Predicting Job Automation: What have we observed?

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Abstract

*This research considers the ability to predict job automation based on two models. The first is a job model developed by Frey and Osborn and published in 2017. With 12000+ citations, that article appears to be the most highly cited academic article on predicting job automation. The second is a job automation model developed by Sampson and published in 2021. Coincidentally, both models were developed using the same U.S. Department of Labor database called O*Net, although using different data from different years. We use historical and current O*Net data to see how each model does in predicting observed changes in job automation over a wide range of jobs. A surprising finding is a negative correlation between degrees of automation for various jobs and changes in the degree of automation over the subsequent decade. This analysis leads to interesting theories about how job automation can be predicted, including an AI explanation.*

Keywords: job automation, technology forecasting

1. Introduction

This research assesses our ability to predict job automation, which Andreassen et al. (Andreassen et al., 2018) define as "the replacement of people with machines and technology." Predicting job automation will be helpful for educational institutions that want to understand how to prepare graduates for future jobs, helpful for government economists who want to understand shifts in labor force, and helpful for individuals in jobs who are wondering how their job will change or be displaced in the future.

There is some disagreement in research literature about the extent to which jobs will be automated in the future. Some authors have predicted extensive job displacement due to automation. For example, Frey and Osborn (Rifkin, 1995) estimate that around 47% of total U.S. employment is at high risk of being disrupted by computer automation. Other estimates are more conservative. Chui, Manyika, and Miremadi (2015) suggest that only about 5 percent of jobs will be replaced by automation. However, they also project that most jobs will have as much as a third or more of their tasks become automated, which also will adversely impact employment statistics.

Research and empirical evidence have also demonstrated that some jobs are particularly susceptible to automation. For example, routine jobs have been shown to be particularly suitable for being automated (Autor et al., 2003; Bresnahan et al., 2002; Violante, 2008). This will be especially true of repetitious jobs that can be relegated to tightly defined rule systems.

Manufacturing jobs have already been significantly impacted by automation. The decline in U.S. employment in manufacturing has been attributed to productivity gains due to automation (Hicks & Devaraj, 2015). Service jobs have also been disrupted by automation (Rifkin, 1995). The U.S. Bureau of Labor Statistics (2017) reports significant declines in service jobs including telephone operators (down 90% from 2001 to 2017), telemarketers (down 61%), survey researchers (down 51%), medical transcriptionists (down 47%), and travel agents (down 45%).

Research also suggests that some jobs are resistant to automation. This includes jobs in professional services such as healthcare, education, engineering, and education. Professional services are considered non-routine and exhibit characteristics that are resistant to automation (Autor et al., 2003). We will discuss some of those characteristics below. Suffice it to say that workers in professional service jobs may feel little threat of automation. We wonder if this is a false sense of security, especially given recent advances in artificial intelligence (AI) including machine learning and natural language processing.

Other jobs that were once considered resistant to automation have since become automated. For example, physical tasks that involve manual dexterity were thought to be resistant to automation (Autor, 2015), but recent advances in robotics has proven otherwise. Another example is autonomous driving. Not long ago Levy and Murnane (2004) pointed out that that the complexity of driving an automobile would inhibit automating the job of a human driver, which again has been proven wrong (Brynjolfsson & McAfee, 2012).

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The bottom line is that predicting job automation is no easy task. In this research we will consider two published methods for predicting the extent of job automation for specific jobs. Our research purpose is to determine how well the methods do at predicting job automation given historical data. We will compare the two job automation forecasting methods against a naïve forecasting approach. This includes analyzing how automation has infiltrated jobs over the past decade. In this analysis we found some surprising findings that prompt theories for future job automation research.

The next section will review two published methods for predicting job automation, including a comparison of the methods. The third section provides an assessment of the predictive ability of the two methods based on historical data. The fourth section reviews some counterintuitive findings and makes observations. A final section discusses limitations and directions for future research.

2. Predicting job automation

As mentioned, we will consider two published methods for predicting job automation published in recent literature. The first is a highly cited article by Frey and Osborn (2017) titled "The future of employment: How susceptible are jobs to computerisation?" According to Google Scholar, that article has been cited over 12000 times in the six years since publication (including 1840 citations in 2022 alone), and thus appears to be the most cited article on job automation forecasting. The second is a more recent article by Sampson (2021) titled "A Strategic Framework for Task Automation in Professional Services." We will review the essence of these two approaches to predicting job automation.

2.1. The Frey and Osborn model

The central purpose of the Frey and Osborn (2017) article is to identify how susceptible various jobs are to "computerisation" which they define as "job automation by means of computer-controlled equipment" (p. 254). They treat the concept of computerization as equated with "automation," even though there exist methods of automation that do not involve computers. Their model is based on a machine learning (ML) algorithm. Reasons they cite for using an ML approach is that ML approaches are good with big data sets and are often better able to detect patterns than humans.

