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# Testing the automation revolution hypothesis[☆]

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ABSTRACT

Wages and employment predict automation in 832 U.S. jobs, 1999 to 2019, but add little to top 25 O*NET job features, whose best predictive model did not change over this period. Automation changes predict changes in neither wages nor employment.



## 1. Introduction

Since at least 2013, many have claimed that we are entering an automation revolution, and so should soon expect large trend-deviating increases in job automation, in related job losses, and in the determinants of automation. As context for considering such claims, we study what predicts which jobs have been how automated in the recent past, how the best automation predictors have changed over time, and recent correlations between changes in automation, pay, and employment.

## 2. Material

We combine data from three sources (Scholl and Hanson, 2020).

First, O*NET is a database of U.S. job feature scores made by surveying occupational experts and employees, who compare each job to related jobs. For each of 2144 jobs, O*NET includes 261 job features, many scored on a 0–5 numerical scale. In its current form O*NET started in 2002, though that year's entries include data from 1999. We project these scores onto 881 "six-digit" level jobs, via scaling frequency by importance. We thus have scores of 261 job features for 881 jobs from 1999 to 2019. One key O*NET job feature is years of education, and another is "degree of automation", which seems to represent expert judgments on which workers would have to do each task now done by machines, absent those machines.

Second, from Occupational Employment Statistics (OES), we obtain, for all these jobs and for years 1999 to 2018, U.S. annual averages for employment (i.e., number of employees) and an inflation-adjusted mean hourly pay (in U.S. dollars).

Our third source is two widely-discussed expert-judgment-derived metrics regarding the vulnerability of jobs to near future automation. These metrics do not vary by year. *Computerisable* comes from Frey and Osborne (2017), first published in 2013, and ranges 0 to 1. Building on judgments made by a "group of machine learning researchers", they estimated 47% of U.S. jobs to be at "high risk" of being "computerisable", "perhaps over the next decade or two". *Machine Learning Suitability*, coming directly from an author of Brynjolfsson et al. (2018), was created from machine learning expert judgments using a 23-item rubric, and ranges 2 to 5.

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**Table 1**
Variable statistics.

| Variable | *Untransformed* | | | | *Transformed* | |
|---|---|---|---|---|---|---|
| | Mean | Std Dev | Min | Max | Min | Max |
| *Time* | 2007.50 | 6.16 | 1999 | 2019 | 0 | 1 |
| *Education* | 14.31 | 2.60 | 10.28 | 22.88 | -1.839 | 2.824 |
| *Employees* | 167538 | 387560 | 200 | 4612510 | -3.428 | 2.857 |
| *Pay* | 24.67 | 13.94 | 7.18 | 129.62 | -2.331 | 3.735 |
| *Machine Learning Suitability* | 3.466 | 0.115 | 2.780 | 3.902 | -6.609 | 3.586 |
| *Computerisable* | 0.536 | 0.368 | 0.003 | 0.990 | -2.284 | 0.845 |
| **O*NET:** | | | | | | |
| *Activity* | 3.374 | 0.397 | 1.750 | 4.620 | -5.297 | 2.629 |
| *Advancement* | 2.723 | 0.423 | 1.250 | 4.000 | -4.701 | 2.444 |
| *Cramped* | 1.932 | 0.764 | 1.000 | 4.900 | -1.562 | 2.680 |
| *Dynamic Strength* | 0.079 | 0.086 | 0.000 | 0.736 | -1.389 | 2.303 |
| *Fine Arts* | 0.040 | 0.110 | 0.000 | 0.974 | -0.859 | 3.784 |
| *Gross Body Equilibrium* | 0.060 | 0.072 | 0.000 | 0.574 | -1.326 | 2.450 |
| *Hearing Sensitivity* | 0.125 | 0.090 | 0.000 | 0.904 | -3.253 | 2.944 |
| *Importance of Repeating Same Tasks* | 2.859 | 0.846 | 1.100 | 5.000 | -2.801 | 1.883 |
| *Indoors Environmentally Controlled* | 3.998 | 0.945 | 1.000 | 5.000 | -4.356 | 0.853 |
| *Innovation* | 3.552 | 0.489 | 1.880 | 4.880 | -4.345 | 2.276 |
| *Letters and Memos* | 3.264 | 0.791 | 1.090 | 5.000 | -3.894 | 1.693 |
| *Mathematics* | 0.264 | 0.164 | 0.000 | 0.989 | -4.648 | 2.218 |
| *Number Facility* | 0.199 | 0.117 | 0.000 | 0.800 | -4.712 | 2.491 |
| *On Knees* | 1.982 | 0.689 | 1.000 | 4.660 | -2.205 | 2.794 |
| *Pace Determined by Speed of Equipment* | 1.839 | 0.826 | 1.000 | 4.760 | -1.303 | 2.588 |
| *Physical Proximity* | 3.451 | 0.688 | 1.290 | 5.000 | -4.729 | 1.923 |
| *Spend Time Keeping or Regaining Balance* | 1.570 | 0.525 | 1.000 | 4.310 | -1.321 | 3.486 |
| *Spend Time Sitting* | 3.126 | 0.975 | 1.010 | 5.000 | -3.112 | 1.523 |
| *Supervision Human Relations* | 3.200 | 0.467 | 1.250 | 4.620 | -5.539 | 2.274 |
| *Supervision Technical* | 2.781 | 0.585 | 1.120 | 4.620 | -3.730 | 2.256 |
| *Support* | 3.778 | 0.979 | 1.250 | 7.000 | -5.753 | 2.618 |
| *Thinking Creatively* | 0.312 | 0.206 | 0.000 | 0.928 | -3.456 | 1.507 |
| *Variety* | 2.791 | 0.637 | 1.120 | 4.120 | -3.583 | 1.699 |
| *Visualization* | 0.221 | 0.113 | 0.000 | 0.657 | -5.038 | 2.028 |
| *Wear Common Safety Equipment* | 2.736 | 1.346 | 1.000 | 5.000 | -1.578 | 1.355 |

