Testing The Automation Revolution Hypothesis

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Abstract

We test basic theory, two expert-derived vulnerability metrics, and 251 O*NET job features as predictors of 1505 expert reports regarding automation levels in 832 U.S. job types from 1999 to 2019. Pay, employment, and vulnerability metrics are predictive (R^2~0.15), but add little to the top 25 O*NET job features, which together predict far better (R^2~0.55), seem understandable in terms of traditional types of automation, and did not change over this period. Instead, job features changed to be more suitable for automation. Over this period, job automation increases have predicted neither changes in pay nor employment.

JEL Classification: E24, J22, J23, J24, O33
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Overview

Since at least 2013, many have claimed that we are entering an automation revolution, and so should soon expect large trend-deviating increases in both job automation and related job losses. It is now over six years later, and most revolutions do not appear suddenly or fully-formed, but instead grow from precursor trends. Thus as context for considering such revolution claims, it would help to have a broad study of what predicts which jobs have been how automated in the recent past, of how such automation predictors have changed over time, and of the correlations between changes in automation, pay, and employment.

This paper presents such a study. We use data on 1505 expert reports regarding the degree of automation of 832 U.S. job types over the period 1999-2019, to try to address these questions:

1. Is automation predicted by two features suggested by basic theory: pay and employment?
2. Do expert judgements on which jobs are vulnerable to future automation predict which were how automated recently?
3. How well can we predict each job's recent degree of automation from all available features?
4. Have the best predictors of job automation changed noticeably over the last two decades?
5. On average, how much have levels of job automation changed in the last two decades?
6. Do changes in automation over our period predict changes in job pay or employment?
7. Do other features, when interacted with automation, predict changes in pay or employment?

We find that pay, employment, and vulnerability metrics do predict past automation, but add little to the top 25 O*NET job features, which explain over half of automation variance. Our best predictors have not changed noticeably in two decades, though on average the suitability of jobs for automation has allowed it to increase by roughly a third of a standard deviation. While average reported automation has not changed, controlling for job features it has declined roughly a quarter of a standard deviation, perhaps due to changing reporting standards.

Automation changes do not predict changes in pay or employment, but changes in pay and employment tend to move together, suggesting demand changes are stronger than supply changes. This effect is weaker for jobs where automation is increasing, suggesting a supply-side effect of more automation.

Literature

Over the last decade, we've seen many media articles reporting that experts estimate large trend-deviating fractions of jobs to be lost soon to automation, with estimates varying widely (Winick 2018). For example, a November 2013 poll by Pew Research of 2551 "experts and members of the interested public" found that most "expect dramatic advances in AI and robotics" by 2025, and 48% expected these advances to displace more jobs than they created (Smith and Anderson 2014).

In December 2017, the management consulting organization McKinsey Global Institute estimated 3 to 14% of the global workforce would need to switch occupational categories by 2030 due to automation (Manyika et al. 2017). In November 2018, the market research firm Forrester Research estimated 10% of jobs (at locations unspecified) to be lost to automation in 2019 alone, though offset by 3% new jobs (Gownder 2018). In January 2019, *Fortune* reported that "artificial intelligence expert and venture capitalist" Kai Fu Lee estimated 40% of world jobs to be lost to automation in 15 years (Reisinger 2019).

Such forecasts have been widely noticed and have substantially influenced perceptions. An October 2017 poll of 900 employers in many industries over 38 nations reported that employers said that automation had done 7% of work in 2014, was doing 12% of work in 2017, and they expected it to do 22% in 2020 (Zarkadakis 2018). A summer 2018 poll of 300 technology executives found 61% saying that within ten years they expected to see "AI-assisted machines surpass human intelligence" (Edelman 2019). In the

October 15, 2019 Democratic debate between twelve U.S. presidential candidates, half of them addressed automation concerns introduced via this moderator's statement: "According to a recent study, about a quarter of American jobs could be lost to automation in just the next ten years" (Fix Team 2019).

