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A Statistical Investigation on Workforce Automation

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Abstract: A handful of highly automated businesses are continuing to profit handsomely in the midst of the COVID-19 pandemic. This paper takes interest in the underlying relationship between an occupation's susceptibility to automation and variables of economic interest, controlling for a number of factors to identify high-risk characteristics. Using datasets from the Bureau of Labor Statistics and the Department of Labor's Employment and Training Administration's Occupational Information Network, we find the degree of computerized tasks and wage level to be statistically significant variables. Other predictors, such as the programming skill of workers, are borderline statistically significant, with p-values slightly exceeding 0.10. Overall, we determine that occupational susceptibility to automation is negatively correlated with educational attainment (in the absence of related predictors), wage, and employment growth rates from 2010-2019. However, we find it is positively correlated with real wage growth rates over the same period and again during the pandemic recession. The methods and final results vary from that of the existing literature, most likely due to differences in variable and model selection. This study accomplishes the following: (1) forms a probabilistic model of workforce automation that is accessible to both economists and public policy makers; (2) provides economic interpretations to our model's predictions with additional parametric models.

Introduction

The computerization of work tasks, more commonly known as labor automation, can be attributed to the widespread and growing adoption of advanced technologies (e.g., robotics, specialized software, Cloud-Based tech, Artificial Intelligence, and machine learning) in production and service [1]. **Figure 1** is a time-series plot of private fixed investment in information processing equipment and software from 1990-2021 [2]. The shaded areas indicate periods of economic recession in the United States. Note the rising trend of investments was interrupted in the past two recessions (shaded grey). During the COVID-19 pandemic,

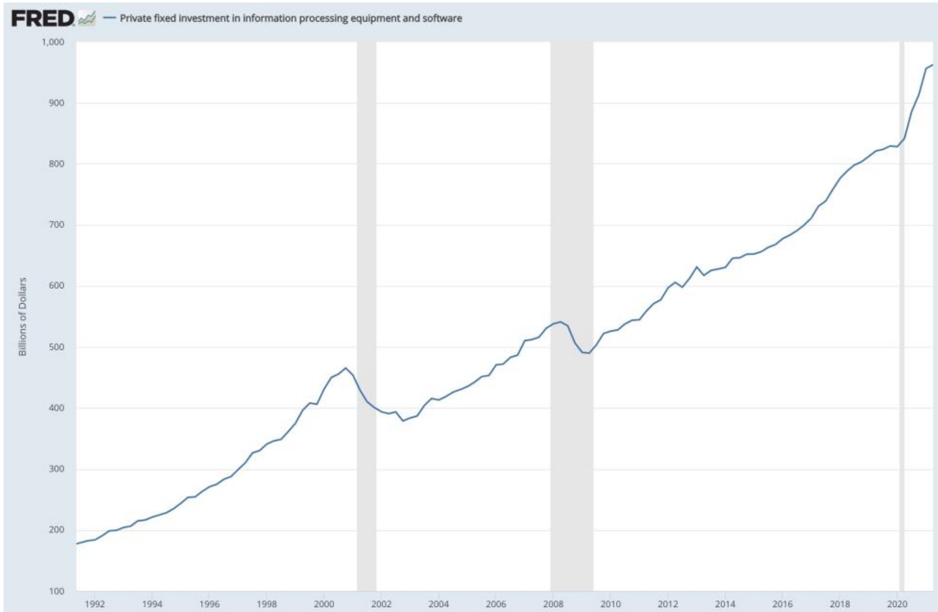


Figure 1: Private Investment in Computer Capital (1990-2021) [2]

Notes: Measurements taken quarterly. Values are seasonally adjusted.

however, there was an uptick in computer capital backing. The sustained investment spike suggests an even greater private sector reliance on advanced technologies in the future. This raises potential concerns, as it is uncertain whether an increase in labor displacement or labor demanded will follow.

Additionally, a handful of tech-based corporations (e.g., Amazon, Apple, Microsoft, and others) profited greatly during the 2020 pandemic and associated recession skyrocketing unemployment rates, collapsing businesses, and plummeting real GDP worldwide [3]. Why is this? Can we simplify this phenomenon down to the laws of supply and demand to conclude that these dominant firms were coincidentally positioned to benefit from a pandemic? Would such an analysis probe deeper than intuitive inspection? We suspect there is something more sophisticated lying beneath the surface that warrants an alternative line of inquiry. In this paper, we form a probabilistic model of workforce automation that is accessible for public policy makers and can help explain static and dynamic trends in the economy.

Literature Review

This paper is not the first to predict an occupation's probability of computerization. In fact, this study closely resembles the work of Oxford's Carl Benedikt Frey and Michael A. Osborne, with a few key differences that we detail below [4].

First, we select different independent variables to predict the propensity for workforce automation, the response in question. Frey and Osborne rely on number of relatively nebulous predictors, such as "social perceptiveness," "manual dexterity," and "originality." While the data source for these variables, O*NET Occupational Data, is highly credible, assigning a specific value to these predictors warrants a high degree of self-reflection from survey participants. Without accounting for the relevant differences among those surveyed, these values can be arbitrary and may perform better as ordinal, rather than cardinal, numbers. Conversely, we use a set of well-defined economic variables, such as wage, programming skill of employees, and minimum education required for entry, conditional on our vector of controls. Our objective is to utilize this set of intuitive predictors to form a model that is more accessible to lawmakers.

Second, we rely on the logit model (or *logistic model*), which Frey and Osborne considered for the purposes of their method but did not ultimately select. Instead, they decided to use the stochastic Gaussian process. To keep our model conservative, we opt for the simpler logistic regression. Using this model, we will also compare the predictive performance of Frey and Osborne's variables with our own.

A large volume of ongoing research is focused on the structural unemployment effects of automating labor [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. We hope to supplement this literature by identifying the common characteristics of occupations at high risk of automation.

Data

To obtain the necessary dataset for our new collection of predictors and corresponding controls, we combined tables from the Bureau of Labor Statistics (BLS) and Department of Labor's Employment and Training Administration's Occupational Information Network (O*NET) , with each row corresponding to a profession, and each column to either a predictor or a control variable. We excluded jobs that were missing in at least one of the original tables, for a total of 608 observations (i.e., occupations).

Further, we use the same 70 hand-labeled occupations as seen in Frey and Osborne's paper. As they explain, a panel of machine learning experts "hand-labeled" each occupation in this sample with the value: 0, if it could not be automated; 1, if it could [4]. While these values were subjectively assigned, we will consider them true for the purpose of fitting our binomial logit regression. We discuss this caveat in more detail in the methodology.

Finally, we use both static (single-year measurements) and dynamic (growth rates) variables for our supplementary parametric models to interpret the results of our main model economically. For our static variables, we use 2019 BLS estimates for education attainment and mean annual wage. For our dynamic variables, we gathered annual employment and wage measurements for years 2008-2020 from the BLS. We calculate the percent change in these quantities for each pair of consecutive years (e.g., 2008-2009, 2009-2010, ..., 2019-2020) to obtain wage and employment growth rates. We take the average growth rate for each of the time periods we study in Section 4.2.2 of the

Methodology (Dynamic Economic Regression). To convert our wage growth rates from nominal to real terms, we employ inflation estimates using BLS Consumer Price Index (CPI) data [21].

Methodology

In this section, we present our generalized regression equations for our main model and our supplementary parametric models, along with our considerations in their design.

Main Model

We use a logit regression with binary random variable Y_{aut_i}, where

$$Y_{aut_i} = \begin{cases} 0, & if\ job\ i\ is\ not\ automatable \\ 1, & if\ job\ i\ is\ automatable \end{cases}$$

and $i \in \{1,2,\dots,608\}$.[5]

Equation (1a) is our main model, which is constructed to predict occupation *i*'s propensity for event $Y_{aut_i} = 1$ using the following variables: programming skill level of workers (x_{pl_i}), degree of automated tasks in the profession (x_{doa_i}), minimum education required (x_{e_i}), mean hourly wage (x_{h-mean_i}) and level of on-the-job training[1] ($x_{T_{ji}}$), conditional on our vector of controls, $\boldsymbol{X_i}$. In this vector, we control for the median hourly wage to have the coefficient of *mean* hourly wage β_4, capture the response of skewing the wage distribution of occupation *i* to a marginally higher mean. The remaining controls are programming importance in the profession and relevant work experience.

$$\ell_i = ln\left(\frac{p_{aut_i}}{1-p_{aut_i}}\right) = \beta_0 + \beta_1 x_{pl_i} + \beta_2 x_{doa_i} + \beta_3 x_{e_i} + \beta_4 x_{h-mean_i} + \beta_5 x_{T_{2i}} + \beta_7 x_{T_{3i}} + \beta_8 x_{T_{4i}} + \beta_9 x_{T_{5i}} + \boldsymbol{\beta X_i} \qquad (1a)$$

where ℓ is occupation *i*'s log-likelihood propensity to be automated (i.e., for event $Y_{aut_i} = 1$), p_{aut_i} is its probability of being automated, and β is a vector of linear parameters for our set of controls. As we are interested in the probability of automation, we can rewrite (1a) to obtain the following:

$$P_{aut_i} = \frac{1}{1+e^{-\ell_i}} = \left[1+e^{(\lambda)}\right] - \mathbf{1}$$

where

$$\lambda = -\beta_0 + \beta_1 x_{pl_i} + \beta_2 x_{doa_i} + \beta_3 x_{e_i} + \beta_4 x_{h-mean_i} + \beta_5 x_{T_{2i}} + \beta_7 x_{T_{3i}} + \beta_8 x_{T_{4i}} + \beta_9 x_{T_{5i}} + \beta X_i$$

Adapted Frey & Osborne Model

Equation (1b) below also measures profession *i*'s propensity to be automated. However, unlike our main model (Equation (1a)), this adapted model uses the same predictors as Frey and Osborne: "finger dexterity level," x_{fdl_i}; "manual dexterity level," x_{mdl_i}; "persuasion level," x_{psl_i}; "negotiation level," x_{nl_i}; "social perceptiveness level," x_{spl_i}; "level of care for others," x_{col_i}; "cramped work space context," x_{cwc_i}; "originality level," x_{ol_i}; and "fine arts level," x_{fal_i} [4].

