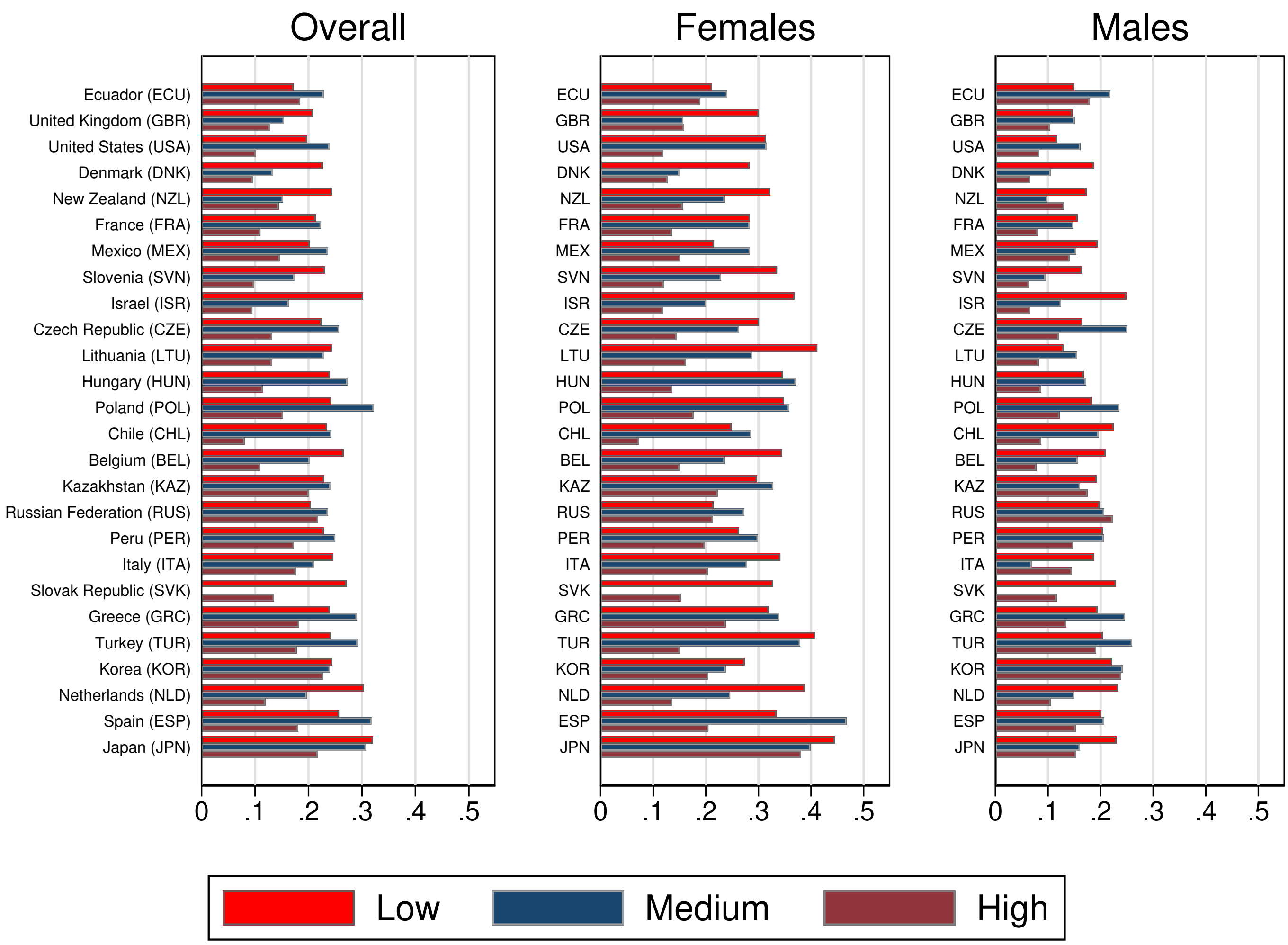
Notes: In this figure and all subsequent bar charts the horizontal bars measure the fraction of the population that work in occupations with automation potential and transmission risk indexes both ≥ 0.5. U.S. values are identical to the corresponding mean values reported in Table 2. Values for all other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

