How predictable is job destruction? Evidence from the Occupational Outlook*

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July 20, 2025

PRELIMINARY AND INCOMPLETE

Abstract

Is it feasible to alert workers of impending job destruction? For 80 years, the US Bureau of Labor Statistics has tried, providing thousands of employment forecasts in its *Occupational Outlook*. I test accuracy by comparing these forecasts to actual job growth. The forecasts were informative: across 4,000 unique predictions, occupations in the top third of projections grew significantly more in the subsequent three decades compared to ones in the bottom third. But the accuracy is similar to simple extrapolations using employment data that would have been available to the authors. The forecasts were especially accurate when they made reference to business practices, like how a shift to cafeteria-style restaurants decreased the demand for waiters. On average, technology-focused forecasts had lower accuracy because they underestimated the extent of job loss. Overall, the results suggest that—at least historically—occupational growth and collapse has been foreseeable.

*Email: maxim.massenkoff@nps.edu. Jalaluddin Khan provided excellent research assistance. For helpful feedback and comments, I thank Alexander Barry, Tyler Borek, Ethan Heppner, Ezra Karger, Evan Rose and Nathan Wilmers. I also thank the Bureau of Labor Statistics for help understanding the historical data sources. All errors are my own.

1 Introduction

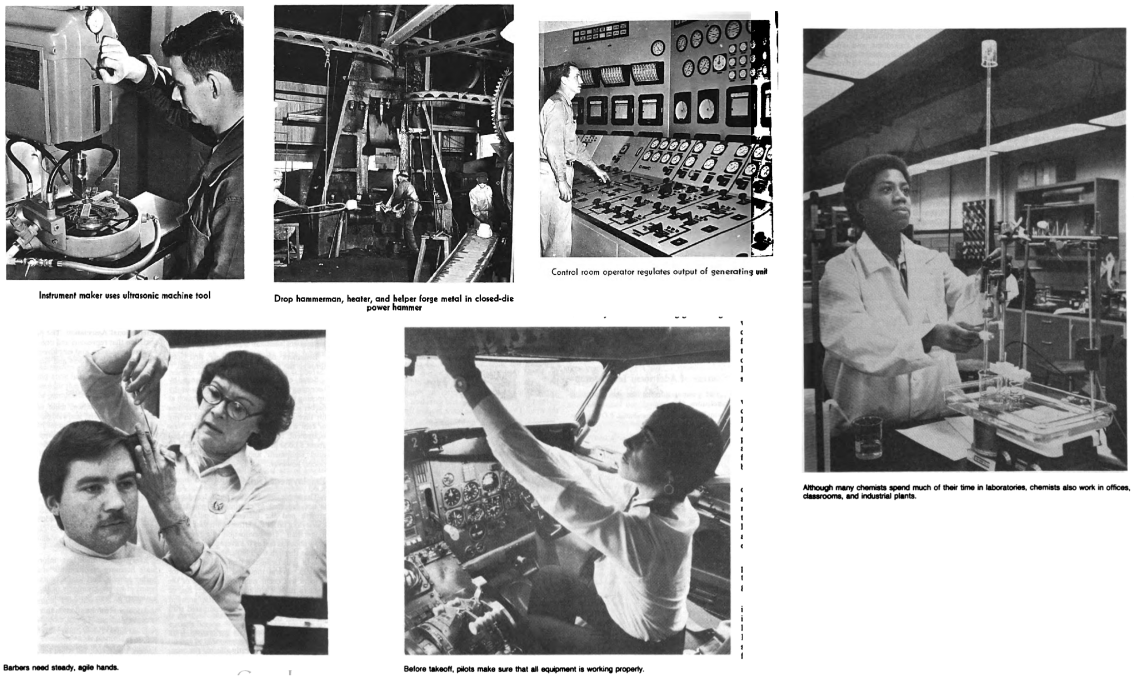
Over the last century, the US occupational structure has been transformed by trade (Autor et al., 2013), technological advances (Autor et al., 2003), and institutional shifts (Fortin and Lemieux, 1997). These changes create winners and losers. College graduates saw decades of relative wage increases (Goldin and Katz, 2008), while blue collar workers like welders, seamstresses, and butchers suffered earnings losses (Edin et al., 2023). Recent advances in artificial intelligence could bring even larger changes to the labor market (Frey and Osborne, 2017), spurring calls for protective policy responses (e.g., Boren, 2024).