[1] Level of on-the-job training is a categorical variable with six classes, such that the binary predictor $x_{T_{ji}} = 1$ if occupation *i* requires training of category j and is 0 otherwise. The interpretation of parameter β_{4+j} is the difference in automation propensity between jobs of training category j and jobs belonging to the sixth training category, which is treated as a baseline. Jobs in this sixth training category (baseline) have $x_{T_{ji}} = 0,\ \forall\ j \in \{1,\dots,5\}$.

$$\ell_{i_{FO}} = ln\left(\frac{p_{aut_{i_{FO}}}}{1 - p_{aut_{i_{FO}}}}\right)$$

$$= \beta_{0_{FO}} + \beta_1 x_{fdl_i} + \beta_2 x_{mdl_i} + \beta_3 x_{psl_i} + \beta_4 x_{nl_i} + \beta_5 x_{spl_i} + \beta_6 x_{col_i} + \beta_7 x_{cwc_i} + \beta_8 x_{ol_i} + \beta_9 x_{fal_i} \quad (1b)$$

Comparing Sets of Predictors

We compare the predictive performance of variables in our main model with Frey and Osborne's by calculating the area under the curve (AUC) for each model's ROC[2] curve. Our procedure to this end is consistently applied to both models. First, we randomly partition Frey and Osborne's 70 hand-labeled occupations, along with their assigned binary values (which we consider valid for this analysis), into groups of 40 and 30 to construct a subset of training data and a subset for testing, respectively. We decided to earmark more occupations for training than testing to better estimate the model coefficients. These subsets include every predictor and control from the two logits. Using the training data, we fit equations (1a) & (1b) and use the resultant parametric estimates to predict the probability of automation[3], p_{aut}, for each occupation in the model's test set. From here, we compute the AUC for each logit model's ROC curve, which is useful for determining which set of variables more accurately estimates the hand-labeled assignments (i.e., the "true" value of Y_{auti}) of professions in the test subset.

Supplementary Parametric Models

The probabilities we obtain from the main model (Equation (1a)) are used as predictors in equations (2-9) below, controlling for certain confounding factors. For each economic outcome of interest, we selected the best-fitting regression among the following models: simple multiple linear parametric model, multiple linear parametric model with quadratic terms, multiple linear parametric model with cubic and quadratic terms, exponential parametric model. As we have a greater interest in the qualitative, rather than quantitative, underlying relationship between susceptibility to automation and economic forces, we do not rigorously design regressions (2-9) to confirm causal interactions.

Static Economic Regressions

Mean Annual Wage

Using job *i*'s probability of automation, we can predict the mean annual wage of workers in the profession. Since we expect educational attainment, relevant work experience[4], and intensity of on-the-job training to have strong associations with mean salary, we control for these variables in vector $\boldsymbol{A_i}$.

[6] The ROC (Receiver Operating Characteristic) curve, for a binary logit regression, is a graphical representation of the confusion matrix at different classification thresholds, or cutoffs, which decide which occupations are "automatable," based on their observed value of p_{aut}. We typically prefer models to have a large AUC for their ROC curve, as a greater value is associated with higher true positive rates for different predetermined levels of specificity.
[7] i.e., the expectation of the binary random variable, Y_{aut}
[8] Relevant work experience is a nominal variable with three different categories.

$$Y_{w_i} = \alpha_0 + \alpha_1 p_{aut_i} + \alpha_2 (p_{aut_i})^2 + \alpha_3 (p_{aut_i})^3 + \boldsymbol{\alpha A_i} + \varepsilon_i \quad (2)$$

where α is a vector of linear parameters for our control variables, and ε_i is an idiosyncratic error term.

Educational Attainment

Using job i's probability of automation, we can predict the average education level of workers in the profession. Since we expect educational attainment[5] to be significantly correlated with mean annual wage, we control for salary with variable x_w.

$$Y_{EDU_i} = \gamma_0 + \gamma_1 p_{aut_i} + \gamma_2 x_w + \varepsilon_i \quad (3)$$

Dynamic Economic Regressions

To account for fluctuations in business cycles in our dynamic models, we partition growth rates from 2008-2020 for employment and wage into three separate time periods: 2008-2009 (Great Recession), 2010-2019, and 2019-2020 (COVID-19 Pandemic). The simple multiple linear parametric model performed the best for each of the dynamic regressions.

Employment Growth

Using job i's probability of automation, we can predict its average annual employment growth rate for each time period, controlling for typical education required for entry (x_{ei}), such that

$$\overline{\boldsymbol{EG}}i_{2008-2009} = \delta_0 + \delta_1 p_{aut_i} + \delta_2 x_{e_i} + \varepsilon_i$$
$$\overline{\boldsymbol{EG}}i_{2010-2019} = \zeta_0 + \zeta_1 p_{aut_i} + \zeta_2 x_{e_i} + \varepsilon_i$$
$$\overline{\boldsymbol{EG}}i_{2019-2020} = \eta_0 + \eta_1 p_{aut_i} + \eta_2 x_{e_i} + \varepsilon_i \quad (4\text{-}6)$$

Real Wage Growth

Using job i's probability of automation, we can predict its average real wage growth rates for each time period. Since we expect higher levels of education to be associated with positive wage growth, via pay raises and promotions, we control for educational attainment[6] with variable x_{EDUi}.

$$\overline{\boldsymbol{RWG}}i_{2008-2009} = \kappa_0 + \kappa_1 p_{aut_i} + \kappa_2 x_{EDU_i} + \varepsilon_i$$
$$\overline{\boldsymbol{RWG}}i_{2010-2019} = \psi_0 + \psi_1 p_{aut_i} + \psi_2 x_{EDU_i} + \varepsilon_i$$
$$\overline{\boldsymbol{RWG}}i_{2019-2020} = \omega_0 + \omega_1 p_{aut_i} + \omega_2 x_{EDU_i} + \varepsilon_i \quad (7\text{-}9)$$

Results

Main Model

The parametric estimates for our main model were predicted by fitting equation (1a) with our training set data. The following regression equation is realized:

$$\ell_i = ln\left(\frac{p_{aut_i}}{1 - p_{aut_i}}\right)$$

[9] Differing from "typical education required for entry", the "educational attainment" variable is defined by the average number of years of post-secondary education obtained by workers in the profession plus 2, since 0 indicates no formal education, and 1 corresponds to a mean education attainment level of a high school diploma or equivalent, whereas "typical education required for entry" measures the minimum degree of education necessary for a given occupation.

[10] Based on BLS data

$$= -6.0031 - 0.496x_{pl_i} + 0.234x_{doa_i} + 0.683x_{e_i} - 1.31x_{h-mean_i} + 3.12x_{T_{1i}} + 0.634x_{T_{2i}} + 11.6x_{T_{3i}} + 0.525x_{T_{4i}} - 15.7x_{T_{5i}} + \boldsymbol{\beta X_i}$$

$$\therefore p_{aut_i} = \frac{1}{1+e^{-\lambda}}$$

where

$$\lambda = -6.0031 - 0.496x_{pl_i} + 0.234x_{doa_i} + 0.683x_{e_i} - 1.31x_{h-mean_i} + 3.12x_{T_{1i}} + 0.634x_{T_{2i}} + 11.6x_{T_{3i}} + 0.525x_{T_{4i}} - 15.7x_{T_{5i}} + \boldsymbol{\beta X_i}$$

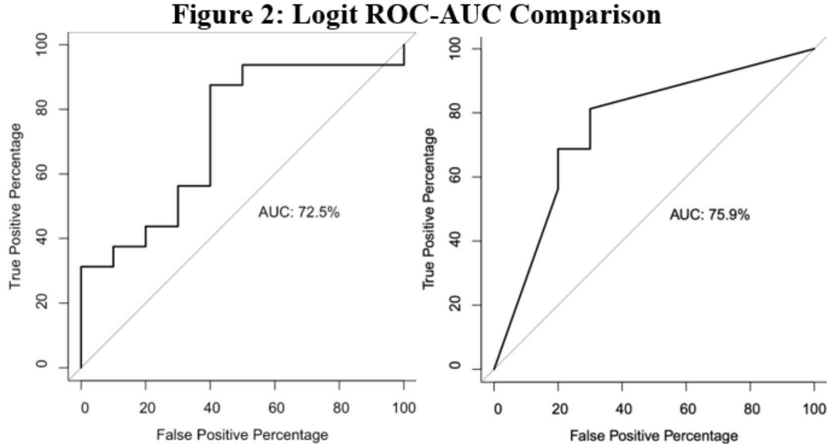
Notice that the estimated parameter for x_{ei} (minimum education required) is positive, which means that jobs requiring higher levels of education are more vulnerable to workforce automation, everything else held constant. The novelty in this result is that it differs from the existing literature. It is understood that education level is *negatively* correlated with likelihood of automation [4]. However, if our model is correct, by controlling for training, wage, and our controls in x_i, the negative association disappears, on account of these predictors. In other words, it is not education alone that reduces automation risk, but the associated variables of training intensity and pay.

Degree of automated tasks in job *i* (x_{doai}) and mean hourly wage (x_{h-mean}) are statistically significant predictor variables, according to their p-values.[7,8] Average programming skill level (x_{pl}) and minimum education required for entry (x_{ei}) are borderline significant.[9,10] We rank the occupations in our dataset by ascending probability of automation, p_{aut}, in **Appendix A1**.

Comparing Sets of Predictors

By exposing models (1a) and (1b) to the same subset of training data and assessing their predictive abilities with the same test data, we achieve a thorough comparison. The left panel of **Figure 2** displays the ROC curve and AUC value obtained from our main

Figure 2: Logit ROC-AUC Comparison



[7] p-value: 0.00868

[8] p-value: 0.09571

[9] p-value: 0.13211

[10] p-value: 0.14161

model (eqn. (1a)). The ROC and AUC in the right panel belong to the adapted Frey and Osborne model (eqn. (1b)).

It is important to acknowledge why there are stark differences in the shapes of the two ROC curves. In fitting the two models with the training data, the logit algorithm converged successfully for our main model, but did not for equation (1b). As a result, the adapted model does not produce a gentle stratification of predicted probabilities. Rather, each value of p_{autF0} is arbitrarily close to either 0 or 1.

Notice that our model captures a larger interval of true positive percentages for various false negative percentages with its distinct staircase shape. That is, our ROC curve's gradual rise in true positive percentage from left to right indicates greater choice in the number of potential "optimal" classification thresholds, relative to the plot on the right.