Many of these estimates and opinions were influenced by and drew upon a widely cited paper by Frey and Osborne (2017), first made public in September 2013. 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." While widely interpreted as estimating actual automation, its authors later emphasized that they only estimated potential, not actual, automation. Other authors, building on this same set of expert judgments, estimate "only 9% of all workers in the US face a risk of automation that exceeds 70%" (Arntz, Gregory, Zierahn 2017).

In our analysis below, we will consider this Frey and Osborne (2017) "computerisable" metric as a predictor of past job automation. We will also consider a related metric of "machine learning suitability", created by Brynjolfsson, Mitchell, and Rock (2018) from machine learning expert judgments using a 23-item rubric (Brynjolfsson and Mitchell 2017), which they have been kind enough to share with us. Other teams have also constructed related metrics, which we do not test here (Felten, Raj, and Seamans 2018; Webb 2019).

The above-mentioned estimates of future automation-induced job losses implicitly combine estimates of future automation changes with estimates of how such changes influence employment. However, when researchers have looked separately at the effects of automation on employment, they have not consistently found that more automation predicts fewer workers. Instead, estimates have varied widely.

For example, some find historical support for the claim that automation can either increase or decrease labor demand, depending on the elasticity of demand for that kind of labor (Bessen 2017). Looking at changes from 1960 to 1998, others find that labor demand changes depend on task type; "computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of nonroutine cognitive tasks" (Autor, Levy, and Murnane 2003). Still others find that across 27 European countries from 1999 to 2010, "routine-replacing technological change" has on net increased labor demand (Gregory, Salomons, and Zierahn 2019).

Looking more narrowly at automation in the form of manufacturing robots, some find that "since 1990, each additional robot per thousand workers reduces local employment to population ratio by 0.39 percentage points and wages by about 0.77 percent" (Acemoglu and Restrepo 2018; 2019). Others find that from 1980-2010, jobs with descriptions related to those in robot and software patents declined significantly in pay and employment, relative to other jobs in the same industry (Webb 2019).

Data

We combine data from three sources.

Our first and main data source is O*NET, a widely-used database of U.S. job features. O*NET job feature scores are made by experts regarding those jobs, who compare each job to related jobs. In its current format O*NET goes back to 2002, though its entries for that year rely on earlier data, last collected in 1999. For each of 2144 jobs, O*NET includes 261 job features, which come from surveying occupational experts as well as employees in that job category. These 2144 jobs are aggregated at various levels, and we focus on the "six-digit" level, at which there are 881 jobs.

Examples of O*NET variables that will turn out to be important below are *Years of Education*, *Thinking Creatively, Hearing Sensitivity, Letters and Memos, Indoors Environmentally Controlled,* and *Importance* *of Repeating Same Tasks.* O*NET job feature scores vary by year. We collect feature scores for years from 1999 to 2019, and use the following process recommended by O*NET to project job feature scores onto a 0-5 numerical scale: we multiply frequency by importance, treating categories as numbers.

For our purposes, a key O*NET job feature is "degree of automation," ranging from "not at all" to "completely." While there may be good reasons to be cautious about interpreting these qualitative expert reports, they seem to offer an unusual opportunity for a systematic and comprehensive study of the predictors and implications of recent job automation. Table 1 shows the ten most and least automated jobs according to this (transformed) automation score; these seem to us reasonable choices. (Note, these scores are expert judgements, not model predictions. Such scores for all jobs are found here: https://www.onetonline.org/find/descriptor/result/4.C.3.b.2?r=1&a=1.) Our impression is that these reports represent rough expert judgements regarding which tasks now done by machines would have to be done by these workers, if those machines were not available, and of how much human effort would be required to do such tasks.

Our second data source is Occupational Employment Statistics, from which we obtain, for each of our job types, U.S. annual averages for number of employees and an inflation-adjusted mean hourly pay (in U.S. dollars). For jobs that list only annual pay, we follow the O*NET assumption of 2080 work hours per year. We have this data for all jobs and all years from 1999 to 2018.