One underexplored measure is alerting workers to imminent technological displacement. In the best cases, occupational decline can be managed by reducing supply of new entrants and allowing incumbents to age out of the workforce proportionately to the occupation's employment decline (Cavounidis et al., 2023). And some evidence suggests that simple information can meaningfully alter economic trajectories. College students respond to earnings information about majors (Wiswall and Zafar, 2015). Workers are able to secure higher paying jobs when provided advance warning of layoffs (Cederlöf et al., 2025). And in a recent survey experiment, information about automation risk changed people's job preferences (Cattaneo et al., 2025). These suggest that if AI-driven changes are foreseeable, forecasts could mitigate the economic costs of displacement through either awareness or targeted policies.

This paper asks how feasible it is to predict the demise of an occupation. My core dataset is 23 issues of the Bureau of Labor Statistics' *Occupational Outlook* (Morisi, 2019; Pilot, 1999), a report meant to advise job seekers on the prospects of most occupations in the US. In the widely-circulated 1948 edition, for example, the authors foresaw the bleak prospects of railroad switchers: "Over the long run employment is expected to decrease, owing to replacement of hand-operated switches by automatic equipment" (US BLS, 1948). Combining these predictions with US Census data, I ask whether the Outlook's advice was predictive, whether it beats a simpler benchmark based on past growth, and where its predictions faltered.

I find that, overall, the authors of the Outlook could predict when jobs were on their way out. I use large language models and semantic embeddings to rate the optimism of their predictions, since the Outlook did not provide quantitative predictions in the years studied. Splitting these verbal as-

Figure 1: Clippings from the Occupational Outlook



Notes: The Outlooks include photographs of workers. Clockwise from top left corner: Instrument maker, 1963. Industrial workers, 1963. Control room operator, 1963. Chemist, 1980. Pilot, 1980. Barber, 1980.

sessments into terciles, and pooling across all reports for which data is available, I find that the top third grew about 50 percentage points faster than the bottom third over the three decades following their publication. This was not from merely predicting the demise of already-small jobs: these results are similar weighting by the occupation shares at the time of the report. The gap in outcomes between the highest and lowest rated jobs grows over time. Sixty years after the initial prediction, employment in the top tercile has quadrupled compared to a doubling in the bottom tercile.

These differences are large, but the forecasting task may not have been that hard in the first place. To approximate a simple hands-off prediction, I rank jobs by their growth over the most recent two decadal Censuses, so that, for example, the naive prediction in 1956 is based on Census-derived occupational growth numbers from 1940 to 1950. These terciles perform similarly to the Outlook's predictions. The best prediction, however, combines both forecasts. And a head-to-head comparison shows that when the Outlook disagrees with the hands-off prediction, the Outlook is right. Although I base my main results on terciles for legibility, I obtain similar evaluations of forecasting accuracy by training machine learning models to make continuous predictions of growth based on the semantic embeddings of the forecasts. In particular, the r-squared is higher for the Outlook-based predictions, and highest when both predictions are combined.

I next dig into the topics covered in the Outlooks. The reports are subjective, at times emphasizing factors like demographics, government spending, and technology. Suburban expansion is argued to increase the demand for veterinarians, and dentistry is expected to grow as people get better at preserving their natural teeth. I find that those referencing the business practices of the employers were most likely to generate accurate predictions. Predictions referencing technology did distinctively worse. On average, they were much more pessimistic—but the Census data shows they were not pessimistic enough.