We transform all variables (besides time and intercept) into rough "z-score" variants. We apply a logarithmic transform to 0.01 plus pay, employment, and each O*NET variable. We then rescale them to have zero mean and unit standard deviation. Time is rescaled to take value zero at 1999, and one at 2019. Our transformed variables look closer to normally distributed. As we use transformed versions in our analysis, most regression coefficients say how many standard deviations of increase in a dependent variable is predicted by a one standard deviation increase in an independent variable.

Most O*NET job features were not scored for each job every year, but were on average scored 3.3 times during our 1999–2019 period. From available scores, we interpolate scores for all years using two methods. In *piecewise-linear* interpolation, we fit straight lines in time between scorings that are adjacent in time, and fit zero-slope lines for years outside the time range of available scorings. In *regression* interpolation, we fit a linear regression in time to all available job-feature scorings. This method requires at least two job-feature scorings.

While our dataset officially includes 881 jobs and 260 O*NET job features (besides education), data limitations force a tradeoff between how many jobs and features we can include. We choose to maximize the product of these at 832 jobs and 251 features. Table 3 further selects for jobs with enough data to allow regression interpolation for all features used.

## 3. Methods

Table 1 gives basic statistics for all variables in the other tables.

Table 2 describes seven ordinary least squares regressions, all predicting automation. Each data point corresponds to a not-interpolated O*NET scoring of an automation value for a job in a year; independent variables are piecewise-linear interpolated. These 25 O*NET variables were selected via the LASSO method out of the 251 available O*NET variables via a structure like Model 3. Models 2,5 add extra columns for each variable multiplied by time, and Models 6,7 apply the same structure of Model 4 separately to times <0.5 and >0.5. A simple model not shown, using only an intercept and time, gives a time coefficient of 0.102, not significant at the 10% level.

Table 3 describes regression models predicting changes in pay and employment. All change variables are constructed via regression interpolation. Changes are not renormalized into z-scores; they are differences in normalized z-scores.

These models help us test these null hypotheses: (1) metrics constructed to forecast future automation do not predict past automation, (2) best predictors of automation have not changed in two decades, (3) automation changes do not predict changes in pay or employment.

## 4. Results

The first two models of Table 2 suggest that five variables, plus time and an intercept, have substantial predictive power, explaining roughly 15% of automation variation.

Automation requires fixed costs, but saves on worker marginal costs. Simple theory thus predicts that, all else equal, employers are more eager to automate jobs with higher pay and employment. These two factors should thus predict job automation, and we do in fact see such effects, though more consistently for pay.

Two automation vulnerability metrics built from expert judgments on which jobs seem easier to automate in the future predict which jobs were more automated in the last two decades. Education does not, after our other controls. Model 4 suggests that, aside perhaps from education, these predictors have little to add to the predictive power of the top 25 O*NET variables, which can explain over half of automation variance, even when interpolated.