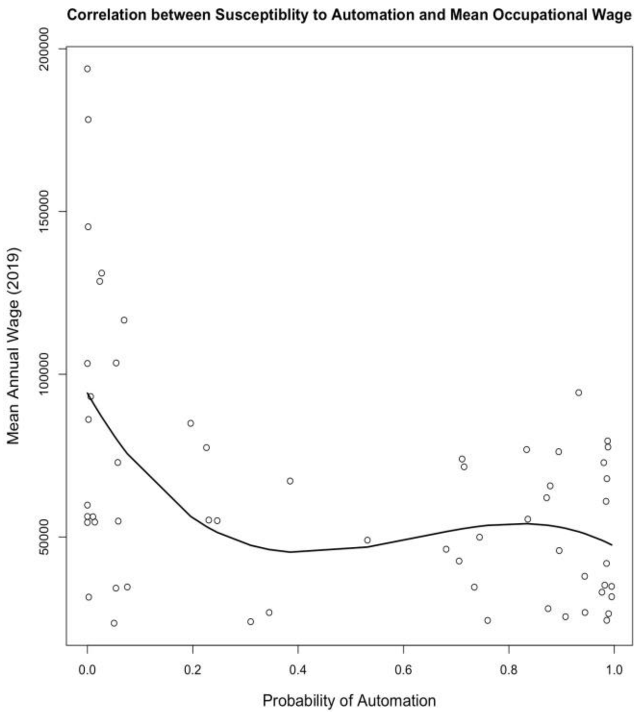
However, our model is at a disadvantage in terms of overall statistical power. This can be attributed to the relatively low true positive percentages our model offers for false positive percentages on the interval of 20 to 40. The greater AUC value in the rightmost ROC plot indicates that Frey and Osborne's predictors produce more accurate estimates overall, despite the algorithm divergence. Thus, the statistician would prefer logit model (1b), unless they are willing to tolerate a false positive rate below 0.2 or above 0.4.

Supplementary Parametric Models

We obtain our least-squares parametric estimates by applying our dataset to our supplementary models (Equations (2-9)). To further demonstrate the qualitative interplay between p_{auti} and the economic outcome in question, we graph their correlation[11]. We limit the display of data points to a random subsample (n = 60) of observations to avoid unnecessary congestion[12].

[11] Figures relying on probabilities gathered from the adapted Frey-Osborne model can be found in the Appendix, for a random sample of occupations. However, due to the near-binary nature of these realized probabilities (see **5.1.1**), they lack utility in predicting economic outcomes for the regression forms we consider in **Section 4.2.** We also plot economic outcomes for the 70 "hand-labeled" jobs using their assigned binary values, which suffers the same complication [4].

[12] All 608 jobs were used in estimating the coefficients, however.



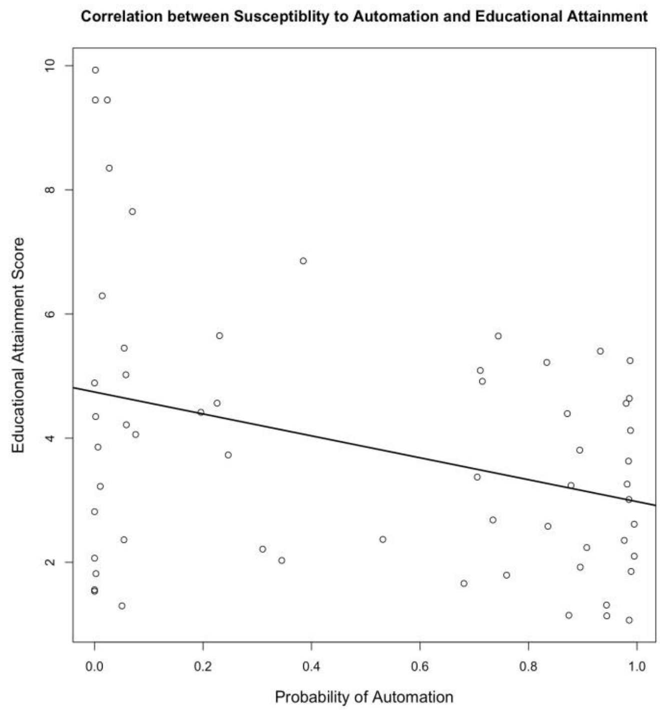


Figure 3: Correlation Susceptibility to Automation and Mean Occupational Wage
Figure 4: Correlation Between Susceptibility to Automation and Educational Attainment

Static Economic Regressions

We find that the mean annual wage and education level of workers behave negatively[13] with an occupation's probability of automation.

Mean Annual Wage

Applying our dataset to equation (2), we obtain:

$$\boldsymbol{Y_{wi} = 24420 - 145038p_{aut_i} + 312581\left(p_{aut_i}\right)^2 - 171986\left(p_{aut_i}\right)^3 + \widehat{\alpha}A_i + \varepsilon_i}$$

Educational Attainment

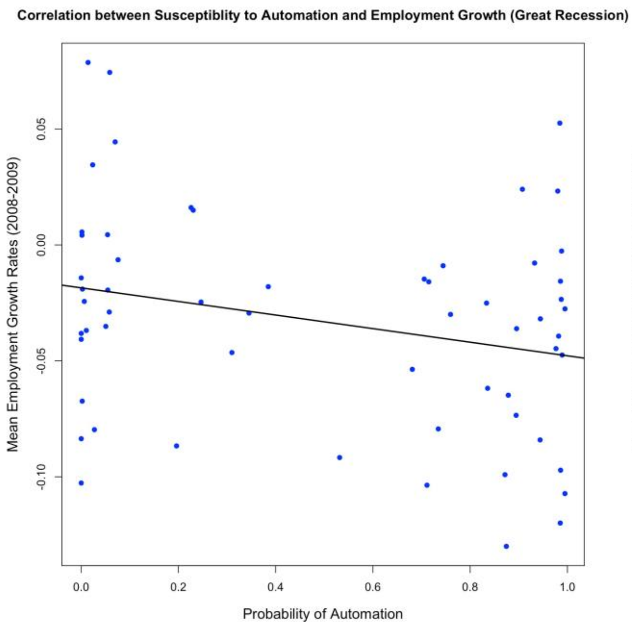
Applying our dataset to equation (3), we obtain:

$$\boldsymbol{Y_{EDU_i} = 0.924 - 0.0497p_{aut_i} + 0.0000451x_w + \varepsilon_i}$$

Dynamic Economic Regressions

We observe that jobs predicted to be at high risk of automation experienced lower mean employment growth during the Great Recession, and again from 2010-2019. However, this dynamic trend was not realized during

[13] *Note*: This does not conflict with the *positive* education coefficient observed in the main model, as equation (3) does not control for training, education, and experience, which may explain this negative behavior in their association with education level.



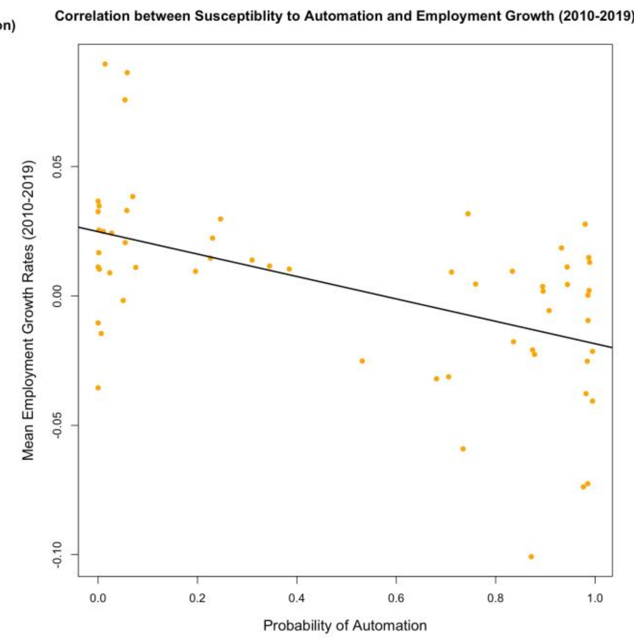


Figure 5: Correlation Between Susceptibility to Automation and Employment Growth (Great Recession)
Figure 6: Correlation Between Susceptibility to Automation and Employment Growth (2010-2019)

the COVID-19 pandemic. Before any conclusions are drawn, it should be said that average employment growth only had significant associations with p_{aut_i} for the period 2010-2019. Regrettably, we observe no significant association between p_{aut_i} and any set of mean real wage growths rates. However, the estimated coefficient for p_{aut_i} grows between each time period for this outcome.

Employment Growth

Applying our dataset to equations (4-6), we obtain:

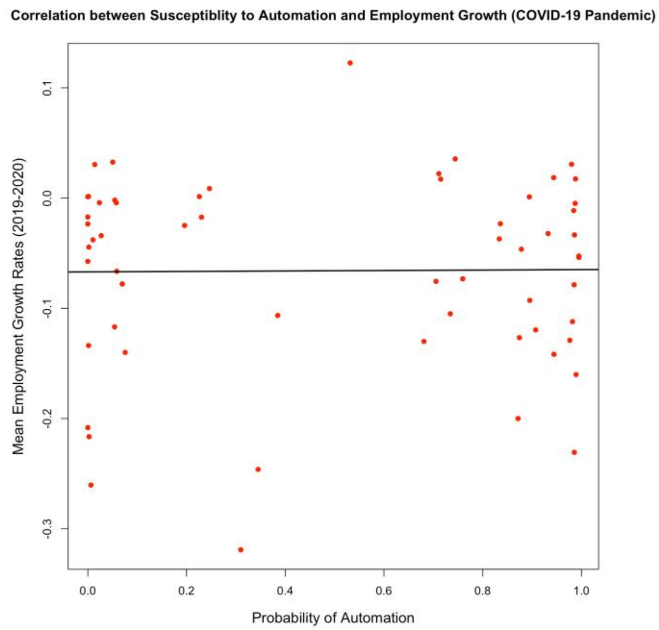
$$\overline{\boldsymbol{EG}}i_{2008-2009} = -0.0450 - 0.0168p_{aut_i} + 0.00615x_{e_i} + \varepsilon_i$$

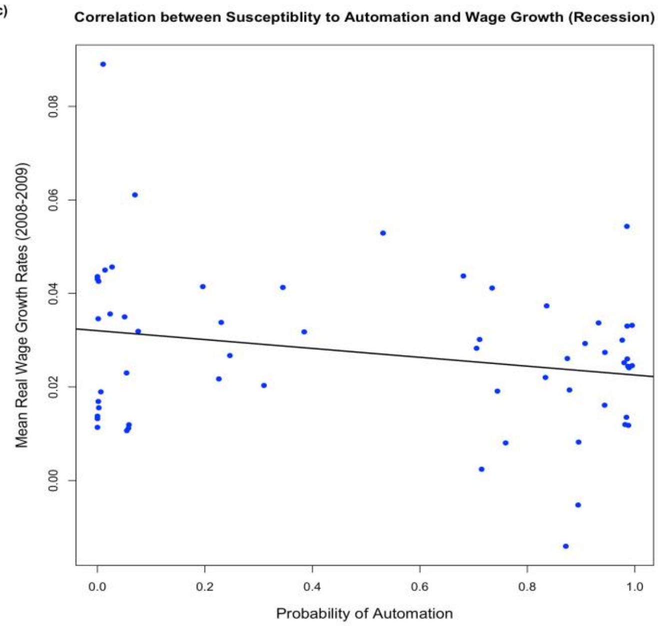
$$\overline{\boldsymbol{EG}}i_{2010-2019} = 0.0123 - 0.0373p_{aut_i} + 0.00294x_{e_i} + \varepsilon_i$$