This paper contributes to research on occupational shifts and job displacement. First, I build on recent papers trying to predict the economic impact of AI (e.g., Acemoglu, 2025; Webb, 2019; Humlum and Vestergaard, 2025; Rock et al., 2023). Second, I provide new evidence on the predictability of occupational transformation (Atalay et al., 2020; Autor et al., 2003). I highlight that, in addition to identifying the jobs whose tasks are automatable, questions about the pace and predictability of change might also help us to understand the economic impacts.

I also contribute to a literature evaluating the quality of predictions (Tetlock, 2017). Numerous studies have evaluated the skills of experts in predicting certain outcomes, such as behavioral scientists predicting experimental results (DellaVigna and Pope, 2018), economists predicting gross domestic product (e.g. Timmermann, 2007), and corporate executives predicting stock returns (Ben-David et al., 2013). And a rich history in finance and macroeconomics debates the predictability of financial asset prices (Fama, 1970), interest rates (Fama and Bliss, 1987), and inflation (Faust and Wright, 2013), often compared to simple heuristics. But evaluations of occupational predictions are scarce. The US BLS has provided some scattered assessments for reports from the 1980s and afterward (e.g., Veneri (1997) and studies reviewed at U.S. BLS (2024)). To my knowledge, this is the first paper to study the long-run accuracy across multiple Outlooks.

2 Background on the Occupational Outlook

The *Occupational Outlook* dates back to a 1938 report by the President's Advisory Committee on Education, which identified significant challenges in providing career guidance to young people (Goldstein, 1999). The committee called for an "occupational outlook service" that would systematically outline job attributes, required training and education, and employment projections (report cited in Goldstein, 1999). Following this recommendation, the Outlook was first published by the Veterans Administration in 1946, with the Bureau of Labor Statistics taking over publication from 1948 to the present, releasing new editions every 2-3 years. It was billed as a resource for career counselors in the Veterans Administration, high schools, vocational schools, and colleges.

The Outlook quickly gained wide circulation. Between 1949 and 1959, each edition sold an average of 40,000 copies (Figure 3 in Morisi, 2019), substantial for a government publication.[1] Occupational forecasting has since been adopted internationally, with several countries including Australia, Canada, Finland, France, Germany, and the United Kingdom developing similar publications (Hughes, 1994).

I digitized the 23 available Outlook editions from 1946 to 1996. The Outlooks provided information on several different areas for on average 238 occupations per publication. Below I show some excerpts for the different sections of "college and university teacher" from the 1951 Outlook:

- **Nature of the Work:** "...Besides teaching, these faculty members frequently do research..."
- **Where Employed:** "...The great majority of faculty members are in 4-year colleges, universities, and professional schools..."
- **Training and Qualifications:** "...In general, a doctor's degree is required for the better college teaching positions, but requirements vary considerably according to institution and type of appointment..."
- **Earnings:** "...Average annual salaries in 1947-48 ranged from $2,780 for lecturers to $5,750 for full professors..."
- **Employment forecast:** "...Opportunities for new entrants in college teaching in the first half of the 1950 decade will be limited largely to replacement needs..."

The primary focus in this study is the employment forecast in the last bullet. U.S. Bureau of Labor Statistics (2021) discusses how the predictions have been made since the 1970s. Before this point, the forecasts were less systematic. In general, these old forecasts do not contain quantitative predictions. Still, the forecasts were sophisticated, drawing from diverse factors like demographics, government spending, consumer preferences, and technology. To give a few examples: in the 1957 Outlook, the

[1] For context, Yucesoy et al. (2018) find that New York Times bestselling books typically sell between 10,000 and 100,000 copies in their first year, using data from 2008 to 2016.

authors note insurance policies affecting x-ray demand; the move to the suburbs predicting a rise in pet ownership and demand for veterinarians; new highway construction causing a surge in archaeology jobs to preserve unearthed artifacts; and new razors allowing men to shave themselves more easily, displacing barbers.

