NBER WORKING PAPER SERIES

# COVID-19 AND IMPLICATIONS FOR AUTOMATION

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Working Paper 27249
http://www.nber.org/papers/w27249

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2020

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NBER Working Paper No. 27249
July 2020
JEL No. I10,I14,I24,J15,J16,J23,J24,R12

## 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 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 mid-educated females are at highest risk, notably including some healthcare, office and administrative support, and protective service occupations.

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# 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. 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 earning 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 threat of future pandemics.

We use information from the O*NET to construct indexes of automation and COVID-19 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 COVID-19 transmission risk and automation potential. We also examine the demographic groups that may be vulnerable to automation due to infection transmission risk.

Similar to previous research, we find that the American Heartland region has the highest concentration of jobs with automation potential. However, there does not appear to be a well-defined spatial pattern in terms of regions that are at high risk of both COVID transmission and automation. This is due to the fact that many of the occupations with high viral transmission risk tend to be in the service sector and are required in all local economies.

Instead, we find important demographic differences. We uncover that 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. Black females tend to be in occupations with slightly higher risk, as are females with mid-level earnings. However educational differences standout as particularly important as females with mid-level education are at highest risk of both transmission and automation.

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 mid-level educational attainment.

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 aggregated demand resulting 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). Our paper is similar to Mauro Caselli and Traverso (2020), who 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. As noted by Mauro Caselli and Traverso (2020), this relation-

[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.

[3]For Canada, the Vancouver School of Economics COVID-19 Nature of Work Risk Team (2020) has 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 characteristics of the workers in each occupation.

ship 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*.[5] We characterize the degree to which an occupation can be automated by using the two O*NET variables, *degree of automation* and *importance of repeating same tasks*.[6]

We then match the risk of automation and viral transmission risk indexes constructed with the O*NET to the 2018 American Community Survey (ACS). Unfortunately, there is not a perfect mapping between the 6-digit ACS occupation variable and the O*NET. At the 6-digit level or on variable labels, we are able to match around 88.6% of the ACS occupation codes, around 3.4% match at the 5-digit level, 6.7% at the 4-digit and the remaining 1.3% at the 3-digit level. We then collapse the 940 O*NET occupations we matched into the 498 relevant ACS occupations.

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

[5]Physical proximity is defined as the extent to which the job requires 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 ranges from "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", "5. Every day". Finally, the exposed to disease or infections variable is categorized by how often the job requires exposure to disease/infections and has 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", "5. Every day".

[6]These are the same variables used by Deming (2017) to define routine task intensity. The degree of automation variable is defined by values: "1. Not at all automated", "2. Slightly automated", "3. Moderately automated", "4. Highly automated" and "5. Completely automated". The importance of repeating same tasks variable is defined by the question: "(h)ow important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?" The categories are "1. Not important at all", "2. Fairly important", "3. Important", "4. Very important", "5. Extremely important".

To aggregate the variables, we pursue two popular methods in the literature. For our main results, we average the O*NET questions for a given index and then normalize that index to be between 0 and 1.[7] Our second method involves performing factor analysis using the U.S. population from the 2018 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 are highly correlated.

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 the distribution of transmission risk is right skewed, with most of the occupations falling below the 0.5 threshold. As a result, only 7.8% of the occupations are categorized as high risk (red squares), even though automation potential is greater than equal to 0.5 for 39.6% of the occupations. This represents around 6% of the 2018 U.S. population with an occupation. Roughly 48.8% of occupations are designated in the low-risk group (green triangles) representing a little less than 54% of the 2018 U.S. population with an occupation. 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 4 highest and lowest ranked occupations for each index. According to our automation index, 'reservation and transportation

[7] Specifically, we use the following equation: normalized index=(index$_i$ - min(index))/(max(index) - min(index))

ticket agents and travel clerks' is the occupation with highest automation potential. This is consistent with success of internet-based travel and ticket service providers, whose market share has increased in recent decades at the expense brick-and-mortar service providers in this industry. Our ranking of manicurists and pedicurists as having the lowest automation potential is consistent with Autor and Dorn's (2013) inclusion of beauticians in their description of in-person service occupations that are difficult to automate. Dental occupations occupy three of the top four 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. At the low end of the index are solitary professions (writers and authors and logging workers), and professions that have very minimal exposure to diseases or infections (tire builders and electronic home entertainment equipment installers and repairers). 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. Medical and healthcare professionals feature prominently in the high-risk occupations,[8] however, the list also includes other occupations that require workers to be in close contact with their clients and co-workers.

Some of the high-risk occupations are only marginally classified as such on both indexes (e.g. customer service representatives). 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 and pharmacy technicians). 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.

[8] 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 as evidenced by the hundreds of health care workers that have lost their lives to COVID-19 in the U.S. and the over 90 thousand that have already been infected within the first few months of the pandemic (Centers for Disease Control and Prevention, 2020).

The medium-risk category provides a few interesting cases of professions that are either high in automation potential and having low transmission risk (accountants and auditors), and 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 partial automation of these jobs, a large fraction of the U.S. labor force could be affected.