They train their ML model using a U.S. Department of Labor database known as the Occupational Information Network, or O*Net. The O*Net data are based on extensive surveys about the characteristics of hundreds of jobs. The O*Net project began in 1992 and has been continually updated at an expense of between US$6.5 and US$6.8 million per year (Tippins & Hilton, 2010). The O*Net researchers have gone to great lengths to assure data reliability and representative sample sizes (Peterson et al., 1999).

Frey and Osborn use the 2010 release of the O*Net database that contains 571 survey items about 1110 distinct jobs. The 571 items are organized into six major categories: worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics, and occupation-specific information. Each of these major categories has subcategories. Some of the O*Net data was provided by career experts called "analysts" and other parts of the data comes from surveys of "job incumbents" (i.e., individuals who have experience working in specific jobs). Each job involves surveys of perhaps 8 analysts or about 30 job incumbents.

Frey and Osborn correlate the O*Net data with 2010 Bureau of Labor Statistics employment and wage data, which they were able to do for 702 of the 1110 jobs. Frey and Osborn manually predicted the computerization of 70 jobs of the 702 jobs to form a ML training set: 33 of the 70 were deemed to <u>not</u> be computerizable and 37 were deemed to be <u>fully</u> computerizable. These initial predictions appear to be based on their own subjective judgements, not on any current or historical data.

Based on prior theories about job automation, Frey and Osborn identify nine items in the O*Net database that are correlated with a propensity for automation. Three of the items were from data collected from job incumbents and six were from analysts. Using scores about those items for the 70 jobs from the O*Net database they trained their ML model. The application of that model to the 702 jobs produced their Computerization Probability values, which we will refer to as **FreyCompProb**. Values range from 0.28% to 99% with an average across the 702 jobs of 53.6%.

Frey and Osborn provide the FreyCompProb values for all 702 jobs in their paper. Figure 1 provides our summary of the FreyCompProb values by industry according to the U.S. Standard Occupational Classification (SOC) system. The industries at the top of Figure 1 have a high computerization probability and thus are considered highly susceptible to automation. The industries at the bottom of the chart are considered resistant to automation. (The four highlighted bars will be explained below.)

Figure 1 also include a line showing average annual wages for each job category. Frey and Osborn also compared computerization with wages and showed an inverse relationship. We repeated that analysis using