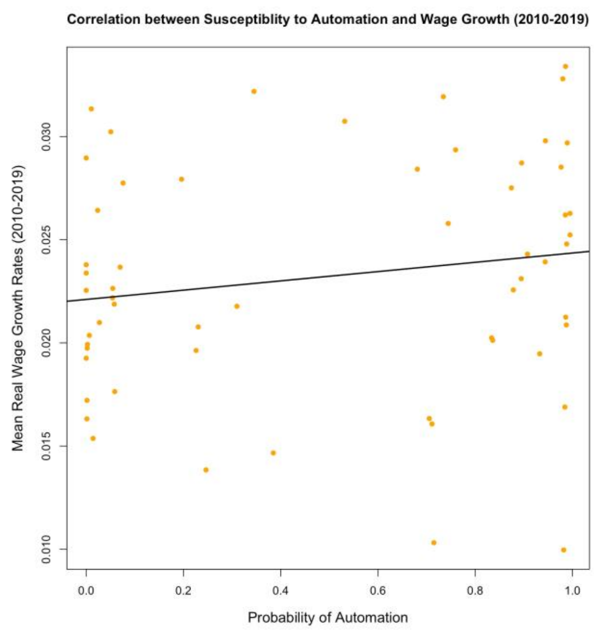
$$\overline{\boldsymbol{EG}}i_{2019-2020} = -0.133 + +0.0333p_{aut_i} + 0.0154x_{e_i} + \varepsilon_i$$

Employment growth is only significantly correlated[14] with p_{aut_i} over the time period 2010-2019. Assuming our model is accurate to some extent, one possible interpretation for this result is that professions vulnerable to computerization may observe slower job growth during times of economic well-being, such as 2010-2019. Conversely, employment growth may behave randomly, with respect to the profession's inclination to becoming automated, during times of economic hardship (hence no significant p-values for p_{aut_i} during Great Recession & COVID pandemic). Of course, to firmly validate this claim, we require data from additional time periods and would need to control for a number of potential confounding factors. It may be

[14] p-value: 0.000319







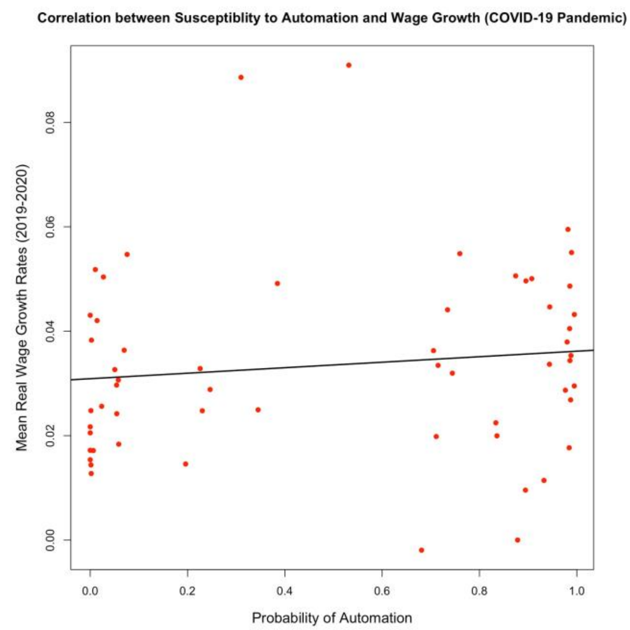


Figure 7: Correlation Between Susceptibility to Automation and Employment Growth (COVID-19 Pandemic)
Figure 8: Correlation Between Susceptibility to Automation and Wage Growth (Recession)
Figure 9: Correlation Between Susceptibility to Automation and Wage Growth (2010-2019)
Figure 10: Correlation Between Susceptibility to Automation and Wage Growth (COVID-19 Pandemic)

worthwhile to study the historical interaction between GDP and the observed significance level of p_{auti} in predicting employment growth.

Real Wage Growth

Applying our dataset to equations (7-9), we obtain:

$$\overline{\boldsymbol{RWG}}i_{2008-2009} = 0.0313 - 0.00923p_{aut_i} + 0.000147x_{EDU_i} + \varepsilon_i$$

$$\overline{\boldsymbol{RWG}}i_{2010-2019} = 0.0277 + 0.000115p_{aut_i} - 0.00118x_{EDU_i} + \varepsilon_i$$

$$\overline{\boldsymbol{RWG}}i_{2019-2020} = 0.0388 + 0.00226p_{aut_i} - 0.00166x_{EDU_i} + \varepsilon_i$$

There is not a significant association between p_{auti} and real wage growth for any of the three time periods. However, the estimated coefficients for p_{auti} increase with time[15]. If our probabilities are adequate estimates, there are two interpretations worth considering. First, it may be the case that being employed in an occupation susceptible to workforce automation is advantageous for pay bumps. Alternatively, it is possible that as some workers are phased out for computer capital, the remaining employees receive raises. However, we could not find credible literature to substantiate either interpretation. As such, future examination is encouraged as automation data and modeling improves.

Obstacles

The advantage of our model is that the predictors are intuitive in terms of interpretation and measurement. However, we are aware of a number of limitations in this paper, beyond the irony in working with machine learning utilities to study the effect of machine learning utilities on labor.

First, while our AUC value is not significantly lower than that of the Frey-Osborne ROC curve (see **Section 5.1.1**), it may not be a just comparison. Since the logit algorithm did not converge for equation (1b), it is possible we are not comparing the Frey and Osborne's predictors at their highest ground of performance. If we were to form a larger training set, perhaps by simulating the "hand-labelling" procedure for more occupations with a team of University of Minnesota computer science and machine learning experts, the divergence problem may cease. From a software utilization perspective, adjustments could be made to the learning rate to improve the likelihood of convergence.

However, even if we achieve this with future research, we should acknowledge that Frey and Osborne rejected the logit form model in favor of the stochastic Gaussian process [4]. Thus, it is possible that this set of predictors does not perform well in a logit regression in the first place.

Additionally, while degree of automated tasks in job *i* (x_{doai}), was found to be a robust predictor, its interpretation is very similar to the response in our logit model. While the variable serves as an accurate automation measure, it may be better used in fitting a regression model of a different form, perhaps multiple linear regression. This method is worth our consideration.

Finally, in the construction of our main model, we did not ensure the

[15] *Note*: the slope of **Figure 10** is shallower than **Figure 9**'s because they are *univariate* correlation plots, whereas the supplementary parametric models in equations (7-9) also control for education level with variable x_{EDUi}

predictors were sufficiently uncorrelated with each other, as there are competing ways to define correlation for nonlinear relationships. However, if we settle for strictly linear correlations, the multicollinearity issue can be easily resolved if we can closely estimate the (potentially) dependent predictors using other predictors in the model. Further, it is possible a number of controls went unaccounted for, and/or the ones included are poor proxies for the controls. We hope to address this with further adjustments to our control variables.

Conclusions

Our study provides a few key contributions to the developing knowledge of workforce automation. Principally, we form a probabilistic model of automation risk using variables accessible to economists and policymakers. While lawmakers may consider a variety of measures upon reviewing, we strongly advocate for higher quality and quantity of automation data, per the Government Accountability Office's recommendation [1]. Still, we determined an occupation's mean wage and programming skill level to be negatively associated with automation risk, while the degree of automated tasks and minimum education required for entry are positively associated, holding everything else constant. In a given occupation, we found the degree of automated tasks and mean hourly wage to be significant predictors in our main model, while the programming skill level of workers and minimum education required perform decently, with slightly larger observed significance levels of 0.13211 and 0.14161, respectively.

Additionally, we qualitatively consider what the probabilities acquired from our main model suggest in economic terms by applying additional regressions. We identify negative correlations between automation likelihood and our static economic variables, annual wage and educational attainment. In terms of dynamic economic variables, we find automation risk has a significant negative association with the mean employment growth rates from 2010-2019, yet a growing positive association with real wage growth over time, although the latter trend could be due to randomness, as our probabilities lack predictive strength for this outcome in each period. Although these supplementary models introduce more questions than answers, with high probability, we hope they motivate further investigation.

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Appendix

A1 Occupational Ranking Based Regression Coefficients

	Occupation	Probability of Automation
1	General and Operations Managers	2.356561e-13
2	First-Line Supervisors of Construction Trades and Extraction Workers	3.337308e-12
3	Education Administrators; Postsecondary	3.947099e-12
4	Art Directors	7.783453e-12
5	Chefs and Head Cooks	7.846631e-12
6	Farmers; Ranchers; and Other Agricultural Managers	1.489312e-11
7	Training and Development Managers	2.619255e-11
8	Instructional Coordinators	3.090396e-11
9	Financial Managers	3.623356e-11
10	Marketing Managers	7.166263e-11
11	Natural Sciences Managers	8.534493e-11
12	Emergency Management Directors	1.756226e-10
13	Musical Instrument Repairers and Tuners	2.218035e-10
14	Human Resources Managers	2.614678e-10
15	Transportation; Storage; and Distribution Managers	2.775214e-10
16	Architectural and Engineering Managers	3.376937e-10
17	Computer and Information Systems Managers	3.895503e-10
18	Industrial Production Managers	5.199643e-10
19	Construction and Building Inspectors	7.988542e-10
20	Fire Inspectors and Investigators	9.003160e-10
21	Glaziers	9.057540e-10
22	Insulation Workers; Mechanical	1.371756e-09
23	Structural Iron and Steel Workers	2.284447e-09
24	Stonemasons	2.854829e-09
25	Plumbers; Pipefitters; and Steamfitters	3.181005e-09
26	Terrazzo Workers and Finishers	4.219215e-09
27	Choreographers	4.391898e-09
28	Carpenters	4.874762e-09
29	Compensation and Benefits Managers	5.696822e-09
30	Reinforcing Iron and Rebar Workers	1.323697e-08
31	Millwrights	1.505887e-08
32	Chief Executives	1.585591e-08
33	Sheet Metal Workers	2.308288e-08
34	Electricians	2.991692e-08