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.[9] 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.[10] 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.

We also re-estimate all our results using the "computerisable" index constructed by Frey and Osborne (2017) and generally find qualitatively similar results despite their index having a higher mean and different distribution than the automation potential index we have

[9] In another robustness check we also 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.

[10] 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.

constructed.

## 3 Results

Figure 2(a) shows the fraction of individuals whose automation potential index is over 0.5 for each Commuting Zone (CZ).[11] Similar to Muro et al. (2019), we find a concentration of CZs with high automation potential in the American Heartland.[12] Figure 2(b) shows that CZs with high transmission risk are relatively diffuse and more evenly distributed across the United States. This reflects the fact that occupations with high transmission risk are often in the service sector and are typically non-tradable, and hence are less prone to being concentrated in a single region.[13] 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 primarily reflects the underlying distribution of viral transmission risk.

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 $\geq 0.5$ and under 0.5 by sex in Figure 4 and then for $\geq 0.5$ by sex and education level in Figure 5.

Overall, the columns titled 'Both $\geq 0.5$' 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 fully explained by the preponderance of females in medical professions. The row 'Non-Medical' in Table 2 removes medical professions,[14] and shows that females remain roughly 83 percent more likely to have high occupational risk of both COVID transmission and automation.

The columns titled 'Both $\geq 0.4$' show the fraction of females and males whose automa-

[11] 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).

[12] 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.

[13] Healthcare, protective service, and personal care, and community/social service occupations represent 79 percent of the occupations with transmission risk above 0.5.

[14] Medical professions are defined as occupations in the healthcare practitioners and technical occupations SOC major group.

tion 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 66% 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. 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.

In Figure 4, we show separate maps for males and females for 'Both $\geq 0.5$' (high risk) on the left-hand side, and 'Both $< 0.5$' (low risk) on the right-hand side. For the high-risk figures, the darker the red, the higher the fraction of the population with both indexes $\geq 0.5$. For the low-risk figures, the darker green indicates a higher the fraction of the population with both indexes less than 0.5. As was shown in Table 2, males are less likely to be in a high-risk job and much more likely to be in a low-risk job. A key takeaway from these figures, is that the darker red for women and darker green for men is pervasive across the U.S., suggesting that geographic or local economic differences are not dominating this relationship.

To better understand our main result, we further disaggregate the average index values for women and men across other demographic characteristics.[15] We begin by showing dif-

[15] In the remainder of this section we 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. We also considered differences in automation and transmission risk by sex and age. While there is relatively little variation across age groups, for each age group we that find women are more likely than men to be in occupations that have a high risk of both automation and transmission. These results are omitted from Table 2 to preserve on space, however they are available upon request.

ferences in automation and transmission risk by sex and race. Some differences are apparent, including that occupations held by black individuals are at a 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.[16] We find that the occupations held by mid-income earning females entail highest risk. Females at each income level are more likely to be at high risk of both automation and transmission as compared with males with the same average income level.

Finally, at the bottom of Table 2 we consider the risk associated with the occupations of males and females across different education attainment levels.[17] For each level of education attainment, females are again at a higher risk of both transmission and automation. However, females with mid-level educational attainment (some post-secondary but less than bachelor's) stand out as the highest risk sub-group. This is true for both sexes, but females with mid-level education are more than twice as likely to be in high-risk occupations than are males with the same level of educational attainment. Figure 5 shows this geographically, and illustrates that the higher risk occupations held by females with mid-level education are evenly distributed across CZs in the U.S. The non-tradable nature of the female dominated mid-skill level service sector jobs, such as office tellers and medical assistants, explain the diffuse spatial distribution of risk.

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). Mid and high-level educated females are the least likely to be in the low-risk category, indicating that over half of the individuals in this group are categorized as medium risk.[18] Another important finding

[16]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 threshold for high-pay is one and a half times median state-level earnings. We use the remainder to classify the medium pay occupations.

[17]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.

[18]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.

is that males with high school or less are heavily concentrated below the low-risk threshold. Adjusting the high-risk threshold from 0.5 to 0.4 results in a relatively small increase in the fraction of males with high school or less that are at high risk. Together, this suggests that less educated males are at less risk from pandemic-induced automation.

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 mid-level education face the highest risk, 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 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. 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 mid-level education face the highest joint risk from COVID-19 transmission and automation. Conversely, males with high school or less, have on average, the lowest risk based on these criteria.

Geographically, our results indicate that while automation potential tends to be concentrated in the American Heartland, commuting zones where both the automation and transmission risk are high are diffusely distributed across the U.S. This is largely due to the fact that the occupations that have highest transmission risk tend to be in the services and are ubiquitous across U.S. local labor markets.