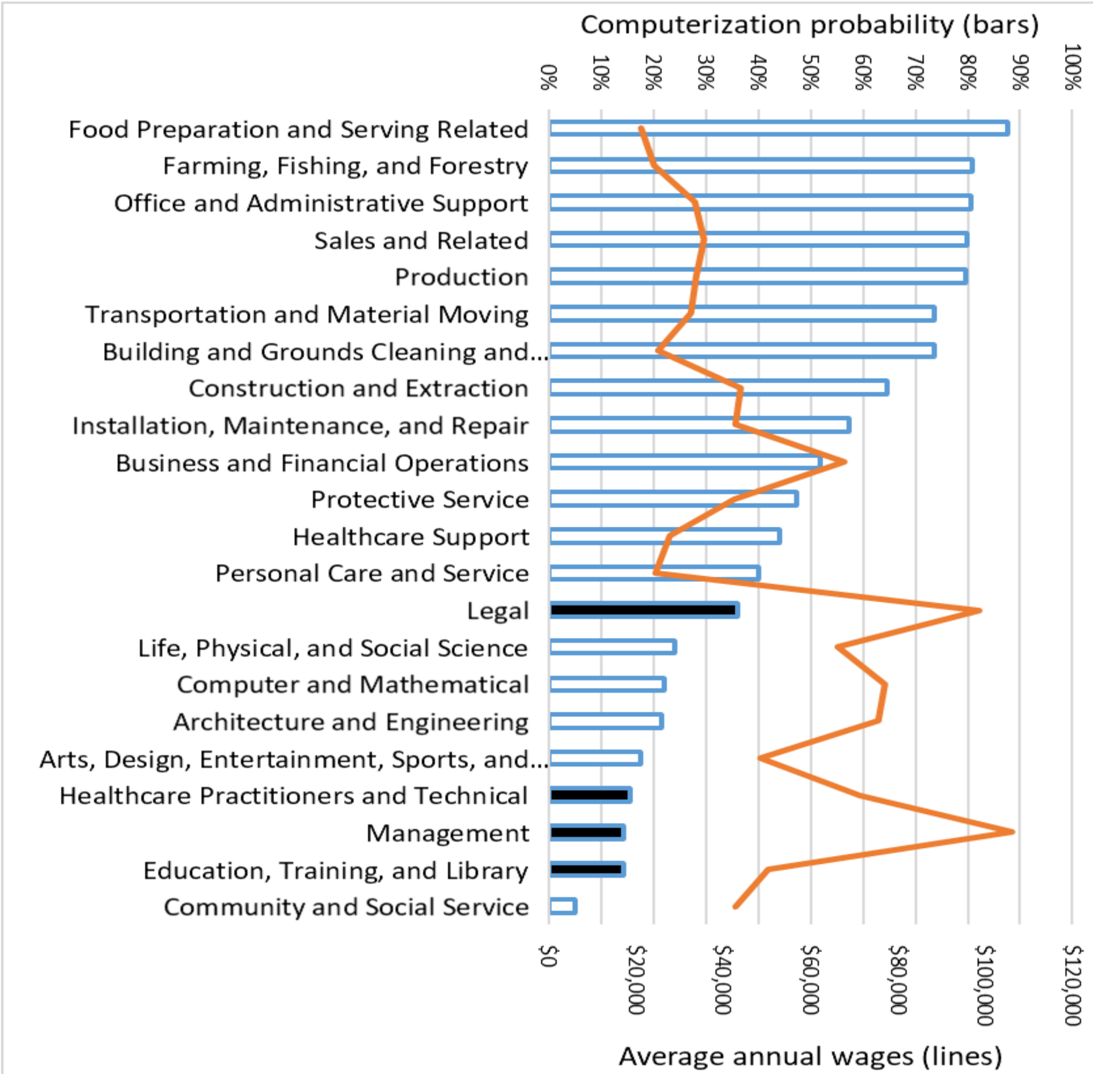

Figure 1. FreyCompProb summary by industry

data retrieved from the Bureau of Labor Statistics for a similar timeframe as the Frey and Osborn study. While there is a correlation between automation and wages, at the industry level it is not fully precise. A research question (not for this study but for future research) is the relationship between susceptibility to automation and wages – whether job automation causes wages to increase or decrease. Figure 1 suggests that there might be a relationship, but issues of causality are uncertain.

2.2. Sampson Job Automation model

The primary focus of the Sampson (2021) research paper was not job automation in general, but more specifically on automation of professional service jobs. His purpose was to develop a model that would predict the automation of professional service jobs (as defined below), although his model could also be applied to any job in general. While professional services can exist in many industries, in Figure 1 we highlight four industries that have been recognized to have a high concentration of professional service jobs (Sampson, 2018): legal services, healthcare, management, and education. Note that these are among the least likely to be computerized, according to the Frey and Osborn model.

We consider the automation of professional service jobs to be an especially relevant topic given recent advancements in AI. As we will next discuss, the nature of professional service jobs has made them resistant to earlier forms of job automation, but potentially disrupted by the emerging natural language models.

2.2.1. Characterizing Professional Service jobs. Understanding the Sampson model requires understanding how professional service jobs are characterized and delineated. The literature sometimes defines professional services by enumeration. Commonly listed examples include healthcare, accounting, and legal services. An enumeration definition is less than helpful because it does not indicate what characteristics make them professional services. Researchers have provided evidence about what these characteristics might be.

Abbot (1988a) defined professional services in terms of applying abstract knowledge to specific cases. The assertion that the knowledge is abstract implies that it is not easily codified, and thus not easily programmed into a robot or other computer system. The application to "specific cases" suggests that the work is non-routine, with each instance of work being different from each other.

Others have built on this idea of the distinctive knowledge involved in professional services. This professional service knowledge idea has been described in terms of distinctive expertise (Verma, 2000) and specialized education (Abbott, 1988b; Shapero, 1985). von Nordenflycht (2010) stated that, "Perhaps the central characteristic associated with professionals is their mastery of a particular expertise or knowledge base" (p. 156).

As with Fray and Osborn, Sampson used the O*Net database as his primary data source. The O*Net database helped him operationalize these characterizations of professional services. O*Net data include a classification of jobs according to their preparation and skill requirements, which they call "job zones." Jobs in zone 1 require little or no preparation, perhaps not even a high school diploma. At the other extreme is job zone 5, which require extensive skills, knowledge, and experience. In our research we will consider jobs categorized in zone 5 to be professional services.

Most zone 5 jobs require postgraduate college education. Recent DOL data show that 81.4 percent of zone 5 jobs require a Master's degree or higher. Zone 5 jobs represent about 6.9 percent of U.S. employment and have average annual wages that are 71 percent higher than the average for all jobs (Sampson, 2021).

2.2.2. Measuring Automation of Professional Services. As mentioned, the literature has suggested that professional services are resistant to automation. To test this theory, Sampson used data from the O*Net database. One of the O*Net survey items is "Degree of automation" wherein subjects are simply asked "How automated is your current job?" Responses are on a 1 to 5 scale from "not at all automated" to "completely automated." We will refer to these values as **DegAuto**. In recent years the DegAuto data comes from surveys of job incumbents.

Jobs in zones 1-4 zones have DegAuto means of 2.23, 2.24, 2.17, and 2.23, which are statistically identical. In other words, automation is spread somewhat consistently across job zones 1 through 4. Jobs in zone 5, which we consider to be professional services, have a DegAuto mean of 1.89, which is significantly lower than the other job zones both statistically and practically. This supports the theory that professional service jobs are resistant to automation. Sampson's primary research question was exploring why that was the case.