35	Agents and Business Managers of Artists; Performers; and Athletes	5.694945e-08
36	Captains; Mates; and Pilots of Water Vessels	9.735577e-08
37	Brickmasons and Blockmasons	1.027322e-07
38	Purchasing Managers	1.044013e-07
39	Elevator Installers and Repairers	3.759079e-07
40	Funeral Service Managers; Directors; Morticians; and Undertakers	7.960990e-07
41	Producers and Directors	1.708470e-06
42	Self-Enrichment Education Teachers	2.863979e-06
43	Computer Programmers	3.158266e-06
44	Securities; Commodities; and Financial Services Sales Agents	3.219998e-06
45	Real Estate Brokers	3.273704e-06
46	Music Directors and Composers	5.215975e-06
47	Film and Video Editors	6.418639e-06
48	Boilermakers	1.574012e-05
49	Advertising and Promotions Managers	3.530662e-05
50	Property; Real Estate; and Community Association Managers	3.866804e-05
51	Advertising Sales Agents	3.871303e-05
52	Arbitrators; Mediators; and Conciliators	5.578051e-05
53	Commercial Divers	7.199150e-05
54	Petroleum Engineers	8.970897e-05
55	Geoscientists; Except Hydrologists and Geographers	1.157293e-04
56	Directors; Religious Activities and Education	1.201209e-04
57	Gaming Managers	1.525169e-04
58	Real Estate Sales Agents	2.186852e-04
59	First-Line Supervisors of Non-Retail Sales Workers	2.325128e-04
60	Insurance Sales Agents	2.457733e-04
61	Makeup Artists; Theatrical and Performance	2.760372e-04
62	Editors	2.896110e-04
63	Models	3.256438e-04
64	Career/Technical Education Teachers; Middle School	4.541439e-04
65	Computer Numerically Controlled Machine Tool Programmers; Metal and Plastic	4.670503e-04
66	Electric Motor; Power Tool; and Related Repairers	4.707475e-04
67	Sailors and Marine Oilers	6.333228e-04
68	Secondary School Teachers; Except Special and Career/Technical Education	7.221496e-04

69	First-Line Supervisors of Retail Sales Workers	7.226620e-04
70	Agricultural Engineers	7.395992e-04
71	First-Line Supervisors of Correctional Officers	8.543287e-04
72	Photographers	8.770003e-04
73	Animal Trainers	9.552416e-04
74	Forest Fire Inspectors and Prevention Specialists	9.652540e-04
75	Sales Representatives; Wholesale and Manufacturing; Technical and Scientific Products	1.021508e-03
76	First-Line Supervisors of Farming; Fishing; and Forestry Workers	1.131159e-03
77	Private Detectives and Investigators	1.177579e-03
78	Career/Technical Education Teachers; Secondary School	1.340976e-03
79	Lawyers	1.407821e-03
80	Dentists; General	1.570701e-03
81	Operating Engineers and Other Construction Equipment Operators	1.788526e-03
82	Fashion Designers	2.065277e-03
83	First-Line Supervisors of Personal Service Workers	2.476486e-03
84	Hairdressers; Hairstylists; and Cosmetologists	2.524518e-03
85	Door-to-Door Sales Workers; News and Street Vendors; and Related Workers	2.747191e-03
86	Fabric and Apparel Patternmakers	2.870385e-03
87	Automotive Glass Installers and Repairers	2.935961e-03
88	Industrial-Organizational Psychologists	3.003599e-03
89	Software Developers; Systems Software	3.681642e-03
90	Forest and Conservation Workers	4.219825e-03
91	Occupational Health and Safety Technicians	4.312759e-03
92	Outdoor Power Equipment and Other Small Engine Mechanics	4.490345e-03
93	Sales Managers	4.631024e-03
94	Security and Fire Alarm Systems Installers	4.658815e-03
95	Bicycle Repairers	4.823269e-03
96	Management Analysts	5.601981e-03
97	Sales Representatives; Wholesale and Manufacturing; Except Technical and Scientific Products	5.724688e-03
98	Electronic Equipment Installers and Repairers; Motor Vehicles	6.130258e-03
99	Athletes and Sports Competitors	6.313616e-03
100	First-Line Supervisors of Fire Fighting and Prevention Workers	6.535602e-03
101	First-Line Supervisors of Office and Administrative Support Workers	6.931435e-03
102	Police and Sheriffís Patrol Officers	7.266673e-03

103	Umpires; Referees; and Other Sports Officials	7.355435e-03
104	Information Security Analysts; Web Developers; and Computer Network Architects	7.446599e-03
105	Coaches and Scouts	7.613338e-03
106	Animal Breeders	8.108981e-03
107	Special Education Teachers; Secondary School	8.520945e-03
108	Food Scientists and Technologists	8.688877e-03
109	Massage Therapists	9.490241e-03
110	Athletic Trainers	9.582691e-03
111	Mental Health and Substance Abuse Social Workers	1.027597e-02
112	Camera Operators; Television; Video; and Motion Picture	1.041810e-02
113	Ship Engineers	1.045715e-02
114	Flight Attendants	1.050482e-02
115	Elementary School Teachers; Except Special Education	1.133919e-02
116	Musicians and Singers	1.192225e-02
117	Pile-Driver Operators	1.268383e-02
118	Home Appliance Repairers	1.335073e-02
119	Service Unit Operators; Oil; Gas; and Mining	1.360181e-02
120	Marriage and Family Therapists	1.408316e-02
121	Merchandise Displayers and Window Trimmers	1.445236e-02
122	Interpreters and Translators	1.475014e-02
123	Correctional Officers and Jailers	1.510327e-02
124	Gaming Surveillance Officers and Gaming Investigators	1.741448e-02
125	Education Administrators; Elementary and Secondary School	1.827187e-02
126	Carpet Installers	1.831642e-02
127	Medical Appliance Technicians	1.897439e-02
128	Fallers	1.990288e-02
129	Manicurists and Pedicurists	2.101928e-02
130	First-Line Supervisors of Food Preparation and Serving Workers	2.153485e-02
131	First-Line Supervisors of Landscaping; Lawn Service; and Groundskeeping Workers	2.203827e-02
132	Demonstrators and Product Promoters	2.255183e-02
133	Bailiffs	2.350976e-02
134	Judges; Magistrate Judges; and Magistrates	2.355074e-02
135	Personal Financial Advisors	2.466989e-02
136	Chiropractors	2.493582e-02

137	Patternmakers; Metal and Plastic	2.515953e-02
138	Museum Technicians and Conservators	2.554845e-02
139	Curators	2.570744e-02
140	Floral Designers	2.624068e-02
141	Physicists	2.715877e-02
142	Audio and Video Equipment Technicians	2.722984e-02
143	Executive Secretaries and Executive Administrative Assistants	2.732791e-02
144	Welders; Cutters; Solderers; and Brazers	2.753114e-02
145	Upholsterers	2.755473e-02
146	Engine and Other Machine Assemblers	2.797576e-02
147	Excavating and Loading Machine and Dragline Operators	2.849237e-02
148	Radio; Cellular; and Tower Equipment Installers and Repairs	2.901171e-02
149	Kindergarten Teachers; Except Special Education	2.994611e-02
150	Set and Exhibit Designers	2.996612e-02
151	Floor Layers; Except Carpet; Wood; and Hard Tiles	3.018211e-02
152	Mechanical Engineering Technicians	3.071385e-02
153	Graphic Designers	3.236728e-02
154	Occupational Therapy Aides	3.413590e-02
155	First-Line Supervisors of Police and Detectives	3.428297e-02
156	Interior Designers	3.507846e-02
157	Social Science Research Assistants	3.606503e-02
158	First-Line Supervisors of Production and Operating Workers	3.646893e-02
159	Sound Engineering Technicians	3.760096e-02
160	Aircraft Cargo Handling Supervisors	3.808322e-02
161	Dietetic Technicians	3.905090e-02
162	Construction Managers	4.067212e-02
163	Locomotive Engineers	4.111464e-02
164	Software Developers; Applications	4.124696e-02
165	Construction Laborers	4.193923e-02
166	Heat Treating Equipment Setters; Operators; and Tenders; Metal and Plastic	4.466977e-02
167	Physical Therapist Assistants	4.759505e-02
168	Parts Salespersons	4.914546e-02
169	First-Line Supervisors of Helpers; Laborers; and Material Movers; Hand	4.934739e-02
170	Structural Metal Fabricators and Fitters	5.017226e-02

171	Cooks; Fast Food	5.056639e-02
172	Shoe and Leather Workers and Repairers	5.084621e-02
173	Podiatrists	5.199591e-02
174	Commercial Pilots	5.341742e-02
175	Costume Attendants	5.398258e-02
176	Concierges	5.418804e-02
177	Aerospace Engineering and Operations Technicians	5.449700e-02
178	Electrical Engineers	5.463531e-02
179	Network and Computer Systems Administrators	5.616108e-02
180	Social and Community Service Managers	5.772697e-02
181	Meeting; Convention; and Event Planners	5.861366e-02
182	Lodging Managers	6.002370e-02
183	Tank Car; Truck; and Ship Loaders	6.159480e-02
184	Coating; Painting; and Spraying Machine Setters; Operators; and Tenders	6.237093e-02
185	Veterinary Technologists and Technicians	6.541593e-02
186	Food Service Managers	6.668766e-02
187	Economists	6.979258e-02
188	Education Administrators; Preschool and Childcare Center/Program	7.066256e-02
189	Preschool Teachers; Except Special Education	7.577328e-02
190	Sales Engineers	7.987630e-02
191	Epidemiologists	8.095767e-02
192	Etchers and Engravers	8.271063e-02
193	Hazardous Materials Removal Workers	8.345379e-02
194	Medical Equipment Repairers	8.393902e-02
195	Special Education Teachers; Middle School	8.890149e-02
196	Dental Laboratory Technicians	8.958008e-02
197	First-Line Supervisors of Mechanics; Installers; and Repairers	9.295132e-02
198	Wellhead Pumpers	9.557928e-02
199	Environmental Science and Protection Technicians; Including Health	9.807668e-02
200	Aircraft Mechanics and Service Technicians	9.825054e-02
201	Animal Control Workers	9.851193e-02
202	Septic Tank Servicers and Sewer Pipe Cleaners	9.942291e-02
203	Timing Device Assemblers and Adjusters	9.981501e-02
204	Administrative Services Managers	9.999323e-02