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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# 5 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** | | | |
| **Highest index values** | | | |
| Reservation and transportation ticket agents and travel clerks | 1.000 | 0.429 | 112,678 |
| telephone operators | 0.995 | 0.182 | 24,691 |
| Air traffic controllers and airfield operations specialists | 0.950 | 0.347 | 36,845 |
| Payroll and timekeeping clerks | 0.900 | 0.178 | 143,326 |
| **Lowest index values** | | | |
| Manicurists and pedicurists | 0.000 | 0.449 | 202,813 |
| Helpers, installation, maintenance, and repair workers | 0.070 | 0.415 | 17,735 |
| Directors, religious activities and education | 0.080 | 0.288 | 54,729 |
| Upholsterers | 0.087 | 0.178 | 26,525 |
| **Viral transmission risk** | | | |
| **Highest index values** | | | |
| Dental hygienists | 0.661 | 1.000 | 136,296 |
| Respiratory therapists | 0.551 | 0.960 | 97,768 |
| Dental assistants | 0.471 | 0.947 | 247,349 |
| Dentists | 0.525 | 0.947 | 139,654 |
| **Lowest index values** | | | |
| Tire builders | 0.824 | 0.000 | 13,455 |
| Writers and authors | 0.304 | 0.025 | 172,007 |
| Logging workers | 0.402 | 0.034 | 46,357 |
| Electronic home entertainment equipment installers and repairers | 0.253 | 0.073 | 27,406 |
| **Joint risk of viral transmission and automation potential, 5 largest occupations** | | | |
| **High-risk occupations** | | | |
| Customer service representatives | 0.543 | 0.510 | 3,863,976 |
| Licensed practical and licensed vocational nurses | 0.529 | 0.923 | 1,076,689 |
| Medical assistants | 0.788 | 0.796 | 647,090 |
| Correctional officers and jailers | 0.588 | 0.709 | 443,206 |
| Pharmacy technicians | 0.683 | 0.758 | 438,432 |
| **Medium-risk occupations** | | | |
| Elementary and middle school teachers | 0.267 | 0.618 | 4,590,547 |
| Registered nurses | 0.456 | 0.907 | 3,799,883 |
| Secretaries and administrative (except legal, medical, and executive) | 0.565 | 0.325 | 3,336,141 |
| Accountants and auditors | 0.709 | 0.204 | 2,322,413 |
| Stockers and order fillers | 0.573 | 0.404 | 2,254,411 |
| **Low-risk occupations** | | | |
| Cashiers | 0.424 | 0.458 | 4,827,834 |
| Driver/sales workers and truck drivers | 0.324 | 0.278 | 4,465,011 |
| Retail salespersons | 0.494 | 0.435 | 4,412,672 |
| First line supervisors of retail sales workers | 0.467 | 0.382 | 3,622,093 |
| Janitors and building cleaners | 0.307 | 0.377 | 3,511,529 |

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 2018 ACS. Sample restricted to individuals who were between age 18 and 69.

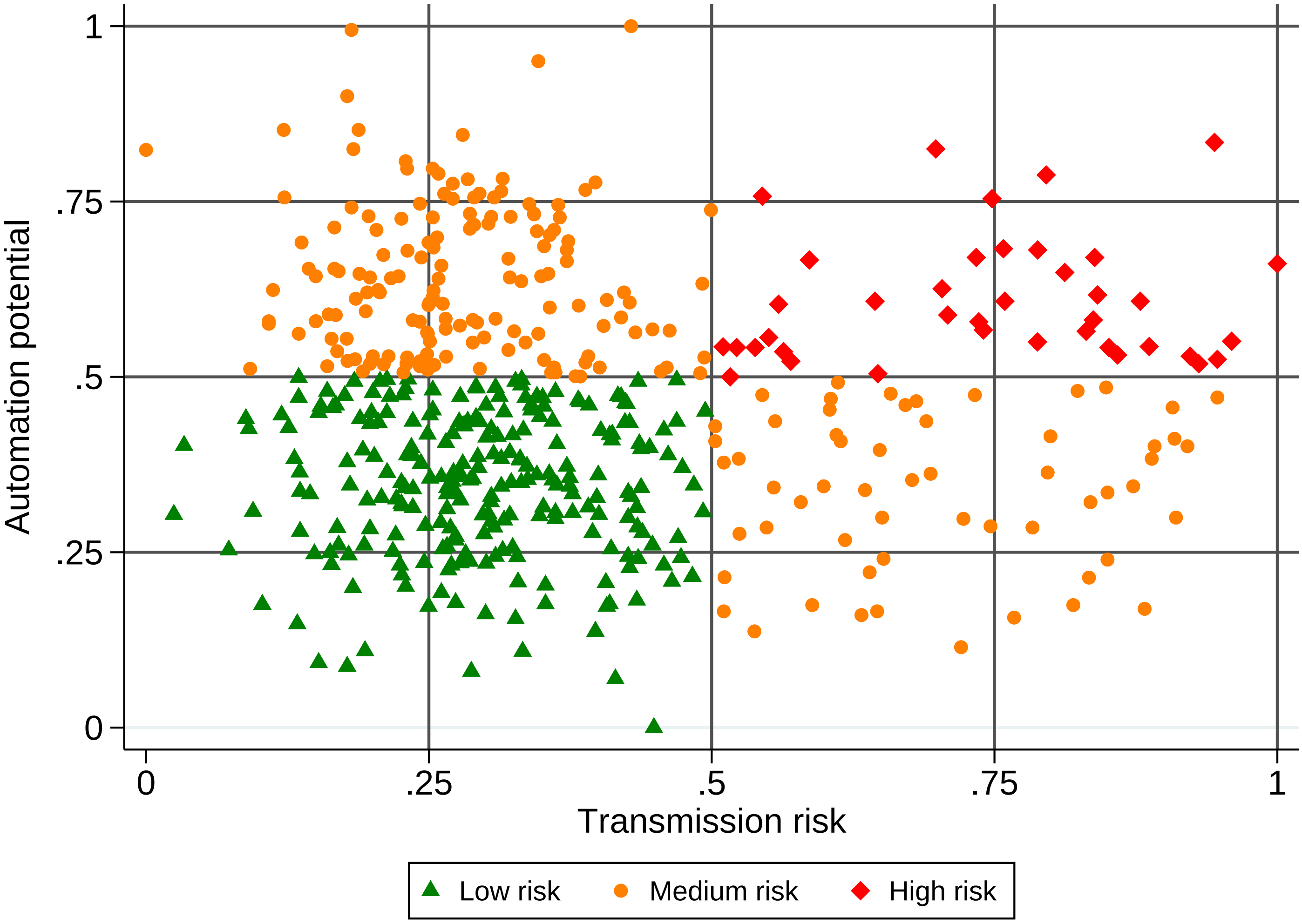
Table 2: Mean automation and risk indexes by demographic characteristics