2.2.3 Inhibitors of Professional Job Automation. Research literature identifies job characteristics that make jobs resistant of automation. One of these is requiring manual dexterity, as mentioned above. This is not relevant to professional services, which Sampson reports have lower requirements for manual dexterity than jobs in general. Two other inhibitors of job automation cited in the literature are creative skill requirements and interpersonal skill requirements.

Autor (2015) states that jobs involving intuition and creative problem solving are difficult to automate. Huang and Rust (2018) refer to this as "intuitive intelligence," which they define as "the ability to think creatively and adjust to novel situations." Frey and Osborn (2017) refereed to a similar concept that they called "creative intelligence." Other research echoes the idea that creative problem solving makes jobs difficult to automate.

The second inhibitor of automation frequently cited in the literature is interpersonal skills (Acemoglu & Autor, 2011; Autor & Dorn, 2013). Frey and Osborn called this "social intelligence." Huang and Rust [2018] call it "empathetic intelligence" which they define as including "interpersonal, social, and people skills."

Sampson addressed whether professional service jobs are distinctive in terms of creative and interpersonal skills. The above-cited literature points out that professional services involve abstract knowledge, which we might infer pertains to creativity. Still, it is unclear from prior literature if professional service jobs require above-average creative skills, let alone interpersonal skills.

After some extensive analysis, Sampson identified the following O*Net database item to measure job requirement for creativity. (measured on a 5-point scale):

- **Innovation**: "Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems."

Using correlations and exploratory factor analysis (EFA), Sampson identified the following two items that measured interpersonal skills:

- **Concern for Others**: "Job requires being sensitive to others' needs and feelings and being understanding and helpful on the job."
- **Social Orientation**: "Job requires preferring to work with others rather than alone, and being personally connected with others on the job."

These items all come from surveys of job incumbents. Sampson compared mean scores for these three items between professional service jobs in zone 5 and jobs in zone 3 and zone 4. In all cases the unpaired means tests showed statistically significant difference (all $p<0.001$ except for Concern for Others between zone 3 and 5, which was significant at a 0.01 level). This supports a supposition that professional jobs require greater levels of creative and interpersonal skills than less-professional jobs, which provides theory about why professional jobs seem to be resistant to automation.

The Sampson model for predicting job automation is, in essence, a linear function of creative and interpersonal skill requirements, as measured by the above three O*Net items. While Sampson did not report job automation scores for items in the database, we can easily synthesize that prediction.

2.3. Consistency between Sampson model and Frey and Osborn model

Although Frey and Osborn did not focus on automation of professional services, they unwittingly predicted less automation of professional service jobs. We identified job zones for 494 of the 702 jobs included in their data set. Figure 2 shows a summary of average FreyCompProb scores for each job zone. As observed, FreyCompProb decreases with job zone with the lowest probability for professional service jobs in zone 5. This suggests that we will expect some similarity in predictions coming from either the Sampson model or the Frey and Osborn model.

2.4. Differences between the models

Both models used items from the O*Net database, but each used different items. Perhaps the biggest difference between the two approaches is that Frey and Osborn used expert judgement to train their ML model, which is supervised learning. As with all supervised learning, the predictive quality of the model will depend heavily upon the accuracy of the labeled data (i.e., the 70 jobs they manually classified according to potential computerization).

On the other hand, the Sampson model came from statistical analysis of historical data, thus not requiring subjective judgements of job classification. This approach is not influenced to subjective bias, but also lacks insights that subjective judgement might provide.

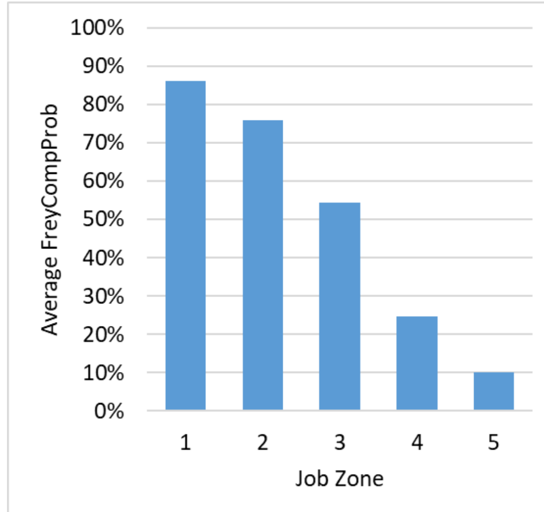

Figure 2. FreyCompProb by job zone

3. How have automation forecasts panned out?

The primary purpose of this research project is to assess how these forecasts have panned out over the past dozen years. Although the Frey and Osborn article appeared in print in 2017, they developed their predictions of computerization using O*Net data from 2010. Therefore, their predictions are as of 2010. It would be interesting to know how the predictions would change if they reran their model using current O*Net data. We do not have the precise parameters of their model, so they would have to provide that update. However, something we can do is see how their predictions have panned out in the ensuing dozen years.