Our third data source is two expert-judgment-derived metrics of the vulnerability of jobs to future automation. The metric *Computerisable* comes directly from the publication by Frey and Osborne (2017), while the metric *Machine Learning Suitability* comes via private communication from the authors of Brynjolfsson, Mitchell, and Rock (2018). These metrics are static, and do not vary by year.

To help our estimated coefficients be more easily understood and compared, we transform all our variables (besides time and intercept) into rough "z-score" variations. To achieve this, we apply a logarithmic transform to 0.01 plus each OES variable of hourly pay, number of workers, and years of education, and also to each 0-5 scaled O*NET variable. After applying these logarithmic transformations, our variables look closer to normally distributed. Finally, we rescale all variables (besides time and intercept) to have zero mean and unit standard deviation. Time is rescaled so as to take value zero at our earliest date of 1999, and value one at our latest date of 2019.

Most O*NET job features were not scored for each job in every year. During our 1999-2019 time period, most descriptors were scored in 2-4 years per job, for an average of 3.3 scorings per job-feature pair. From the available scores for each job-feature pair, we create interpolated scores for all years, using two different interpolation methods.

In *piecewise-linear* interpolation, we fit straight lines in time between (transformed) scorings that are adjacent in time, and fit zero-slope lines to cover years outside the time range of available scorings. We use this method for the models in Table 3 to generate the values of independent variables used to predict automation.

In *regression* interpolation, we fit a linear regression in time to all available (transformed) job-feature scorings. This method requires at least two job-feature scorings. We use this method for the models described in Table 4 to calculate changes in variables over our time period. As both interpolation methods probably add noise, they limit how strongly we can expect to predict when using them.

While our dataset officially includes 881 jobs and 260 O*NET job features (besides education), there are some job and feature combinations where we lack scores for any of our years. So we face a tradeoff between how many jobs and job features we can include in our analysis. For the analysis of Table 3 below, we have chosen to maximize the product of those two numbers with 832 jobs and 251 O*NET job features (besides education). Table 4 uses this same data, but further selected to only include jobs with at least two scorings per each independent variable, for regression interpolation.

Analysis

Table 2 gives basic statistics regarding the variables used in the models described in Tables 3 and 4. For those variables, Table 2 gives a min, max, mean, and standard deviation for untransformed versions, and also a min and max for transformed versions (which have zero mean and unit standard deviation).

Table 3 describes statistical models that predict job automation. It has nine columns of model coefficients, which describe seven numbered ordinary least squares regression models. All these models predict our main dependent variable, transformed degree of automation, using transformed versions of our other variables. Each actual (i.e., not interpolated) O*NET scoring of an automation value for a job in a year corresponds to one data point, and for that data point other independent variables (besides time) are interpolated as needed via the piecewise linear method. All models use intercept and time variables, and vary in which other variables they add to these.

Model 1 of Table 3 adds education, pay, employment, and the two vulnerability metrics. Model 2 (which takes two columns) is similar, but also includes a second column for each of these variables interacted with (i.e., multiplied by) time. Model 3 adds only O*NET variables (minus education) to an intercept and time, while Model 4 includes all our variables (not including time interactions) in a single model. These 25 O*NET variables were selected via the LASSO method out of the set of 251 available O*NET variables using models with a structure like Model 3.

Model 5 of Table 3 (which takes two columns) adds interactions of all these variables with time in its second column, while Models 6 and 7 apply the same method of Model 4 separately to the first and then the second half of our period (i.e., to times <0.5 and times >0.5). Together with Model 2, Models 5, 6, and 7 help us to see whether the best predictors of automation have changed substantially over the time period of our data.

A very simple regression model (not shown) predicts (transformed) automation from only an intercept and time. This model estimates that automation has increased by 0.102 standard deviations over this time period, an estimate that is not significantly different from zero at the 10% level.