| | 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 | 0.437 | 0.460 | 0.083 | 0.282 | 0.401 | 0.345 | 0.431 | 0.040 | 0.170 | 0.658 |
| | (0.207) | (0.168) | (0.275) | (0.450) | (0.490) | (0.142) | (0.134) | (0.197) | (0.376) | (0.475) |
| Non-medical | 0.396 | 0.456 | 0.055 | 0.228 | 0.441 | 0.335 | 0.429 | 0.030 | 0.157 | 0.671 |
| | (0.164) | (0.169) | (0.228) | (0.419) | (0.497) | (0.122) | (0.132) | (0.171) | (0.363) | (0.470) |
| White | 0.436 | 0.461 | 0.078 | 0.269 | 0.389 | 0.341 | 0.434 | 0.039 | 0.164 | 0.653 |
| | (0.211) | (0.168) | (0.269) | (0.443) | (0.487) | (0.143) | (0.133) | (0.193) | (0.370) | (0.476) |
| Black | 0.463 | 0.467 | 0.107 | 0.350 | 0.362 | 0.365 | 0.438 | 0.052 | 0.214 | 0.611 |
| | (0.209) | (0.162) | (0.309) | (0.477) | (0.481) | (0.148) | (0.136) | (0.221) | (0.410) | (0.488) |
| Latino or Hispanic | 0.422 | 0.451 | 0.080 | 0.275 | 0.462 | 0.346 | 0.413 | 0.036 | 0.160 | 0.715 |
| | (0.181) | (0.165) | (0.272) | (0.446) | (0.499) | (0.128) | (0.128) | (0.186) | (0.366) | (0.452) |
| Asian American | 0.425 | 0.457 | 0.078 | 0.275 | 0.436 | 0.348 | 0.449 | 0.048 | 0.175 | 0.606 |
| | (0.218) | (0.179) | (0.268) | (0.446) | (0.496) | (0.167) | (0.146) | (0.214) | (0.380) | (0.489) |
| All other races | 0.433 | 0.461 | 0.083 | 0.299 | 0.427 | 0.356 | 0.432 | 0.045 | 0.198 | 0.653 |
| | (0.199) | (0.164) | (0.276) | (0.458) | (0.495) | (0.143) | (0.135) | (0.206) | (0.399) | (0.476) |
| Low pay | 0.441 | 0.447 | 0.084 | 0.296 | 0.428 | 0.351 | 0.414 | 0.034 | 0.171 | 0.720 |
| | (0.183) | (0.169) | (0.277) | (0.457) | (0.495) | (0.127) | (0.128) | (0.182) | (0.376) | (0.449) |
| Medium pay | 0.438 | 0.490 | 0.104 | 0.263 | 0.299 | 0.348 | 0.436 | 0.044 | 0.167 | 0.619 |
| | (0.224) | (0.171) | (0.305) | (0.440) | (0.458) | (0.147) | (0.137) | (0.206) | (0.373) | (0.486) |
| High pay | 0.422 | 0.466 | 0.060 | 0.218 | 0.420 | 0.324 | 0.449 | 0.040 | 0.142 | 0.629 |
| | (0.254) | (0.155) | (0.237) | (0.413) | (0.494) | (0.159) | (0.130) | (0.197) | (0.349) | (0.483) |
| High school or less | 0.413 | 0.458 | 0.071 | 0.298 | 0.480 | 0.339 | 0.411 | 0.026 | 0.155 | 0.736 |
| | (0.166) | (0.159) | (0.256) | (0.457) | (0.500) | (0.112) | (0.122) | (0.159) | (0.362) | (0.441) |
| Post-secondary < BA | 0.452 | 0.490 | 0.120 | 0.352 | 0.355 | 0.359 | 0.442 | 0.053 | 0.218 | 0.626 |
| | (0.214) | (0.166) | (0.325) | (0.478) | (0.479) | (0.145) | (0.132) | (0.224) | (0.413) | (0.484) |
| BA or higher | 0.442 | 0.432 | 0.056 | 0.199 | 0.380 | 0.339 | 0.446 | 0.047 | 0.141 | 0.586 |
| | (0.228) | (0.171) | (0.230) | (0.399) | (0.485) | (0.172) | (0.147) | (0.211) | (0.348) | (0.493) |