To test the empirical validity of their predictions we compare the automation of jobs (DegAuto scores) at the time of the Frey and Osborn study (which used 2010 data) with the automation of those same jobs a twelve years later. Major revisions of O*Net data are released on an annual basis, with minor revisions sometimes released in between. The release for 2010 was O*Net version 15.0. In February of 2011, a version 15.1 of the database released with a new 2010 classification, but otherwise the same job statistics as the 2010 version.

We therefore use version 15.1 as the baseline. In that database the number of survey subjects for each job varies from 13 to 208 with a mean of 31.8 (standard deviation of 16.8). We will analyze how mean degree of automation scores for specific jobs have changed in the ensuing years.

For comparison we use the most recent O*Net data distribution, which is version 27.3 released May of 2023, which is a minor update of version 27.0 that was released in August of 2022. The O*Net researchers readminister surveys to update approximately 100 jobs for each major (annual) release. Some of the jobs in the May 2023 database have been updated since 2010 and some have not. We will focus specifically on jobs that were updated in the past seven years, from the August 2016 version (21.0) on. Of the 836 jobs in the May 2023 database, 397 were tagged as having been updated since 2016. Of those 397 jobs, 151 (38.0%) were reported as having increased in degree of automation, 243 (61.2%) were reported as having decreased in degree of automation, and 3 (0.8%) were reported to be at the same degree of automation.

It is interesting to observe that more jobs have decreased in degree of automation than increased. These 397 jobs decreased an average of 0.121 on a five-point scale, which is statistically significant ($p<0.001$) if not practically significant. Figure 3 shows the changes in DegAuto for the 397 jobs over the twelve-year period. The subscript for this and other variables indicates the year, e.g., $DegAuto_{2011}$ is Degree of Automation values from the 2011 O*Net database (version 15.1), and $DegAuto_{2023}$ is from the 2023 (version 27.3) database. The slanted line marks equal degrees, with jobs below (above) the line decreasing (increasing) in automation. Indeed, there appear to be more jobs below the line than above the line.

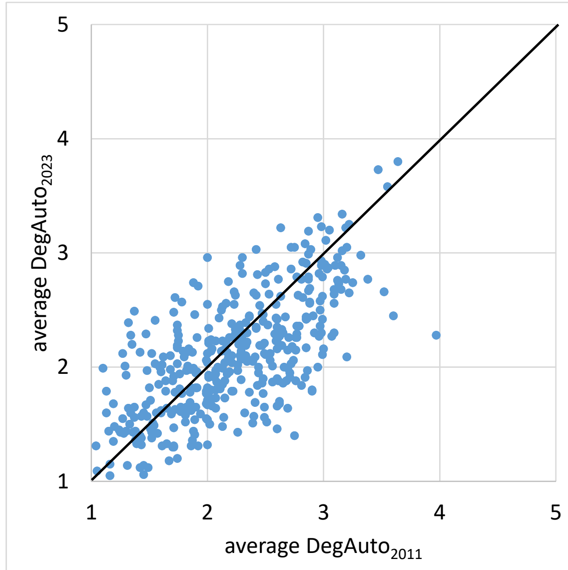

Figure 3. Changes in Degree of Automation

3.1. Testing of forecasts of job automation

Our research question is how the Frey and Osborn model and the Sampson model do in predicting changes in automation from 2010 through 2023. The Frey and Osborn predictions are based on 2010 O*Net data, and we can test the Sampson model also based on 2010 O*Net data.

There are three ways we can handle this comparison.

a) How do $DegAuto_{2023}$ values correspond to the predictions?
b) Do $DegAuto_{2023}$ values correspond to the Frey and Osborn predictions any better than they correspond with $DegAuto_{2011}$ values? In other words, might Frey and Osborn simply be predicting $DegAuto_{2011}$, which was historical the time of their research. The value of any technology forecast is more about predicting the future than it is about predicting the present.
c) Do the changes in DegAuto values between 2011 and 2023 correspond to the Frey and Osborn or the Sampson job automation predictions? In other words, does either model predict how the automation of various jobs will change over time.

We will consider these three questions in sequence. Our methodology is OLS regressions.

a) Predicting future job automation ($DegAuto_{2023}$)

We regressed FreyCompProb on $DegAuto_{2023}$ with results shown as Model 1a in Table 1. The correlation between $DegAuto_{2023}$ and FreyCompProb is statistically significant with an R^2 value of 0.105. Therefore, FreyCompProb does predict $DegAuto_{2023}$, explaining just over 10% of the variance.

We tested the Sampson model which measures a degree of professionalism according to creative skill and interpersonal skill requirements. As mentioned above, creative skill requirements are measured with the Innovation O*Net item, and interpersonal skill requirements are measured with a combination of Concern for Others and Social Orientation.