**Table 2**
Predicting Automation.

| Model | (1) | (2) | | (3) | (4) | (5) | | (6) | (7) |
|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | 0.2146*** | 0.3397*** | | 0.1474*** | 0.1755*** | 0.1939* | | 0.2809*** | -0.0097 |
| | (0.0550) | (0.1043) | | (0.0435) | (0.0456) | (0.1011) | | (0.0828) | (0.1545) |
| *Time* | -0.2982*** | -1.0041** | 0.7372** | -0.2451*** | -0.2682*** | -0.5104 | 0.2796 | -0.6632*** | -0.0351 |
| | (0.0944) | (0.3948) | (0.3538) | (0.0849) | (0.0857) | (0.4035) | (0.3918) | (0.2386) | (0.1984) |
| *Education* | 0.0099 | -0.1101 | 0.2452 | | 0.0906** | 0.0370 | 0.0630 | 0.0938 | 0.0681 |
| | (0.0444) | (0.1114) | (0.1925) | | (0.0453) | (0.1093) | (0.1929) | (0.0657) | (0.0637) |
| *Employees* | 0.0893*** | 0.0422 | 0.0883 | | 0.0362* | -0.0024 | 0.0611 | 0.0339 | 0.0296 |
| | (0.0248) | (0.0593) | (0.1056) | | (0.0201) | (0.0496) | (0.0865) | (0.0295) | (0.0288) |
| *Pay* | 0.2286*** | 0.2734*** | -0.0937 | | 0.0508 | 0.0527 | -0.0267 | 0.0586 | 0.0206 |
| | (0.0369) | (0.0905) | (0.1555) | | (0.0342) | (0.0856) | (0.1445) | (0.0518) | (0.0464) |
| *Computerisable* | 0.3356*** | 0.3771*** | -0.0820 | | 0.0048 | 0.0067 | 0.0069 | 0.0012 | 0.0232 |
| | (0.0312) | (0.0754) | (0.1326) | | (0.0276) | (0.0679) | (0.1180) | (0.0411) | (0.0368) |
| *M.L. Suitability* | 0.2161*** | 0.2786*** | -0.1212 | | 0.0006 | 0.0273 | -0.0463 | 0.0188 | -0.0181 |
| | (0.0246) | (0.0581) | (0.1005) | | (0.0202) | (0.0482) | (0.0825) | (0.0289) | (0.0281) |
| *Activity* | | | | 0.0336 | 0.0142 | -0.0448 | 0.1116 | -0.0082 | 0.0340 |
| | | | | (0.0210) | (0.0220) | (0.0527) | (0.0938) | (0.0320) | (0.0301) |
| *Advancement* | | | | 0.0656*** | 0.0551** | 0.1036* | -0.0991 | 0.0605 | 0.0346 |
| | | | | (0.0250) | (0.0254) | (0.0618) | (0.1086) | (0.0370) | (0.0346) |
| *Cramped* | | | | -0.0527 | -0.0594 | -0.1391 | 0.1811 | -0.1138* | 0.0161 |
| | | | | (0.0393) | (0.0399) | (0.0975) | (0.1672) | (0.0592) | (0.0542) |
| *Dynamic Strength* | | | | -0.0663 | -0.0552 | -0.0060 | -0.1442 | -0.0420 | -0.1199* |
| | | | | (0.0505) | (0.0508) | (0.1228) | (0.2159) | (0.0751) | (0.0706) |
| *Fine Arts* | | | | -0.0463* | -0.0358 | -0.0932 | 0.1117 | -0.0706* | -0.0157 |
| | | | | (0.0267) | (0.0270) | (0.0637) | (0.1108) | (0.0401) | (0.0368) |
| *Gross Body Equilibrium* | | | | 0.0036 | -0.0024 | 0.0260 | -0.0247 | 0.0269 | 0.0112 |
| | | | | (0.0489) | (0.0489) | (0.1182) | (0.2042) | (0.0732) | (0.0664) |
| *Hearing Sensitivity* | | | | -0.0713** | -0.0757*** | -0.0311 | -0.0857 | -0.0560 | -0.0966** |
| | | | | (0.0291) | (0.0291) | (0.0615) | (0.1218) | (0.0383) | (0.0477) |
| *Importance of Repeating Same Tasks* | | | | 0.2240*** | 0.2254*** | 0.1513** | 0.1302 | 0.1975*** | 0.2587*** |
| | | | | (0.0317) | (0.0326) | (0.0770) | (0.1458) | (0.0449) | (0.0546) |
| *Indoors Environmentally Controlled* | | | | 0.1375*** | 0.1357*** | 0.1491*** | -0.0382 | 0.1358*** | 0.1316*** |
| | | | | (0.0242) | (0.0245) | (0.0553) | (0.1003) | (0.0330) | (0.0376) |