3 Illustrative examples

The Outlooks contain employment predictions, identifying jobs likely to grow and shrink. Here I dig into the 1946 and 1948 issues to provide illustrative examples. Table 1 shows excerpts for four selected occupations: teachers, dentists, locomotive firemen, and telegraph operators. I give more example occupations in Table 2, and for reference I excerpt the entire section on physicians in Section A.1.

Table 1 gives excerpts of the employment predictions for these four occupations. The Outlook predicted many employment opportunities for teachers, especially at lower grade levels (top right cell of Table 1). The authors cite an increasing birthrate and "a trend toward extending public school training to the younger groups." The Outlook also predicted growing demand for dentists due to "a long-run trend toward better oral health" and government-sponsored dental care for military veterans.

On the other hand, the Outlook was more pessimistic about opportunities for telegraph operators and locomotive firemen. Telegraph operators are predicted to have slowly declining employment due to the adoption of the telephone and teletype machines. Locomotive firemen (who help operate steam trains) are predicted to be displaced by the adoption of "Diesels or other powerful new engines."

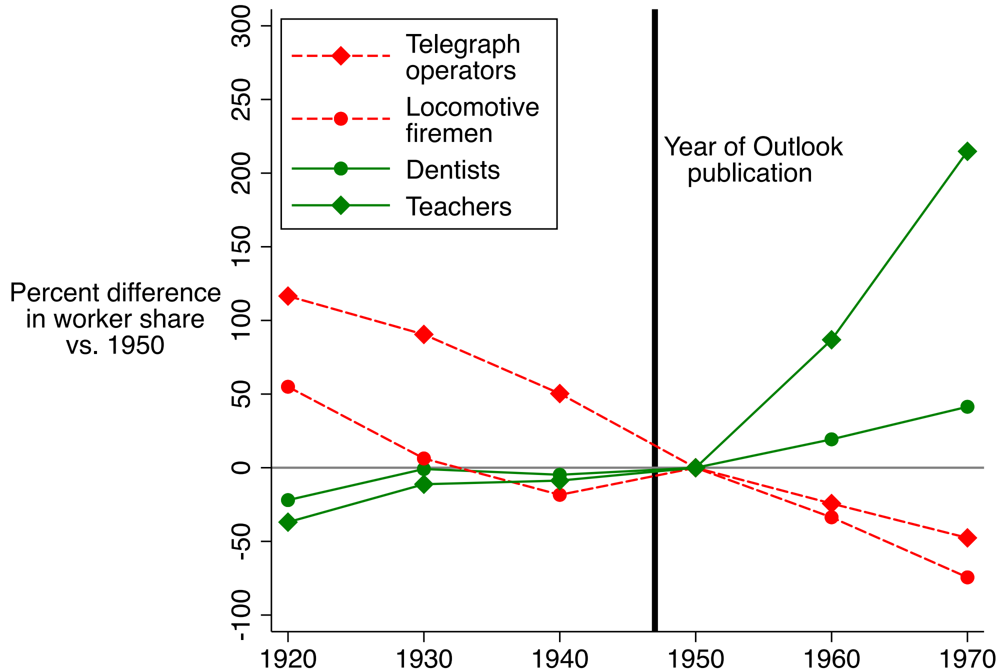
How well did these predict employment trends? To illustrate the empirical approach, I next analyze employment data from the US Census (Ruggles et al., 2025) for those same occupations. As I document in Figure 2, the predictions were broadly correct. Employment of dentists and teachers (green lines) grew following the report, while furriers and switch operators (red lines) saw employment decline. In both cases, the occupations with pessimistic predictions were already shrinking, and those with optimistic predictions were (more slightly) growing. This raises a core methodological question: were the Outlooks more accurate than simple trend extrapolation? I discuss this more below.