Model 1b in Table 1 shows the regression for the Sampson model using measures from the 2011 O*Net database, which produces an R^2 value that is slightly higher than the FreyCompProb model. Model 1c includes both the FreyCompProb and the Sampson model in the same regression, which again provides a higher predictive value. This is to suggest that the two models are not completely redundant.

b) Using the past ($DegAuto_{2011}$) to predict the future ($DegAuto_{2023}$)

The prior statistical tests showed that the Frey and Osborn model did predict job automation to some degree. However, from their 2017 report the Frey and Osborn model did not take into account the current state of automation as reported in the 2010 O*Net database. Instead, Frey and Osborn manually predicted the computerization of 70 jobs in the database as described above. The question remails how DegAuto in 2010 might serve as a predictor of DegAuto a decade later.

Table 1. Regression results for predicting $DegAuto_{2023}$

DV: $DegAuto_{2023}$	Model 1a	Model 1b	Model 1c
$FreyCompProb_{2010}$	0.434***		0.267**
	6.799		3.307
$Innovation_{2011}$		-0.273***	-0.171**
		-5.909	-3.119
$ConcernForOthers_{2011}$		-0.190**	-0.181*
		-2.478	-2.384
$SocialOrientation_{2011}$		0.075	0.099
		1.066	1.411
Constant	1.878***	3.524***	2.912***
	45.159	16.795	10.482
R^2	0.105	0.115	0.139
F statistic	46.230	17.101	15.885
p value	0.000	0.000	0.000
No. observations	397	397	397

Showing unstandardized β values (t statistics in parentheses)
$*p<0.05$, $**p<0.01$, $***p<0.001$

This implies a naïve predictive model, meaning we simply use the past DegAuto values to predict future DegAuto values. For our analysis we will use the DegAuto at our base time period ($DegAuto_{2011}$) to predict how automation would be in the future ($DegAuto_{2023}$). Regression results are show as Model 2a in Table 2.

As we observe, $DegAuto_{2011}$ is a tremendous predictor of $DegAuto_{2023}$, explaining almost 46 percent of the variance. This is significantly better than the FreyCompProb prediction from Model 1a, implying that thus far (as of 2023) the FreyCompProb model is less accurate than a naïve model. We recognize that the FreyCompProb model might provide greater predictive value for the future.

We do consider the combination of the naïve model ($DegAuto_{2011}$) and the FreyCompProb model, as shown in Model 2b in Table 2. Adding the FreyCompProb model improved the R^2 value by a small amount (0.018). We also tested combining the Sampson model with the naïve model, which is Model 2c. This produced even better predictive results, improving the R^2 to 0.482.

Table 2. Using $DegAuto_{2011}$ to predict $DegAuto_{2023}$

DV: $DegAuto_{2023}$	Model 2a	Model 2b	Model 2c
$DegAuto_{2011}$	0.602***	0.566***	0.562***
	10.138	16.760	16.643
$FreyCompProb_{2010}$		0.189***	
		3.700	
$Innovation_{2011}$			-0.121***
			-3.320
$ConcernForOthers_{2011}$			-0.097*
			-1.641
$SocialOrientation_{2011}$			0.037
			0.690
Constant	0.767***	0.747***	1.519***
	10.138	10.010	7.562
R^2	0.459	0.477	0.482
F statistic	335.425	179.943	91.077
p value	0.000	0.000	0.000
No. observations	397	397	397

Showing unstandardized β values (t statistics in parentheses)
$*p<0.05$, $**p<0.01$, $***p<0.001$

We conclude that the naïve model is the best predictor of job automation for the time period considered. The FreyCompProb and Sampson models provide incremental improvement.

c) Predicting changes in job automation

Since past job automation is a strong predictor of future job automation, it will be more valuable to predict how job automation will change over a given time horizon. Again, we are studying a relatively short time horizon of measurement, which is jobs that have changed over the given decade. Note that most of the jobs listed in the 2011 version 15.1 O*Net database were updated in prior versions, meaning that even if a job was updated in 2016 the prior update was still likely a decade before.

To test this time frame issue, we calculated the difference in years between update dates (for DegAuto values) recorded in the 2023 database and the update dates recorded in the 2011 database. Assuming there were not multiple updates of a given job during that interval, the average time between job updates is 11.60 years (st dev 2.70 years). This suggests that we are indeed considering changes in DegAuto values over a decade.

Table 3. Predicting changes in DegAuto

DV: DeltaDegAuto	Model 3a	Model 3b	Model 3c
$DegAuto_{2011}$	-0.398***	-0.434***	-0.438***
	-12.121	-12.858	-12.993
$FreyCompProb_{2010}$		0.189***	
		3.700	
$Innovation_{2011}$			-0.121***
			-3.320
$ConcernForOthers_{2011}$			-0.097*
			-1.641
$SocialOrientation_{2011}$			0.037
			0.690
Constant	0.767***	0.747***	1.519***
	10.138	10.010	7.562
R^2	0.271	0.296	0.287
F statistic	146.925	82.666	30.443
p value	0.000	0.000	0.000
No. observations	397	397	397

Showing unstandardized β values (t statistics in parentheses)
*p<0.05, **p<0.01, ***p<0.001

We then calculate the change in DegAuto values which we label DeltaDegAuto, as follows.

$$DeltaDegAuto = DegAuto_{2023} - DegAuto_{2011}$$

Predicting DeltaDegAuto proved to be somewhat difficult. A simple regression shows that FreyCompProb does not predict DeltaDegAuto (R^2 = 0.000). The Sampson model does not do much better (R^2 = 0.001). The one thing that we found will predict DeltaDegAuto is $DegAuto_{2011}$, as shown in Model 3a of Table 3.