Notes: Standard deviations in parenthesis under the mean. Automation and Transmission risk indexes are normalized to range between zero and one.

## 6 Figures

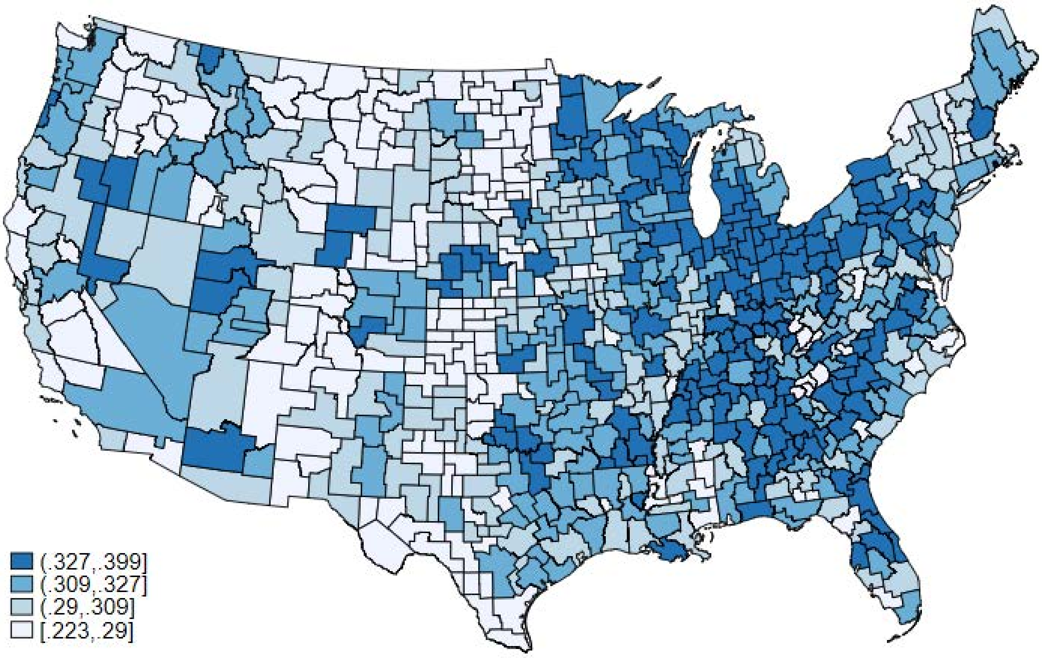
Figure 1: Automation potential versus transmission risk of occupation



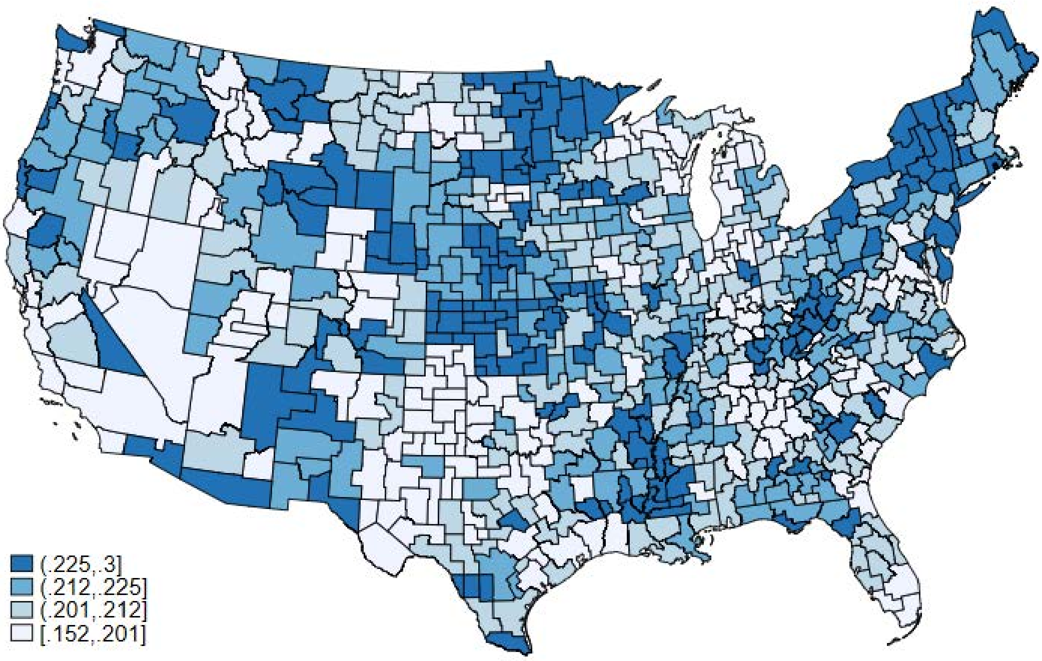

Notes: Automation potential and transmission risk indexes are created from the O*NET and are normalized to range between zero and one. High-risk occupations are defined as those with both indexes being greater than or equal to 0.5 and are indicated by red squares. Low-risk occupations are defined as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