Table 4 describes statistical models that predict changes in pay and employment from changes in automation and other variables. All these change variables are estimated via regression interpolation, and are regarding our entire two-decade time period. These changes are not renormalized into z-scores; they are instead differences in z-scores. Table 4 has six columns, which describe model coefficients for six numbered ordinary least squares regression models. In models 1,2,3, the dependent variable is the change in (transformed) pay for each job over our total time period, while in models 4,5,6 the dependent variable is the change in (transformed) number of workers for each job over that period.

For independent variables, all these models include an intercept and also the change in automation level. Models 1 and 4 of Table 4 add no other independent variables, while models 2 and 5 also add change in education, squared change of automation, and change in automation interacted with initial automation level. Models 3 and 6 also add as independent variables the other main dependent variable (i.e., pay for employment and employment for pay), and also that variable interacted with automation change.

Results

Recall that we have transformed the time variable so that it ranges from zero to one over our time period, and have transformed other variables (besides changes) into mean-zero, unit-standard-deviation z-scores that are distributed roughly normally. So most coefficients say how many standard deviations of change in a dependent variable is predicted by a one standard deviation change in an independent variable. The one exception is time, for which a coefficient says how many standard deviations of change in the dependent variable is predicted by a change in time from 1999 to 2019.

The first two models of Table 3 suggest that a simple set of five variables, plus time and an intercept, have substantial predictive power regarding the degree of automation of jobs in our 1999-2019 time period. These few variables can explain roughly 15% of the variation in automation.

There are large fixed costs involved in automating job tasks, and automation can save on marginal costs to pay workers. Thus, simple economic theory predicts that, all else equal, employers are more eager to automate jobs with higher pay and more workers. So these two factors should predict job automation. And we do in fact see such effects in Table 3, though more consistently for pay than employment. (This same theory effect can also help explain the correlation of automation and employment changes seen in Table 4, model 6.)

Two metrics built from expert judgements regarding which jobs seem easier to automate in the future seem to substantially predict which jobs were more automated in the last two decades. Both metrics have large coefficients, though *Computerisable* predicts somewhat better. These metrics are thus far from arbitrary, though it remains unclear if they will capture what might be different about which jobs get automated faster in any future automation revolution.

Worker education level does not seem to predict job automation, once we control for pay, employment, and these vulnerability metrics.

Model 4 of Table 3 suggests that, aside perhaps from education, these predictors have little to add to the predictive power of the top 25 O*NET variables. With or without the other variables, O*NET predictors explain over half of the variation in reported job automation. The fact that we are predicting using interpolated values of the O*NET variables makes this a more noteworthy accomplishment.

The strongest O*NET predictor is *Pace Determined By Speed Of Equipment*, for which a one standard deviation change predicts a 0.58 standard deviation change in automation level. The next strongest predictor is *Importance of Repeating Same Tasks*, with a coefficient of 0.23. Following these, we find four predictors at roughly a 0.14 level: *Letters and Memos, Thinking Creatively, Wear Common Safety Equipment,* and *Indoors Environmentally Controlled.* The five other consistently significant predictors, at roughly a 0.08 level, are *Advancement*, *Innovation*, *Mathematics*, *Physical Proximity*, and *Variety*.

Most of these O*NET predictors of automation seem understandable in terms of traditional mechanical 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. *Variety* picks out an opposite case of dissimilar tasks.

The job features *Wear Common Safety Equipment* and *Indoors Environmentally Controlled* pick out tasks done in calm stable environments, where machines function better, while *Hearing Sensitivity* picks out less suitable complex subtle environments. In jobs with frequent *Letters and Memos,* such memos tend to be short and standardized. Jobs with more *Advancement* are “results oriented”, with more clearly measurable results. Simple machines tend to be bad at *Thinking Creatively, Innovation* and *Mathematics*.

Physical Proximity picks out jobs done close to humans, usually because of needed human interactions, which tend to be complex, and where active machines risk hurting humans.