| *Innovation* | | | | -0.0887*** | -0.0924*** | -0.0723 | -0.0407 | -0.0919*** | -0.0938** |
| | | | | (0.0248) | (0.0251) | (0.0545) | (0.0999) | (0.0346) | (0.0385) |
| *Letters and Memos* | | | | 0.1624*** | 0.1457*** | 0.0748 | 0.1467 | 0.1185*** | 0.1882*** |
| | | | | (0.0273) | (0.0281) | (0.0653) | (0.1151) | (0.0399) | (0.0408) |
| *Mathematics* | | | | 0.0979** | 0.0838** | 0.0770 | 0.0699 | 0.0734 | 0.1610** |
| | | | | (0.0407) | (0.0412) | (0.0968) | (0.1893) | (0.0569) | (0.0661) |
| *Number Facility* | | | | 0.0415 | 0.0400 | -0.0151 | 0.0795 | 0.0177 | 0.0141 |
| | | | | (0.0359) | (0.0359) | (0.0794) | (0.1679) | (0.0467) | (0.0624) |
| *On Knees* | | | | -0.0462 | -0.0303 | -0.0072 | -0.0695 | 0.0150 | -0.0991* |
| | | | | (0.0418) | (0.0427) | (0.0997) | (0.1721) | (0.0632) | (0.0581) |
| *Pace Determined by Speed of Equipment* | | | | 0.5638*** | 0.5805*** | 0.6974*** | -0.2315* | 0.6360*** | 0.5221*** |
| | | | | (0.0288) | (0.0295) | (0.0726) | (0.1223) | (0.0444) | (0.0397) |
| *Physical Proximity* | | | | -0.0694*** | -0.0735*** | -0.0440 | -0.0496 | -0.0755** | -0.0641* |
| | | | | (0.0217) | (0.0221) | (0.0508) | (0.0912) | (0.0301) | (0.0330) |
| *Spend Time Keeping or Regaining Balance* | | | | -0.0480 | -0.0492 | -0.0531 | 0.0049 | -0.0599 | -0.0368 |
| | | | | (0.0395) | (0.0400) | (0.0953) | (0.1632) | (0.0587) | (0.0546) |
| *Spend Time Sitting* | | | | 0.0545* | 0.0428 | 0.1454* | -0.2272* | 0.0472 | 0.0122 |
| | | | | (0.0304) | (0.0310) | (0.0742) | (0.1270) | (0.0460) | (0.0430) |
| *Supervision Human Relations* | | | | -0.0117 | -0.0025 | -0.0562 | 0.0714 | -0.0059 | -0.0156 |
| | | | | (0.0318) | (0.0322) | (0.0895) | (0.1505) | (0.0542) | (0.0424) |
| *Supervision Technical* | | | | 0.0607* | 0.1068*** | -0.0361 | 0.2352 | 0.0554 | 0.1366** |
| | | | | (0.0350) | (0.0400) | (0.1013) | (0.1734) | (0.0617) | (0.0539) |
| *Support* | | | | 0.0539* | 0.0363 | 0.2297** | -0.2896* | 0.1004 | 0.0055 |
| | | | | (0.0314) | (0.0320) | (0.1067) | (0.1557) | (0.0725) | (0.0361) |
| *Thinking Creatively* | | | | -0.1375*** | -0.1543*** | -0.1222 | 0.0477 | -0.1019* | -0.0987 |
| | | | | (0.0436) | (0.0447) | (0.0957) | (0.1922) | (0.0596) | (0.0884) |
| *Variety* | | | | -0.0647** | -0.0697** | -0.0950 | 0.0547 | -0.0656 | -0.0596 |
| | | | | (0.0309) | (0.0311) | (0.0737) | (0.1281) | (0.0442) | (0.0439) |
| *Visualization* | | | | -0.0190 | -0.0160 | 0.0597 | -0.2230 | -0.0246 | -0.0508 |
| | | | | (0.0319) | (0.0322) | (0.0686) | (0.1395) | (0.0423) | (0.0534) |
| *Wear Common Safety Equipment* | | | | -0.1384*** | -0.1470*** | -0.1847** | 0.0813 | -0.1579*** | -0.1352*** |
| | | | | (0.0329) | (0.0333) | (0.0831) | (0.1426) | (0.0508) | (0.0444) |
| N | 1505 | 1505 | | 1505 | 1505 | 1505 | | 821 | 684 |
| R2 Adjusted | 0.1481 | 0.1509 | | 0.5392 | 0.5407 | 0.5441 | | 0.5288 | 0.5595 |
| R2 | 0.1515 | 0.1576 | | 0.5471 | 0.5501 | 0.5628 | | 0.5466 | 0.5795 |