205	Log Graders and Scalers	1.012280e-01
206	Orthotists and Prosthetists	1.058003e-01
207	Rehabilitation Counselors	1.061316e-01
208	Medical Equipment Preparers	1.105121e-01
209	Detectives and Criminal Investigators	1.105956e-01
210	Training and Development Specialists	1.108924e-01
211	Traffic Technicians	1.116221e-01
212	Tool Grinders; Filers; and Sharpeners	1.255738e-01
213	Furniture Finishers	1.284983e-01
214	Bartenders	1.312210e-01
215	Adult Basic and Secondary Education and Literacy Teachers and Instructors	1.358915e-01
216	Inspectors; Testers; Sorters; Samplers; and Weighers	1.383343e-01
217	Clinical; Counseling; and School Psychologists	1.406759e-01
218	Legal Secretaries	1.440257e-01
219	Rail Yard Engineers; Dinkey Operators; and Hostlers	1.443951e-01
220	Recreation Workers	1.508080e-01
221	Librarians	1.521555e-01
222	Sociologists	1.534775e-01
223	Pesticide Handlers; Sprayers; and Applicators; Vegetation	1.559391e-01
224	First-Line Supervisors of Housekeeping and Janitorial Workers	1.584394e-01
225	Billing and Posting Clerks	1.621651e-01
226	Crossing Guards	1.768743e-01
227	Cabinetmakers and Bench Carpenters	1.838076e-01
228	Helpers--Extraction Workers	1.844719e-01
229	Licensed Practical and Licensed Vocational Nurses	1.919255e-01
230	Residential Advisors	1.933992e-01
231	Drywall and Ceiling Tile Installers	1.960330e-01
232	Credit Analysts	1.960575e-01
233	Middle School Teachers; Except Special and Career/Technical Education	1.963959e-01
234	Coil Winders; Tapers; and Finishers	1.971528e-01
235	Tax Preparers	2.036100e-01
236	Manufactured Building and Mobile Home Installers	2.052768e-01
237	Cardiovascular Technologists and Technicians	2.076126e-01
238	Recreational Therapists	2.141411e-01

239	Actors	2.150069e-01
240	Speech-Language Pathologists	2.178146e-01
241	Historians	2.216613e-01
242	Anthropologists and Archeologists	2.224981e-01
243	Occupational Therapists	2.235364e-01
244	Registered Nurses	2.259295e-01
245	Clergy	2.303395e-01
246	Amusement and Recreation Attendants	2.308714e-01
247	Veterinary Assistants and Laboratory Animal Caretakers	2.379697e-01
248	Geological and Petroleum Technicians	2.434158e-01
249	Maintenance and Repair Workers; General	2.440120e-01
250	Paralegals and Legal Assistants	2.464241e-01
251	Retail Salespersons	2.628521e-01
252	Psychiatric Technicians	2.684223e-01
253	Mechanical Door Repairers	2.689090e-01
254	Forensic Science Technicians	2.715651e-01
255	Continuous Mining Machine Operators	2.720797e-01
256	Crane and Tower Operators	2.867245e-01
257	Floor Sanders and Finishers	2.875668e-01
258	Occupational Therapy Assistants	2.888438e-01
259	Operations Research Analysts	2.905340e-01
260	Veterinarians	2.914925e-01
261	Mechanical Drafters	2.948964e-01
262	Avionics Technicians	2.984965e-01
263	Oral and Maxillofacial Surgeons	2.999797e-01
264	Insulation Workers; Floor; Ceiling; and Wall	3.006991e-01
265	Sewers; Hand	3.023359e-01
266	Railroad Conductors and Yardmasters	3.033023e-01
267	Environmental Engineering Technicians	3.064479e-01
268	Baggage Porters and Bellhops	3.077557e-01
269	Gaming Dealers	3.099065e-01
270	Automotive and Watercraft Service Attendants	3.099519e-01
271	Painters; Construction and Maintenance	3.193027e-01
272	Mining and Geological Engineers; Including Mining Safety Engineers	3.265756e-01

273	Environmental Engineers	0.32969940
274	Model Makers; Metal and Plastic	0.34045590
275	Waiters and Waitresses	0.34506980
276	Dining Room and Cafeteria Attendants and Bartender Helpers	0.34671940
277	Secretaries and Administrative Assistants; Except Legal; Medical; and Executive	0.35019140
278	Ambulance Drivers and Attendants; Except Emergency Medical Technicians	0.35524880
279	Telecommunications Equipment Installers and Repairers; Except Line Installers	0.35873280
280	Gaming Change Persons and Booth Cashiers	0.35883820
281	Woodworking Machine Setters; Operators; and Tenders; Except Sawing	0.37592130
282	Dental Assistants	0.37721270
283	Animal Scientists	0.37766560
284	Grinding and Polishing Workers; Hand	0.38437280
285	Zoologists and Wildlife Biologists	0.38476390
286	Mechanical Engineers	0.38479980
287	Materials Scientists	0.40942230
288	Rotary Drill Operators; Oil and Gas	0.41052180
289	Industrial Engineers	0.41098580
290	Roofers	0.42143240
291	Soil and Plant Scientists	0.43195630
292	Fiberglass Laminators and Fabricators	0.43242720
293	Automotive Service Technicians and Mechanics	0.43972520
294	Control and Valve Installers and Repairers; Except Mechanical Door	0.44732880
295	Tree Trimmers and Pruners	0.45096580
296	Archivists	0.45241490
297	Coin; Vending; and Amusement Machine Servicers and Repairers	0.46251220
298	Transit and Railroad Police	0.46885640
299	Helpers--Pipelayers; Plumbers; Pipefitters; and Steamfitters	0.47887930
300	Electro-Mechanical Technicians	0.48782870
301	Security Guards	0.48977050
302	Helpers--Painters; Paperhangers; Plasterers; and Stucco Masons	0.49157820
303	Textile Cutting Machine Setters; Operators; and Tenders	0.49235490
304	Commercial and Industrial Designers	0.49581720
305	Judicial Law Clerks	0.49769450
306	Motorcycle Mechanics	0.50448860

307	Health and Safety Engineers; Except Mining Safety Engineers and Inspectors	0.51225640
308	Helpers--Electricians	0.51307100
309	Dietitians and Nutritionists	0.51554330
310	Tailors; Dressmakers; and Custom Sewers	0.52183310
311	Architects; Except Landscape and Naval	0.52935220
312	Motorboat Operators	0.53150240
313	Diagnostic Medical Sonographers	0.53449530
314	Barbers	0.54873180
315	Transportation Inspectors	0.55183090
316	Railroad Brake; Signal; and Switch Operators	0.55265460
317	Locker Room; Coatroom; and Dressing Room Attendants	0.55428120
318	Pipelayers	0.56066810
319	Roof Bolters; Mining	0.57330930
320	Nuclear Engineers	0.59494220
321	Skincare Specialists	0.59611520
322	Production; Planning; and Expediting Clerks	0.59983550
323	Packers and Packagers; Hand	0.60812660
324	Tapers	0.60892240
325	Tire Builders	0.61414590
326	Compensation; Benefits; and Job Analysis Specialists	0.61781230
327	Personal Care Aides	0.61866430
328	Postmasters and Mail Superintendents	0.62318260
329	Model Makers; Wood	0.63526280
330	Marine Engineers and Naval Architects	0.64102940
331	Welding; Soldering; and Brazing Machine Setters; Operators; and Tenders	0.64715030
332	Aerospace Engineers	0.65692060
333	Patternmakers; Wood	0.66121850
334	Cement Masons and Concrete Finishers	0.67215410
335	Dental Hygienists	0.67321970
336	Pest Control Workers	0.67467150
337	Meter Readers; Utilities	0.68096140
338	Office Clerks; General	0.68705490
339	Painting; Coating; and Decorating Workers	0.69583960
340	Architectural and Civil Drafters	0.70375250

341	Human Resources Assistants; Except Payroll and Timekeeping	0.70549640
342	Landscape Architects	0.71112890
343	Market Research Analysts and Marketing Specialists	0.71491870
344	Chemists	0.73350490
345	File Clerks	0.73442280
346	Molding; Coremaking; and Casting Machine Setters; Operators; and Tenders; Metal and Plastic	0.74294370
347	Substance Abuse and Behavioral Disorder Counselors	0.74430710
348	Helpers--Installation; Maintenance; and Repair Workers	0.74491300
349	Electrical and Electronic Equipment Assemblers	0.74722780
350	Ushers; Lobby Attendants; and Ticket Takers	0.74891890
351	Conservation Scientists	0.74953490
352	Library Assistants; Clerical	0.75608040
353	Bookkeeping; Accounting; and Auditing Clerks	0.75907030
354	Physical Therapist Aides	0.75933970
355	Cashiers	0.75961230
356	Pharmacy Technicians	0.76527700
357	Riggers	0.77821880
358	Biological Technicians	0.78000470
359	Rolling Machine Setters; Operators; and Tenders; Metal and Plastic	0.78353050
360	Highway Maintenance Workers	0.78473250
361	Occupational Health and Safety Specialists	0.78949920
362	Foresters	0.79976530
363	Electronics Engineers; Except Computer	0.80046130
364	Dispatchers; Except Police; Fire; and Ambulance	0.80606230
365	Child; Family; and School Social Workers	0.81128740
366	Semiconductor Processors	0.81371270
367	Photographic Process Workers and Processing Machine Operators	0.81958240
368	Cargo and Freight Agents	0.82149860
369	Multiple Machine Tool Setters; Operators; and Tenders; Metal and Plastic	0.82448650
370	Cleaning; Washing; and Metal Pickling Equipment Operators and Tenders	0.82513530
371	Radiologic Technologists and Technicians	0.82589850
372	Janitors and Cleaners; Except Maids and Housekeeping Cleaners	0.82794360
373	Technical Writers	0.83364550
374	Layout Workers; Metal and Plastic	0.83403720

375	Astronomers	0.8344446
376	Civil Engineering Technicians	0.8358708
377	Derrick Operators; Oil and Gas	0.8384963
378	Shoe Machine Operators and Tenders	0.8390481
379	Mixing and Blending Machine Setters; Operators; and Tenders	0.8463850
380	Prosthodontists	0.8474972
381	Printing Press Operators	0.8476808
382	Aircraft Structure; Surfaces; Rigging; and Systems Assemblers	0.8517570
383	Grinding; Lapping; Polishing; and Buffing Machine Tool Setters; Operators; and Tenders; Metal and Plastic	0.8521756
384	Stock Clerks and Order Fillers	0.8537995
385	Signal and Track Switch Repairers	0.8553767
386	Surveying and Mapping Technicians	0.8570624
387	Counter and Rental Clerks	0.8577386
388	Medical Scientists; Except Epidemiologists	0.8628503
389	Word Processors and Typists	0.8638720
390	Roustabouts; Oil and Gas	0.8645297
391	Psychiatric Aides	0.8671809
392	Audiologists	0.8676235
393	Industrial Engineering Technicians	0.8682551
394	Refractory Materials Repairers; Except Brickmasons	0.8705510
395	Farm Labor Contractors	0.8716105
396	Light Truck or Delivery Services Drivers	0.8717850
397	Fine Artists; Including Painters; Sculptors; and Illustrators	0.8720320
398	Cutting and Slicing Machine Setters; Operators; and Tenders	0.8733780
399	Sewing Machine Operators	0.8743662
400	Fence Erectors	0.8770013
401	Electrical and Electronics Drafters	0.8783844
402	Pourers and Casters; Metal	0.8785204
403	Electrical and Electronics Repairers; Powerhouse; Substation; and Relay	0.8788523
404	Extruding and Drawing Machine Setters; Operators; and Tenders; Metal and Plastic	0.8805210
405	Chemical Equipment Operators and Tenders	0.8858517
406	Proofreaders and Copy Markers	0.8859491
407	Computer and Information Research Scientists	0.8866465
408	Plating and Coating Machine Setters; Operators; and Tenders; Metal and Plastic	0.8868782