The models in Table 3 that allow time-interactions, or that apply to time subsets, don't offer much support for the claim that the predictors of automation have changed significantly over our time period. Model 5, which adds 31 time-interaction coefficients, finds only three of them significant at a 10% level, which is the number to be expected at random if they all had zero mean. And Models 6 and 7, fitting the different time periods, show no clear differences from each other.

The Table 3 coefficients on time and time squared seem to present an interpretive challenge. We expect automation to have increased substantially over our twenty year period. But using only an intercept and time, we estimate no significant time coefficient. Furthermore, after controlling for our many predictors, job automation seems to have significantly *decreased*, though perhaps more rapidly during the first half of our time period.

As our job automation scores come from expert judgments made at different times, one possible source for this decline is drifting linguistic standards regarding what it takes for a job to be considered "slightly" versus "highly" automated. Linguistic standards that change with context are often observed (Levari et al. 2018).

If reporting standards can drift, then the total reported increase in average automation should reflect a sum of three effects: (1) *standards* - more forgiving reporting criteria, (2) *ease* - falling costs of automating jobs, holding the features of such jobs constant, and (3) *suitability* - jobs changing to have features that are more suitable for automation. If automation increases over time, we expect stricter reporting standards, increasing ease of automation, and we have no expectations on job suitability.

The Table 3 coefficients on time should only combine these first two standards and ease effects, as they control for suitability effects. Thus the difference between our overall automation change estimate of 0.1 and our time coefficient of roughly -0.27 gives an estimate that the average suitability of jobs for automation increased by roughly 0.37 standard deviations of automation over this period. As the coefficient of -0.27 combines an ease and a standards effect, it is consistent with large increases in actual automation, as long as those were matched by even larger increases in reporting strictness. Alas, it seems that our data says little about how much automation actually changed over our time period.

The combination of a stable technology of automation with large increases in job suitability for automation can make sense if we see increasing automation as a wave passing slowly through a landscape of connected tasks. Two tasks are near each other in this landscape if they coordinate more closely with one another, such as by exchanging info or product, by happening close in space and time, or by being assigned to the same worker. On average, when a task gets more automated, its environment gets more controlled and stable, its info inputs get more formalized, its output is more easily measured, and related info and objects get simpler, more standardized, and more reliably available. All of which tend to make it easier to automate nearby tasks.

In Table 4, we find that we can only predict small fractions of the variance in changes in pay or employment. They are only significantly predicted by changes in job automation in one model out of six, and in that one case more automation predicts more jobs, the opposite of the usual fear. If real, that one coefficient can be seen as confirming the basic theory that employers are more eager to automate 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 over this period are better seen as changes in demand, and less as changes in supply.

Increases in job education levels consistently predict *declines* in pay and employment, though with small coefficients. It seems that over this period falling labor demand has been positively correlated across jobs with increasing education levels. One possible explanation for this pattern is that labor shortages induce firms to adopt weaker education requirements, while labor surpluses induce stricter requirements.

The terms in Table 4 that interact change in automation with itself and with initial automation levels do not predict pay or employment. However, the terms in Table 4 that interact changes in employment and pay with changes in automation do predict changes in those variables. These terms say that the correlation between pay and employment is weaker for jobs which saw a substantial increase in automation. While in theory automation changes are changes to labor demand, not supply, here we see a puzzling inverse correlation between the strength of automation changes and demand effects, relative to supply effects.

Discussion

Recently, many have said that we are entering a big new automation revolution, based on powerful new methods. Many say that this revolution will soon produce large trend-deviating increases in automation levels and resulting job losses, and also big changes in which kinds of jobs are most vulnerable to automation. As we've heard such forecasts since at least 2013, it may not be too early to seek evidence of this revolution in data on reported automation levels for most U.S. jobs over the period 1999-2019.

Our analysis of this data does not yet find evidence of such a revolution. Reported automation levels have not changed noticeably, though changing reporting standards could mask large automation increases. Jobs with larger automation increases did not on average see noticeable changes in pay or employment, though there's weak evidence for an increase in employment.