Dependent variable is Automation (A); *p < .1, **p < .05, ***p < .01, Standard errors in parentheses.

Our two strongest O*NET predictors are *Pace Determined By Speed Of Equipment* and *Importance of Repeating Same Tasks*, with coefficients of 0.58 and 0.23. Following these, we find a set of four predictors at roughly 0.14, and a set of five at roughly 0.08. Most of these predictors seem understandable in terms of traditional styles of job automation. For example, *Pace Determined By Speed Of Equipment* picks out jobs that coordinate closely with machinery, while *Importance of Repeating Same Tasks* picks out jobs with many similar and independent small tasks.

**Table 3**
Predicting △ Pay, △ Employees.

| Model | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: | △ Pay | △ Pay | △ Pay | △ Empl. | △ Empl. | △ Empl. |
| Intercept | 0.376*** | 0.387*** | 0.386*** | -0.021** | -0.002 | -0.088*** |
| | (0.008) | (0.011) | (0.010) | (0.008) | (0.012) | (0.022) |
| △ A | -0.006 | -0.007 | -0.009 | 0.001 | 0.000 | 0.041*** |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.015) |
| △ A * A(0) | | 0.013 | 0.011 | | 0.009 | 0.008 |
| | | (0.008) | (0.008) | | (0.009) | (0.009) |
| △ A * △ A | | 0.006 | 0.007* | | 0.003 | 0.003 |
| | | (0.004) | (0.004) | | (0.004) | (0.004) |
| △ Education | | -0.015** | -0.011* | | -0.021*** | -0.016** |
| | | (0.006) | (0.006) | | (0.007) | (0.007) |
| △ Employees | | | 0.172*** | | | |
| | | | (0.040) | | | |
| △ A * △ Employees | | | -0.078*** | | | |
| | | | (0.028) | | | |
| △ Pay | | | | | | 0.216*** |
| | | | | | | (0.048) |
| △ A * △ Pay | | | | | | -0.104*** |
| | | | | | | (0.035) |
| N | 495 | 495 | 495 | 495 | 495 | 495 |
| R2 Adjusted | 0.0004 | 0.0092 | 0.0586 | -0.002 | 0.0115 | 0.0626 |
| R2 | 0.0024 | 0.0172 | 0.0701 | 0.000 | 0.0195 | 0.0739 |

A = Automation. Standard errors in parentheses. * p<.1, ** p<.05, ***p<.01

The coefficients in Table 2 that probe time effects do not offer much support for the claim that automation predictors have changed noticeably over time. Model 5 finds only three of 31 time-interaction coefficients are 10% significant, the number to be expected at random. Models 6,7, show no clear differences between time periods.

Though we expect automation to have increased over our period, we find no significant time coefficient using only an intercept and time, and adding many controls makes automation seem to have *decreased* with time. As scores come from expert judgments made at different times, this decrease may be due to drifting standards on what it takes for a job to seen as more automated (Levari et al., 2018). If so, the difference between these two time coefficients, roughly 0.37 standard deviations of automation, can be interpreted as estimating this much of an increase in the average suitability of jobs for automation over this period.

In Table 3, changes in pay or employment are only significantly predicted by changes in job automation in one model out of six, where the sign is the opposite of the usual fear. If real, that one coefficient confirms the basic theory that employers gain more from automating jobs with more workers.

Changes in pay and employment consistently predict each other, and with large coefficients. This suggests that, in supply and demand terms, labor market changes are on average better seen as changes in demand, and less as changes in supply.

Increases in education consistently predict *declines* in pay and employment, though with small coefficients, suggesting that falling labor demand has been positively correlated with increasing education. Perhaps labor shortages (surpluses) induce firms to adopt weaker (stricter) education requirements.

Terms in Table 3 that interact changes in employment and pay with changes in automation suggest that the positive correlation between pay and employment changes is weaker for jobs that saw increased automation.

## 5. Conclusions

Recently, many have said we are entering an automation revolution which will soon produce large trend-deviating increases in automation levels and resulting job losses, and also big changes in which kinds of jobs are more vulnerable to automation. We do not yet see evidence of such a revolution.

Using 1505 expert reports on the degree of automation of particular jobs 1999–2019, we find that reported automation levels have not changed noticeably, though changing reporting standards may mask such increases. Jobs with larger automation increases did not on average see noticeable changes in pay or employment.

Both pay and employment predict automation in the direction suggested by simple theory, as do expert judgments on which jobs are vulnerable to future automation. We can explain over half the variance in which jobs have been how automated using the top 25 O*NET variables, which are relatively mundane and understandable in terms of traditional kinds of automation. All these best predictors have not noticeably changed in two decades.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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