Observe $DegAuto_{2011}$ does a pretty good job of predicting DeltaDegAuto (R^2 = 0.271), although shockingly the coefficient is negative. In other words, jobs that were less automated in the early data set were more likely to increase in automation in the ensuing decade. A few theories for this counterintuitive observation are set forth in the conclusion section.

As usual, we attempted to see how the naïve model (3a) could be improved by combining with the FreyCompProb model (shown as Model 3b) and the Sampson model (shown as Model 3c). Once again, both provided additional explanation of variance, with superior results coming from FreyCompProb.

4. Summary of Results and Implications

We observe that it is possible to predict changes in job automation, however it appears that the best predicter may be current degrees of automation (the naïve model). The Frey and Osborn model and the Sampson model are useful, but time will tell if they or other models will provide superior results.

A few surprises came from this analysis. One was that the reported degree of automation actually went down on average over the study period. Intuition suggests that job automation should be rising. Some theories about this counterintuitive observation include:

a) Due to increased automation in society, survey subjects have a higher standard for reporting job automation. For example, in prior decades subjects may have considered the use of a word processor as job automation, but now that word processing is ubiquitous it may be considered just part of a non-automated job.
b) Automated jobs are going away, and the remaining jobs are less automated than the ones that went away. The O*Net data comes from surveying "job incumbents" who work in specific jobs. We have no data on the jobs that are performed by automation, such as travel booking websites. Jobs that become highly automated are unreported in O*Net data because the automation does not complete surveys.

This theory (a) has practical implications. It suggests that survey subjects, and workers in general, are becoming desensitized to the introduction of automation in their jobs. This would imply that, at the margin, the introduction of automation will be considered less disruptive in the future than it has been in the past. For example, there are news reports of unions being upset with the extensive automation of warehouses, but as warehouse automation becomes ubiquitous the theory suggests wider acceptance will ensue.

The other surprise was that the degree of automation was a NEGATIVE predictor of changes in automation. Jobs with lower automation are more likely to increase in automation than jobs with higher automation. Some theories for this counterintuitive effect include:

a) Less automated jobs have greater potential for increases in automation. The low-hanging fruit of job automation has already been harvested, and easily automated jobs are both automated and less susceptible to more automation.
b) Advances in AI and other technologies are encroaching to a greater degree on highly skilled jobs, which have not traditionally been highly automated. We may be seeing a relative surge in automation of professional service jobs.

Both of these theories pertain to technological maturity, where technologies such as AI are encroaching ever higher on the skill ladder. An important research question is how managers of highly skilled workers, such as professional services, should best address increases in automation. On one hand, professional services tend to have high labor costs, implying that there will be significant cost savings from increased automation. On the other hand, the cost of failure in some professional services can be great, suggesting caution in replacing human labor with machines. For example, if a medical operation performed by a surgery robot fails, is the engineer who designed the robot subject to malpractice liability?

Another practical implication of this finding is the need for reskilling across the gamut of jobs. In historical instances of technological disruption, it tended to be the low-skilled workers who needed to continually retrain and adjust their career trajectories. In the recent wave of job automation where semiprofessional and highly skilled professionals are encroached by automation, even they will likely need to expand their skill set beyond their core competencies and into technology.

This technological transformation of skilled professionals can be particularly complex. For example, Siemon and Kedziora (2023) studied a case in which professional accountants were being retrained to become robotic process automation (RPA) developers. The studied accounting firm recognized that developing RPA systems required the expertise of trained professionals. The accountants recognized that the new skills would enable them to automate away much of their work, at least the routine components. As such, the training was both a protector and a threat to job security. The retraining involved an identify shift for the accountants, transforming into developers, and a potential shift for the firm from being a service provider to being a software developer. These and other factors will need significant research attention in this age of rapid AI advancement.

5. Limitations and Future Research

We recognize that this is a preliminary study of predicting job automation based on two studies set forth in prior research. There are some typical limitations including the following.

Using secondary data (in this case, O*Net data) has limitations on the ability to carefully manage survey development and data collection. There are publicly available documents describing the methodology, including reliability statistics (Peterson et al., 1999). Also, the O*Net data has been used by other major studies published in reputable academic journals, including other prominent studies pertaining to job automation (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Brynjolfsson et al., 2018).

One challenge with using O*Net data is that most of the surveys are comprised of single-item constructs. For example, DegAuto was measured as a single construct, preventing us from calculating a Cronbach alpha or other reliability statistics. Although as mentioned, the O*Net researchers reportedly consider data validity and reliability (Borman et al., 1999; Peterson et al., 1999).