409	Hosts and Hostesses; Restaurant; Lounge; and Coffee Shop	0.8907378
410	Packaging and Filling Machine Operators and Tenders	0.8908010
411	Computer Hardware Engineers	0.8931718
412	Rock Splitters; Quarry	0.8935411
413	Respiratory Therapists	0.8936098
414	Shampooers	0.8940397
415	Loan Officers	0.8944890
416	Geographers	0.8953449
417	Bus Drivers; Transit and Intercity	0.8954293
418	Helpers--Brickmasons; Blockmasons; Stonemasons; and Tile and Marble Setters	0.8993643
419	Cooling and Freezing Equipment Operators and Tenders	0.9012219
420	Food Servers; Nonrestaurant	0.9025873
421	Driver/Sales Workers	0.9049547
422	Office Machine Operators; Except Computer	0.9059280
423	Childcare Workers	0.9074229
424	Cartographers and Photogrammetrists	0.9077795
425	Physical Therapists	0.9099025
426	Lifeguards; Ski Patrol; and Other Recreational Protective Service Workers	0.9110974
427	Statisticians	0.9126477
428	Library Technicians	0.9134093
429	Forest and Conservation Technicians	0.9144961
430	Sawing Machine Setters; Operators; and Tenders; Wood	0.9158741
431	Home Health Aides	0.9159216
432	Physician Assistants	0.9182001
433	Social and Human Service Assistants	0.9201164
434	Pump Operators; Except Wellhead Pumpers	0.9221083
435	Cost Estimators	0.9255541
436	Laborers and Freight; Stock; and Material Movers; Hand	0.9264241
437	Paving; Surfacing; and Tamping Equipment Operators	0.9320708
438	Civil Engineers	0.9325125
439	Print Binding and Finishing Workers	0.9346265
440	Postal Service Clerks	0.9382195
441	Agricultural Inspectors	0.9389772
442	Logging Equipment Operators	0.9409268

443	Human Resources; Training; and Labor Relations Specialists; All Other	0.9417513
444	Bill and Account Collectors	0.9436453
445	Industrial Truck and Tractor Operators	0.9437994
446	Desktop Publishers	0.9441260
447	Maids and Housekeeping Cleaners	0.9443500
448	Atmospheric and Space Scientists	0.9446859
449	Funeral Attendants	0.9450789
450	Helpers--Carpenters	0.9456750
451	Craft Artists	0.9457990
452	Rail-Track Laying and Maintenance Equipment Operators	0.9465204
453	Food Batchmakers	0.9467027
454	Correspondence Clerks	0.9481072
455	Drilling and Boring Machine Tool Setters; Operators; and Tenders; Metal and Plastic	0.9490156
456	Heavy and Tractor-Trailer Truck Drivers	0.9520671
457	Nuclear Technicians	0.9521381
458	Slaughterers and Meat Packers	0.9528696
459	Urban and Regional Planners	0.9532840
460	Ophthalmic Laboratory Technicians	0.9534959
461	Nuclear Medicine Technologists	0.9536875
462	Cooks; Short Order	0.9550114
463	Recreational Vehicle Service Technicians	0.9553813
464	Title Examiners; Abstractors; and Searchers	0.9557629
465	Paper Goods Machine Setters; Operators; and Tenders	0.9591937
466	Crushing; Grinding; and Polishing Machine Setters; Operators; and Tenders	0.9602774
467	Chemical Technicians	0.9603023
468	Weighers; Measurers; Checkers; and Samplers; Recordkeeping	0.9615605
469	Radiation Therapists	0.9625112
470	Furnace; Kiln; Oven; Drier; and Kettle Operators and Tenders	0.9650967
471	Farm and Home Management Advisors	0.9652659
472	Hotel; Motel; and Resort Desk Clerks	0.9658906
473	Cleaners of Vehicles and Equipment	0.9688821
474	Hydrologists	0.9723218
475	Milling and Planing Machine Setters; Operators; and Tenders; Metal and Plastic	0.9746470
476	Payroll and Timekeeping Clerks	0.9747518

477	Conveyor Operators and Tenders	0.9750653
478	Farm Equipment Mechanics and Service Technicians	0.9757793
479	Switchboard Operators; Including Answering Service	0.9765392
480	Tire Repairers and Changers	0.9774593
481	Tellers	0.9775595
482	Cutters and Trimmers; Hand	0.9778243
483	Shipping; Receiving; and Traffic Clerks	0.9783270
484	New Accounts Clerks	0.9788413
485	Forging Machine Setters; Operators; and Tenders; Metal and Plastic	0.9789398
486	Interviewers; Except Eligibility and Loan	0.9793679
487	Compliance Officers	0.9800838
488	Separating; Filtering; Clarifying; Precipitating; and Still Machine Setters; Operators; and Tenders	0.9810863
489	Cutting; Punching; and Press Machine Setters; Operators; and Tenders; Metal and Plastic	0.9811073
490	Medical Transcriptionists	0.9819064
491	Gaming and Sports Book Writers and Runners	0.9820642
492	Microbiologists	0.9827107
493	Broadcast Technicians	0.9827408
494	Order Clerks	0.9831182
495	Automotive Body and Related Repairers	0.9833710
496	Court Reporters	0.9838054
497	Food and Tobacco Roasting; Baking; and Drying Machine Operators and Tenders	0.9838550
498	Tax Examiners and Collectors; and Revenue Agents	0.9843637
499	Credit Authorizers; Checkers; and Clerks	0.9852618
500	Dishwashers	0.9856900
501	Prepress Technicians and Workers	0.9857682
502	Helpers--Production Workers	0.9858549
503	Surveyors	0.9859168
504	Statistical Assistants	0.9859642
505	Political Scientists	0.9861207
506	Insurance Claims and Policy Processing Clerks	0.9865178
507	Graders and Sorters; Agricultural Products	0.9865197
508	Dancers	0.9865383
509	Budget Analysts	0.9869975
510	Accountants and Auditors	0.9873121

511	Insurance Underwriters	0.9880079
512	Medical Assistants	0.9882425
513	Pharmacy Aides	0.9884204
514	Materials Engineers	0.9888824
515	Parking Enforcement Workers	0.9891799
516	Eligibility Interviewers; Government Programs	0.9898071
517	Extruding and Forming Machine Setters; Operators; and Tenders; Synthetic and Glass Fibers	0.9900705
518	Procurement Clerks	0.9903617
519	Bus and Truck Mechanics and Diesel Engine Specialists	0.9906564
520	Lathe and Turning Machine Tool Setters; Operators; and Tenders; Metal and Plastic	0.9910860
521	Textile Winding; Twisting; and Drawing Out Machine Setters; Operators; and Tenders	0.9920368
522	Fish and Game Wardens	0.9926780
523	Tile and Marble Setters	0.9928022
524	Reservation and Transportation Ticket Agents and Travel Clerks	0.9930643
525	Food Cooking Machine Operators and Tenders	0.9930852
526	Optometrists	0.9933089
527	Probation Officers and Correctional Treatment Specialists	0.9938587
528	Helpers--Roofers	0.9941266
529	Extruding; Forming; Pressing; and Compacting Machine Setters; Operators; and Tenders	0.9946974
530	Motorboat Mechanics and Service Technicians	0.9947340
531	Data Entry Keyers	0.9949097
532	Couriers and Messengers	0.9949722
533	Customer Service Representatives	0.9950037
534	Landscaping and Groundskeeping Workers	0.9951527
535	Environmental Scientists and Specialists; Including Health	0.9958012
536	Mobile Heavy Equipment Mechanics; Except Engines	0.9959542
537	Gaming Cage Workers	0.9960856
538	Travel Agents	0.9961896
539	Mail Clerks and Mail Machine Operators; Except Postal Service	0.9964024
540	Writers and Authors	0.9965895
541	Camera and Photographic Equipment Repairers	0.9966690
542	Mathematicians	0.9968248
543	Food Preparation Workers	0.9968423
544	Biochemists and Biophysicists	0.9973651

545	Receptionists and Information Clerks	0.9976088
546	Hoist and Winch Operators	0.9978281
547	Surgical Technologists	0.9979132
548	Buyers and Purchasing Agents; Farm Products	0.9979466
549	Telemarketers	0.9980957
550	Chemical Engineers	0.9982505
551	Foundry Mold and Coremakers	0.9982982
552	Pressers; Textile; Garment; and Related Materials	0.9984300
553	Loading Machine Operators; Underground Mining	0.9985394
554	Telecommunications Line Installers and Repairers	0.9985648
555	Insurance Appraisers; Auto Damage	0.9985688
556	Credit Counselors	0.9986189
557	Locksmiths and Safe Repairers	0.9988933
558	Airline Pilots; Copilots; and Flight Engineers	0.9990082
559	Metal-Refining Furnace Operators and Tenders	0.9990557
560	Postal Service Mail Carriers	0.9990742
561	Brokerage Clerks	0.9990984
562	Loan Interviewers and Clerks	0.9991343
563	Textile Knitting and Weaving Machine Setters; Operators; and Tenders	0.9991555
564	Orthodontists	0.9993031
565	Motion Picture Projectionists	0.9994677
566	Gas Compressor and Gas Pumping Station Operators	0.9994931
567	Logisticians	0.9995265
568	Machine Feeders and Offbearers	0.9995672
569	Paperhangers	0.9996091
570	Jewelers and Precious Stone and Metal Workers	0.9997361
571	Meat; Poultry; and Fish Cutters and Trimmers	0.9997689
572	Petroleum Pump System Operators; Refinery Operators; and Gaugers	0.9998297
573	Telephone Operators	0.9998439
574	Heating; Air Conditioning; and Refrigeration Mechanics and Installers	0.9998592
575	Chemical Plant and System Operators	0.9998705
576	Airfield Operations Specialists	0.9998722
577	Earth Drillers; Except Oil and Gas	0.9998877
578	Textile Bleaching and Dyeing Machine Operators and Tenders	0.9999335