(a) Automation potential $\geq 0.5$

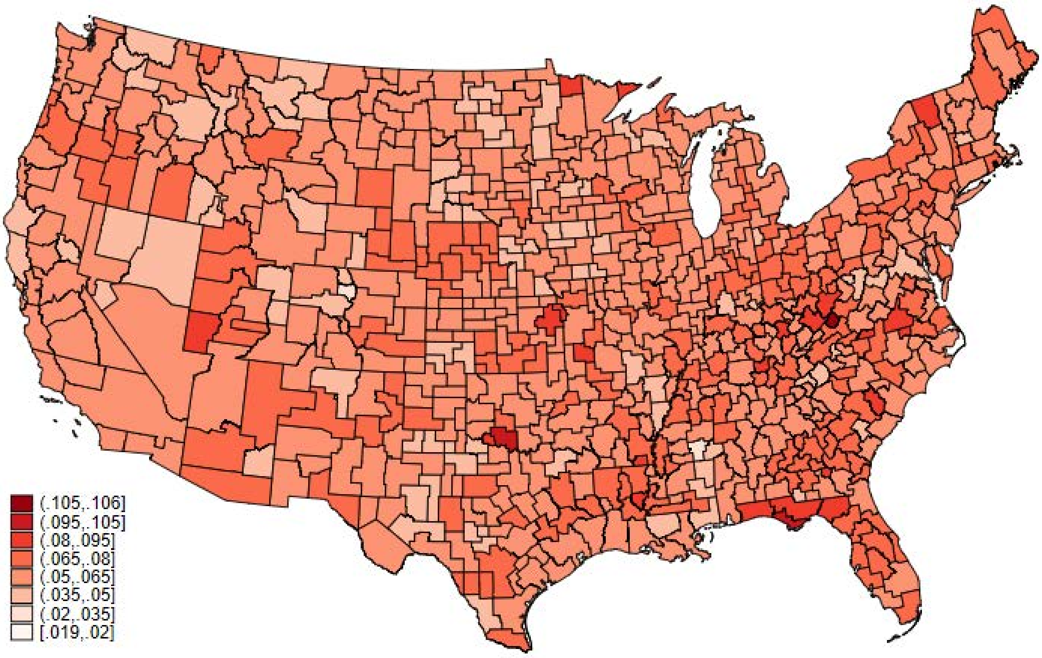



(b) Transmission risk $\geq 0.5$




Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one.

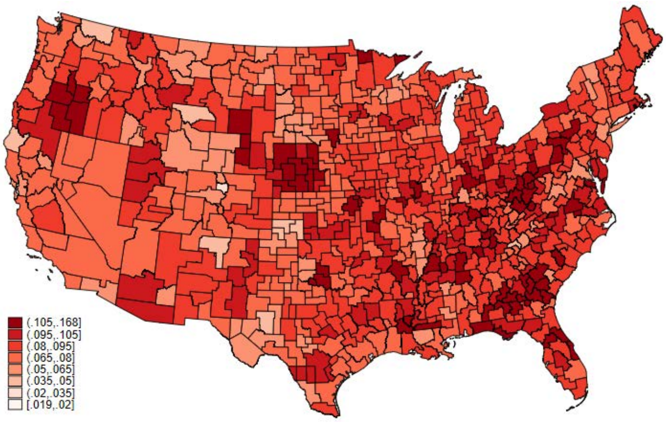
Figure 3: Automation potential and transmission risk both $\geq 0.5$



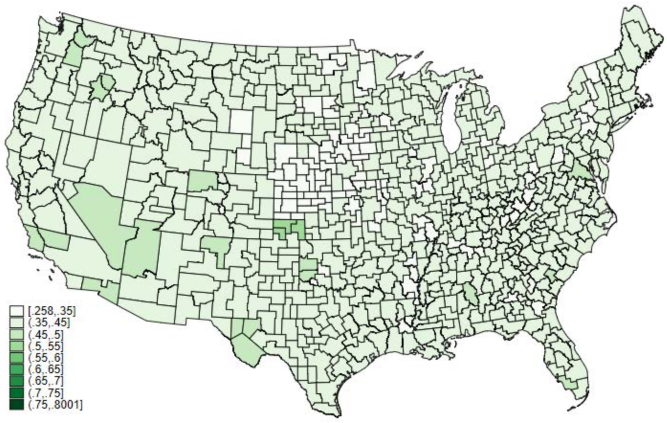

Note: Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one.