We can explain over half the variance in which jobs have been how automated using a handful of relatively mundane and understandable job factors, and these predictors have not noticeably changed in two decades. The average suitability of jobs for automation seems to have increased, however, allowing automation to increase by roughly a third of a standard deviation, suggesting that automation may be a wave passing through a landscape of connected job tasks.

Past automation is predicted by two factors suggested by basic theory, pay and employment, and by metrics intended to forecast which jobs will be more vulnerable to automation in a new revolution. This prediction ability disappears, however, after we control for the mundane job factors.

Of course, it remains possible that a revolution has in fact begun, but has not yet grown large enough to become visible in annual data on automation levels in hundreds of U.S. jobs. If so, continued tracking of this data may allow us to notice it soon.

Conclusion

We take data consisting of 1505 expert reports regarding the degree of automation of particular jobs over the last two decades, and attempt a systematic study of what predicts, and what is predicted by, such automation levels.

We find that both wages and employment predict automation in the direction predicted by simple theory. We also find that expert judgements on which jobs are more vulnerable to future automation predict which jobs have been how automated recently. Controlling for such factors, education does not seem to predict automation.

However, aside perhaps from education, these factors no longer help predict automation when we add (interpolated extensions of) the top 25 O*NET variables, which together predict over half the variance in reported automation. The strongest predictor is *Pace Determined By Speed Of Equipment* and most predictors seem understandable in terms of traditional mechanical styles of job automation.

We see no significant change over our time period in the average reported automation levels, or in which factors best predict those levels. However, we can't exclude the possibility of drifting standards in expert reports; if so, automation may have increased greatly during this period. The main change that we can see is that job factors have become significantly more suitable for automation, by enough to raise automation by roughly one third of the standard deviation of automation across jobs.

Changes in pay and employment tend to predict each other, suggesting that labor market changes tend more to be demand, not supply, changes. Changes in job automation do not predict changes in pay or employment; the only significant term out of six suggests that employment increases with more automation. Rising labor demand correlates with falling job education levels.

None of these results seem to offer much support for claims that we are in the midst of a trend-deviating revolution in levels of job automation, related job losses, or in the factors that predict job automation. If such a revolution has begun, it has not yet noticeably influenced this sort of data, though continued tracking of such data may later reveal such a revolution. Our results also offer little support for claims that a trend-deviating increase in automation would be accompanied by large net declines in pay or employment. Instead, we estimate that more automation mainly predicts weaker demand, relative to supply, fluctuations in labor markets.

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Z-Score	Job Description	Job Code
2.08	Travel Agents	41-3041
2.05	Extruding, Forming, Pressing, & Compacting Machine Setters, O	51-9041
1.82	Airline Pilots, Copilots, & Flight Engineers	53-2011
1.77	Lathe & Turning Machine Tool Setters, Operators, & Tenders, M	51-4034
1.74	Dredge Operators	53-7031
1.70	Air Traffic Controllers	53-2021
1.67	Computer Operators	43-9011
1.64	Bridge & Lock Tenders	53-6011
1.62	Textile Bleaching & Dyeing Machine Operators & Tenders	51-6061
1.62	Chemical Equipment Operators & Tenders	51-9011
	...	
-1.76	Umpires, Referees, & Other Sports Officials	27-2023
-1.77	Choreographers	27-2032
-1.81	Actors	27-2011
-1.85	Art, Drama, & Music Teachers, Postsecondary	25-1121
-1.85	Animal Trainers	39-2011
-1.87	Manufactured Building & Mobile Home Installers	49-9095
-1.87	Watch Repairers	49-9064
-1.89	Musicians & Singers, Singers, Instrumental Musicians	27-2042
-2.01	Makeup Artists, Theatrical & Performance	39-5091
-2.02	Carpet Installers	47-2041

Table 1: Ten Max and Ten Min Automation Jobs

	Untransformed				*Transformed*	
Variable	**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 Balanc	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

Table 2: Variable Statistics

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.

Table 3: Predicting Automation

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

Table 4: Predicting △ Pay, △ Employees