Figure 8: Fractions of population with both indexes >0.5, by wage level



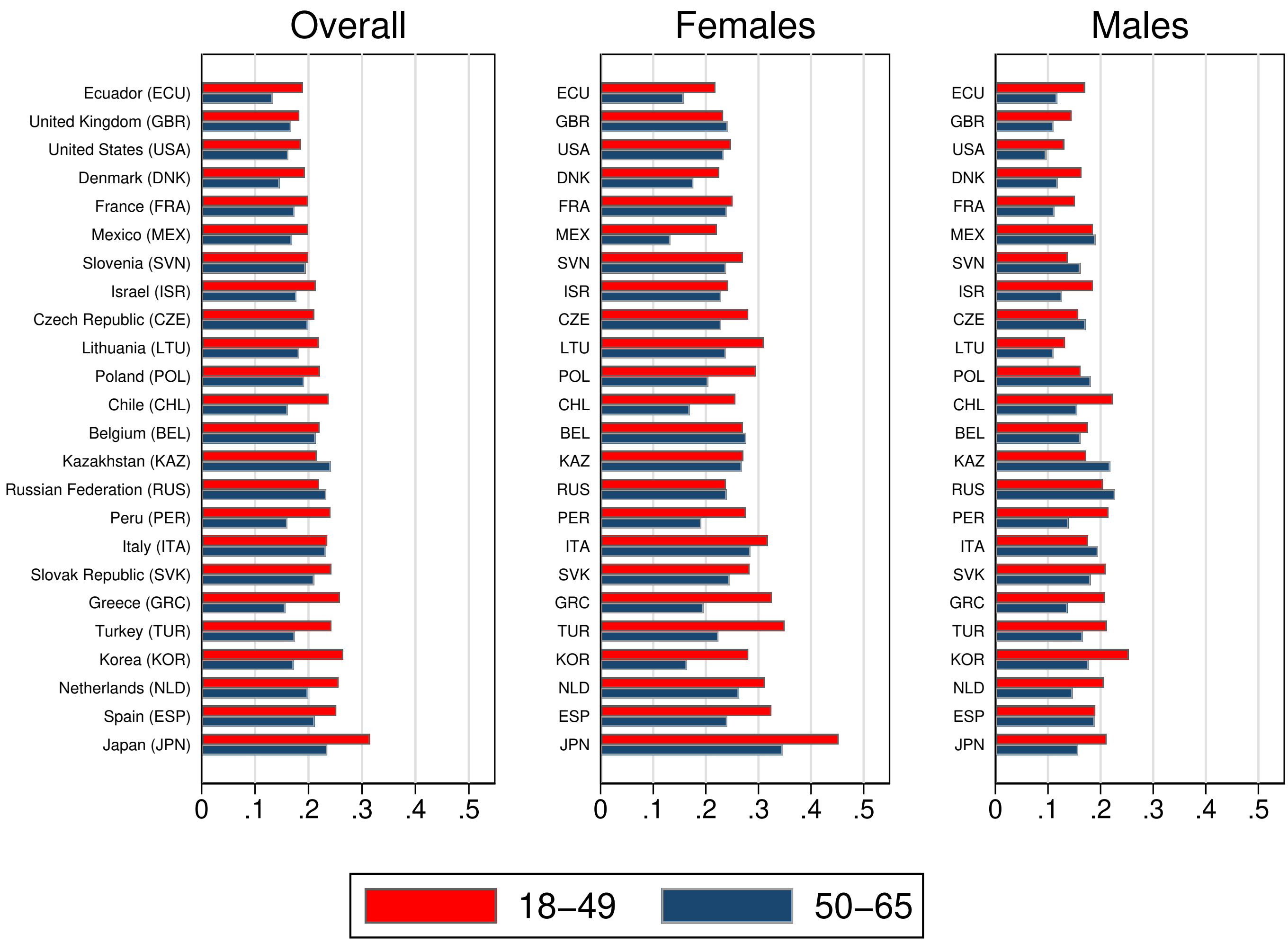
Notes: The upper cutoff for low wage is two-thirds of the median earnings, and the lower threshold for high wage is one and a half times the median earnings. Medium wage earners are defined as those with earnings between the low- and high-wage cutoffs. U.S. values are identical to the corresponding mean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

Figure 9: Fractions of population with both indexes ≥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 10: Fractions 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 obtained 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.