Figure 4: Automation potential and transmission risk, high risk or low risk by commuting zone and sex

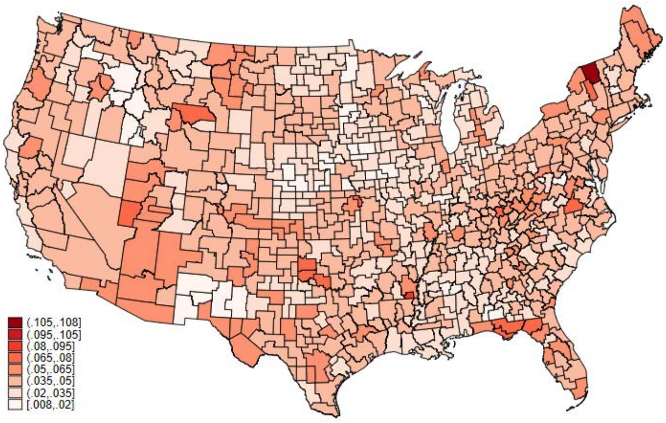
(a) Females High risk: Both $\geq 0.5$



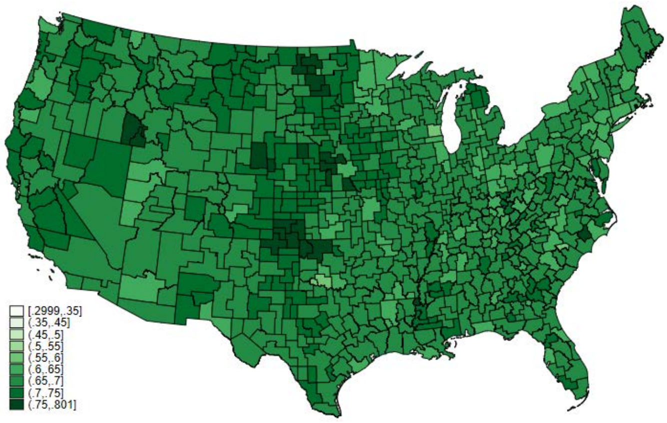

(b) Females Low risk: Both $< 0.5$




(c) Males High risk: Both $\geq 0.5$



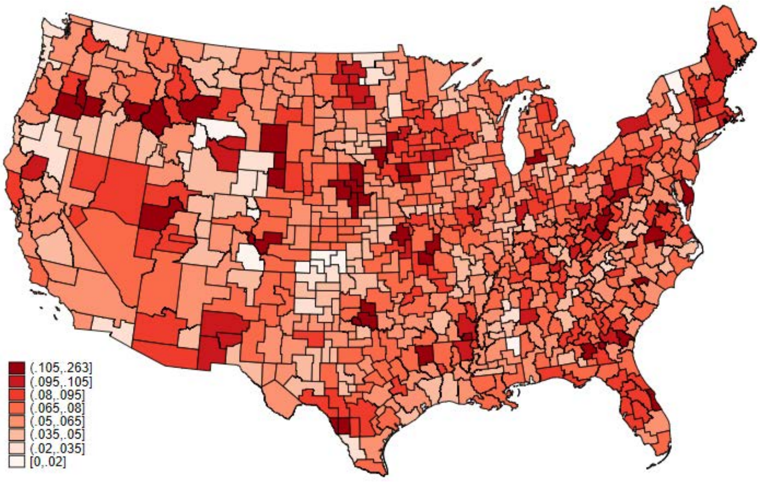

(d) Males Low risk: Both $< 0.5$



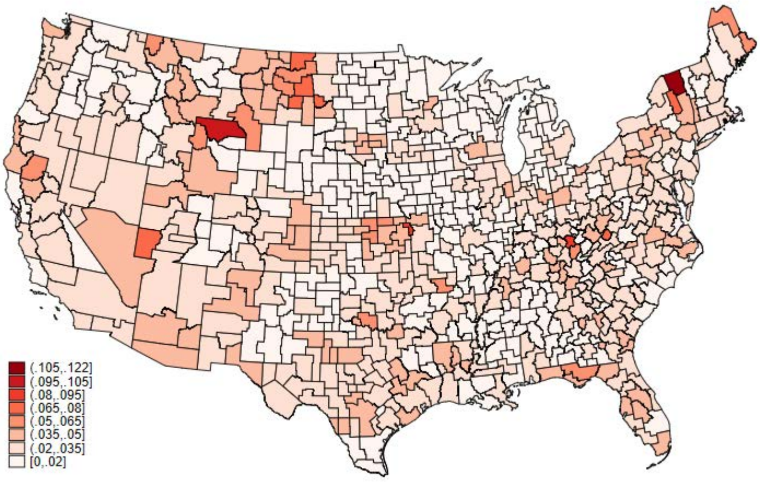

Note: Darker red implies more at risk. Darker green implies less at risk. Automation potential and transmission risk indexes are created from the O*NET and normalized to range between zero and one.