We performed some basic model robustness checks including controlling for job zone. Results for those tests were statistically significant as with the models shown above, except for model 1c which had more significant coefficients for the $\text{FreyCompProb}_{2010}$ and Innovation_{2011} variables. Theories and additional model robustness checks are opportunities for future research.

The time frame over which we did the job automation comparison was obviously limited, and future data will allow additional analysis. We attempted analysis using data from the early days of O*Net. The original data set was in 1998 (called "O*Net 98). The first rigorous database (version 3.0) was released in August of 2000. The file formats and data representation were a mess in those days. The data structures improved in subsequent years. 2011 (version 15.1 that we used) was the first year that the data are available in modern data formats (MySQL, SQL Server, and Oracle). (Admittedly, that is one reason we choose that as our original baseline.)

Future research might include a broader set of components of O*Net data and more advanced models. The O*Net data is updated quite frequently; it can be thought of as more of a stream of data than a static data set. Job automation forecasting models such as FreyCompProb and the Sampson model were designed as traditional models that consider a snapshot of data. Extensions of these models or new models might account for the ways in which O*Net data evolves over time, perhaps producing better forecasts.

This research is preliminary yet provides some interesting insights and theories with practical implications. It is hoped that this research report can help motivate continued progress in our ability to predict job automation.

6. References

Abbott, A. (1988a). *The System of Professions: An Essay on the Division of Expert Labor*. University of Chicago Press.

Abbott, A. (1988b). *The system of professions: An essay on the division of expert labor*. University of Chicago Press.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.

Andreassen, T. W., van Oest, R. D., & Lervik-Olsen, L. (2018). Customer Inconvenience and Price Compensation: A Multiperiod Approach to Labor-Automation Trade-Offs in Services. *Journal of Service Research*, *21*(2), 173-183.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3-30.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553-1597.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, *118*(4), 1279-1333.

BLS. (2017). *U.S. Bureau of Labor Statistics - National Occupational Employment and Wage Estimates*. Retrieved July 2018 from https://www.bls.gov/oes/current/oes_nat.htm

Borman, W. C., Kubisiak, U. C., & Schneider, R. J. (1999). Work Styles. In N. G. Peterson, M. D. Mumford, W. C. Borman, P. R. Jeanneret, & E. A. Fleishman (Eds.), *An occupational information system for the 21st century. Development of O*NET* (pp. 213-226). American Psychological Association.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly journal of economics*, *117*(1), 339-376.

Brynjolfsson, E., & McAfee, A. (2012). *Race Against The Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Digital Frontier Press.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What Can Machines Learn, and What Does It Mean for Occupations and the Economy? *American Economic Association (AEA) Papers and Proceedings*, *108*, 43-47.

Chui, M., Manyika, J., & Miremadi, M. (2015). Four fundamentals of workplace automation. *McKinsey Quarterly*, *29*(3), 1-9.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254-280.

Hicks, M. J., & Devaraj, S. (2015). *The myth and the reality of manufacturing in America* (Center for Business and Economic Research, Issue. https://projects.cberdata.org/reports/MfgReality.pdf

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155-172.

Levy, F., & Murnane, R. J. (2004). *The new division of labor: How computers are creating the next job market*. Princeton University Press.

Peterson, N. G., Mumford, M. D., Levin, K. Y., Green, J., & Waksberg, J. (1999). Research method: Development and field testing of the content model. In N. G. Peterson, M. D. Mumford, W. C. Borman, P. R. Jeanneret, & E. A. Fleishman (Eds.), *An occupational information system for the 21st century. Development of O*NET* (pp. 31-47). American Psychological Association.

Rifkin, J. (1995). *The end of work: The decline of the global labor force and the dawn of the post-market era*. Penguin Group.

Sampson, S. E. (2018). Professional Service Jobs: Highly paid but subject to disruption? *Service Science*, *10*(4), 457-475.

Sampson, S. E. (2021). A Strategic Framework for Task Automation in Professional Services. *Journal of Service Research*, *24*(1), 122-140. https://doi.org/10.1177/1094670520940407

Shapero, A. (1985). *Managing professional people: Understanding creative performance*. Free Press; Collier Macmillan.

Siemon, D., & Kedziora, D. (2023). From Accountant to Software Developer–Transforming Employees with Robotic Process Automation (RPA). 56th Hawaii International Conference on System Sciences, Hawaii.

Tippins, N. T., & Hilton, M. L. (Eds.). (2010). *A database for a changing economy: review of the occupational information network (O* NET)*. National Academies Press.

Verma, R. (2000). An empirical analysis of management challenges in service factories, service shops, mass services and professional services. *International Journal of Service Industry Management*, *11*(1), 8-25.

Violante, G. L. (2008). Skill-biased technical change. In L. E. Blume & S. N. Durlauf (Eds.), *The New Palgrave Dictionary of Economics* (2nd ed.). Palgrave Macmillan.

von Nordenflycht, A. (2010). What is a professional service firm? Toward a theory and taxonomy of knowledge-intensive firms. *Academy of Management Review*, *35*(1), 155-174.