579	Firefighters	0.9999340
580	Opticians; Dispensing	0.9999340
581	Financial Examiners	0.9999495
582	Subway and Streetcar Operators	0.9999514
583	Bridge and Lock Tenders	0.9999539
584	Rail Car Repairers	0.9999547
585	Laundry and Dry-Cleaning Workers	0.9999661
586	Electrical Power-Line Installers and Repairers	0.9999662
587	Plasterers and Stucco Masons	0.9999799
588	Embalmers	0.9999808
589	Actuaries	0.9999821
590	Pharmacists	0.9999951
591	Butchers and Meat Cutters	0.9999957
592	Tool and Die Makers	0.9999961
593	Maintenance Workers; Machinery	0.9999962
594	Court; Municipal; and License Clerks	0.9999974
595	Water and Wastewater Treatment Plant and System Operators	0.9999985
596	Bakers	0.9999991
597	Industrial Machinery Mechanics	0.9999997
598	Machinists	0.9999999
599	Molders; Shapers; and Casters; Except Metal and Plastic	0.9999999
600	Nuclear Power Reactor Operators	0.9999999
601	Power Distributors and Dispatchers	0.9999999
602	Stationary Engineers and Boiler Operators	0.9999999
603	Air Traffic Controllers	1.0000000
604	Claims Adjusters; Examiners; and Investigators	1.0000000
605	Electrical and Electronics Repairers; Commercial and Industrial Equipment	1.0000000
606	Gas Plant Operators	1.0000000
607	Postal Service Mail Sorters; Processors; and Processing Machine Operators	1.0000000
608	Power Plant Operators	1.0000000

Estimated Control Variable Coefficients

We used control vectors for models with more than one control variable (i.e., in equations (1a) and (2)). These vectors not only save space in mathematical expressions but can be redefined to include additional and/or better controls in future research.

Our main model, equation (1a), is conditional on controls in vector X_i, with corresponding vector of parameters, $\boldsymbol{\beta}$. We estimate these parameters with the elements (i.e., estimated coefficient) of $\widehat{\boldsymbol{\beta}}$ in **Table A1**.[16]

[16] Similar to level of on-the-job training in the main model, relevant work experience is categorical variable. Since there are three classes, we use one for the baseline, such that the coefficients of each of the two remaining classes represents the difference in automation propensity between occupation of that category, and those belonging to the “baseline” category.

Table A1: Elements of $\widehat{\beta}$

Variable	Coefficient	Standard Error	p-value
Median Hourly Wage	1.364	0.8293	0.09991*
Importance of Programming	0.4382	0.3488	0.19348
Relevant Work Experience - 1	-1.824	2.439	0.45445
Relevant Work Experience - 2	-20.05	4774	0.99665

Significance codes: 0.001 '***', 0.01 '**', 0.1 '*'

Our static economic regression for mean annual wage, equation (2), is conditional on controls in vector $\boldsymbol{A}_i$, with corresponding vector of parameters $\boldsymbol{\alpha}$. We estimate these parameters with the coefficients of $\widehat{\boldsymbol{\alpha}}$ in **Table A2**.

Table A2: Elements of $\widehat{\alpha}$

Variable	Coefficient	Standard Error	p-value
Education Attainment	12322	1403	$1.77 * 10^{-11}$***
Relevant Work Experience - 1	500	8775	0.954808
Relevant Work Experience - 2	-1.824	2.439	0.000998***
Intensity of on-the-job Training - 1	-13062	7117	0.072788*
Intensity of on-the-job Training - 2	-5936	7885	0.455354
Intensity of on-the-job Training - 3	22108	20233	0.280116
Intensity of on-the-job Training - 4	-20453	11808	0.089813*
Intensity of on-the-job Training - 5	13675	16180	0.402276

Significance codes: 0.001 '***', 0.01 '**', 0.1 '*'

A3 Defining Categorical Variables

Table A3: Intensity of on-the-job Training

Predictor	Category
(baseline)	No Training Required
$x_{T_{1i}}$	Short-Term Training
$x_{T_{2i}}$	Moderate-Term Training
$x_{T_{3i}}$	Long-Term Training
$x_{T_{4i}}$	Internship/Residency
$x_{T_{5i}}$	Apprenticeship

Table A4: Relevant Work Experience Required

Predictor	Category
(baseline)	No experience required
Relevant Work Experience - 1	Less than 5 years
Relevant Work Experience - 2	5 years or more

A4 Calculating Real Wage Growth Rates

To account for inflation in calculating real wage growth, we take the percent change in mean annual wage between each year divided by the appropriate inflation factor (CPI_{t+1}/ CPI_t). We take the average of these real growth rates for each time period we study.

$$\boldsymbol{RWG}\mathrm{i}_{(\mathrm{Year1-Year2})} = \frac{\frac{\mathrm{Wage_{2i}}}{\mathrm{Wage_{1i}}} - 1}{\mathrm{CPI_2/CPI_1}} \tag{A1}$$

$$\overline{\boldsymbol{RWG}}i_t = \frac{1}{n}\Sigma_{k=1}^{n}\boldsymbol{RWG}_{i_k} \tag{A2}$$

A5 ROC Classification Threshold Comparison

We compare the true positive percentages and false positive percentages obtained from adjusting the “automatable” classification threshold in each model.

Table A5: Main Model ROC

tpp	fpp	thresholds
100.00	100	-Inf
93.75	100	0.0007039222
93.75	90	0.0014892612
93.75	80	0.0018179892
93.75	70	0.0128080095
93.75	60	0.0253547559
93.75	50	0.0388625798
87.50	50	0.0526008509
87.50	40	0.1253464131
81.25	40	0.3637799407
75.00	40	0.6062318592
68.75	40	0.6960451071
68.75	30	0.7130237977
62.50	30	0.7372655286
56.25	30	0.7966289375
50.00	30	0.8347581768
43.75	30	0.8538279210
37.50	30	0.9021487468
37.50	20	0.9381559407
31.25	20	0.9440747052
31.25	10	0.9622168880
31.25	0	0.9822237568
25.00	0	0.9848127730
18.75	0	0.9862869373
12.50	0	0.9876599815
6.25	0	0.9914588128
0.00	0	Inf

Table A6: Frey-Osborne ROC

tpp	fpp	thresholds
100.00	100	-Inf
81.25	30	3.608501e-10
75.00	30	4.018373e-09
68.75	30	4.999806e-01
68.75	20	9.999806e-01
62.50	20	1.000000e+00
56.25	20	1.000000e+00
0.00	0	Inf

Additional Economic Plots

Employment Growth by Time Period

Figure A1: Frey-Osborne Model Predictions

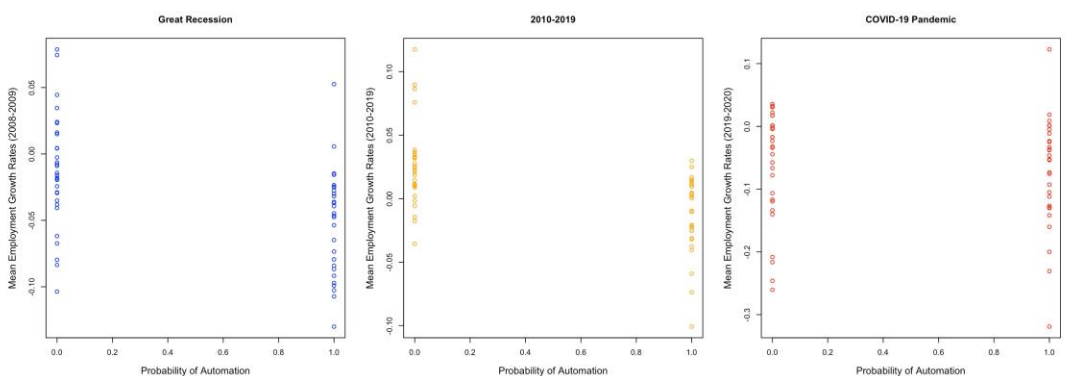
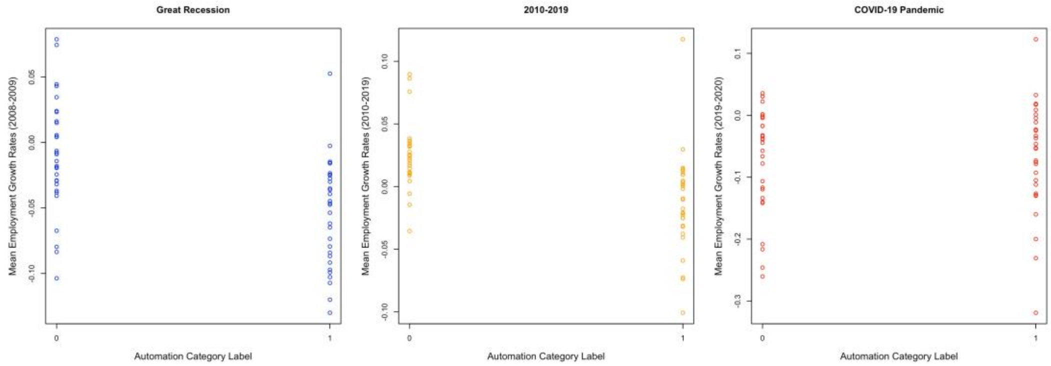


Figure A2: Hand Labeled Assignments



Real Wage Growth by Time Period

Figure A3: Frey-Osborne Model Predictions

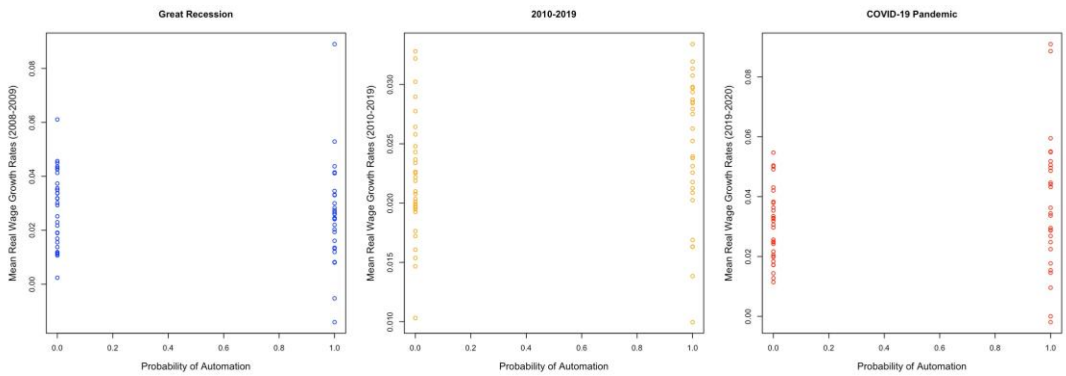


Figure A4: Hand Labeled Assignments