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

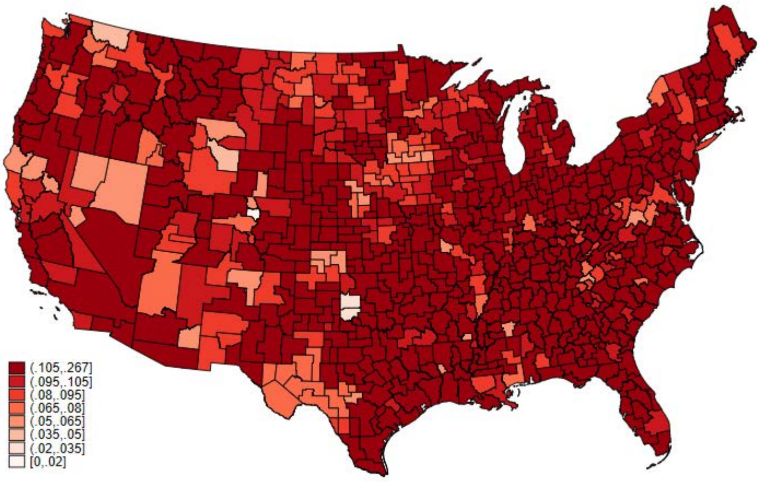
(a) High school or less, females



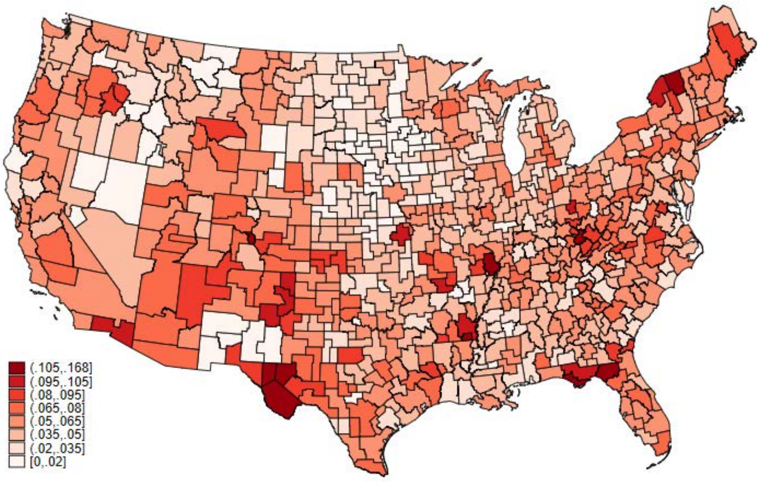

(b) High school or less, males



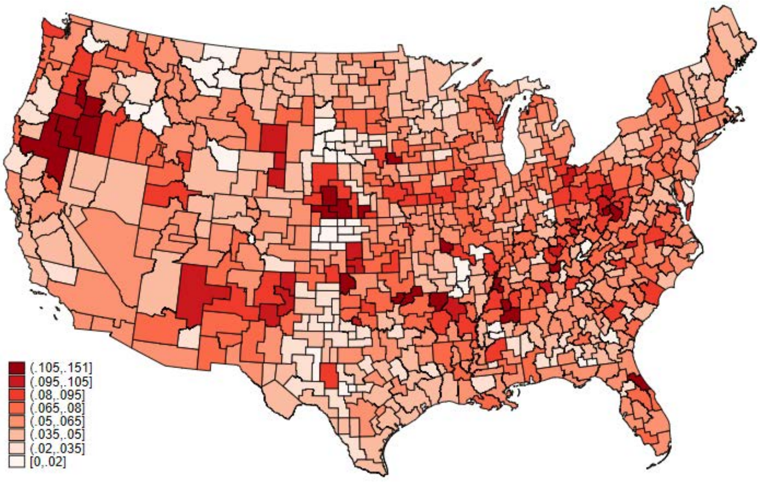

(c) Post secondary $<$ BA, females



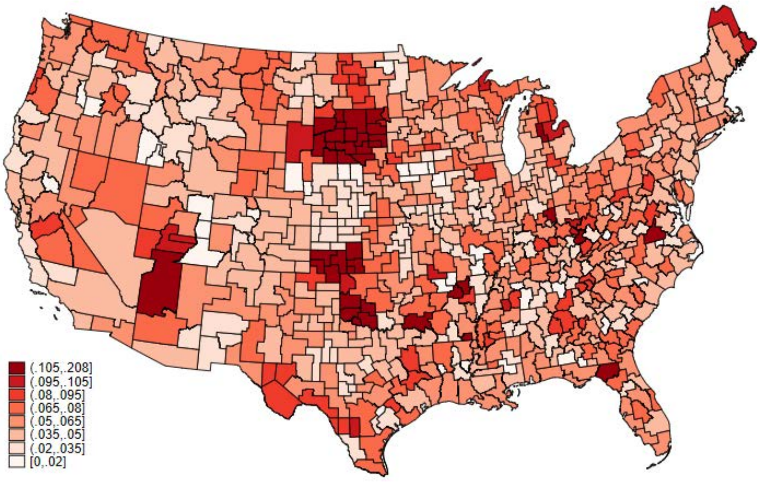

(d) Post secondary $<$ BA, males




(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.