Table 1: Employment Predictions from the 1946 and 1948 Outlook, Selected Examples

Occupation	**Prediction**
	Positive Predictions
Kindergarten and elementary teachers	There is a serious shortage of teachers at the present time. Generally, throughout the Nation, shortages are greatest in kindergartens and other primary grades in the cities and in rural elementary schools... Not only is there a trend toward extending public school training to the younger groups, but the rising birth rate of the past 10 years has already increased the number of teachers needed in kindergartens and primary grades.
Dentists	The annual output of graduates must be raised, in order to maintain even the existing ratio of dentists to population. Furthermore, there is a long-run trend toward better oral health care for the general population, particularly school children, and the Veterans Administration expects to need an increasing number of dentists for care of ex-servicemen and women. For all these reasons, the outlook for young persons having the proper qualifications and interest in the work is exceptionally bright.
	Declining/Stagnating Predictions
Telegraph operators	The downward trend of employment expected in the occupation over the long run will probably not be sharp enough to cause heavy, prolonged lay-offs, though some of the many hundreds of workers who die, retire, or leave for other reasons every year will not be replaced. Among the factors which have in the past reduced the number of Morse telegraphers needed and will continue to do so in the future are the use of telephone in place of telegraph in train dispatching and the introduction of teletype machines in relay offices.
Locomotive firemen	Over the long run, employment of firemen will tend to decrease, although cuts in working hours may at times offset this trend. Increasing use of Diesels or other powerful new engines will cut down employment of firemen, because the same amount of traffic can be hauled with fewer engine crews, especially in mountainous areas where steam "helper" engines and crews can be eliminated.

Notes: This table excerpts employment predictions for four different occupations using the 1946 and 1948 *Occupational Outlook*.

Figure 2: Employment growth in four example occupations from the 1946 and 1948 Outlook



Notes: This figure shows growth in employment for four of the occupations mentioned in the 1946 and 1948 *Occupational Outlook*. The black vertical line marks the year of its publication. Source is the US Census data.

4 Methods

The Outlook was accurate for those four occupations, but these examples are hand-picked. Next I discuss how I systematically evaluate all the predictions made over several decades of reports. There are a few core challenges. One is converting the Outlook text, which primarily included verbal predictions over the years studied, into a quantitative prediction. I also discuss a naive benchmark to contrast with the Outlook's forecast.

Quantifying predictions The early Outlooks give verbal predictions. (I give examples in the "Text" column of Table 2.) Converting these to predictions is similar to a sentiment analysis problem, except that the goal is to uncover sentiment about employment.

I first used a large language model to convert these into numbers. For each occupation in each Outlook, I inputted the sentences relevant to that job's growth into the model and asked it to output a numeric prediction with the following interpretation:

Table 2: Examples from the 1948 *Occupational Outlook*

Occupation	Forecast	Text
Wood Turners (Furniture)	1	Very few additional skilled wood turners (hand) can be employed. Most wood turning nowadays is done by less-skilled automatic lathe operators.
Cabinetmakers	2	Only a few cabinetmakers are now employed in the industry and any additions there are unlikely. A limited number may find jobs in small custom plants or repair shops.
Switch Tenders (Railroads)	2	Very small occupation offering few if any opportunities to men without railroad experience. Long-run downward trend in employment.
Hostlers (Railroads)	3	Hostler jobs are filled only by men with railroad experience; occasional openings for newcomers as helpers. Employment likely to decline slowly over the long run.
Bookbinders	3	Many more openings than usual during the next few years for both journeymen and beginners; decreasing numbers of job opportunities thereafter. Long-run employment trend slowly downward.
Fur Blenders	4	Openings for new workers limited to a small number of replacements for those who leave the occupation from time to time. No increase in employment expected over the longer run.
Electroplaters	4	Few job openings for trainee electroplaters in the next several years. No marked changes in employment over the longer run, with most job openings for replacements of workers who die or retire.
Carmen (Railroads)	5	A good many openings for newcomers as apprentices and helpers in the near future; good prospects for skilled carmen. Long-run employment trend slowly downward.
Blacksmiths	5	There will be a small number of openings for new workers in this occupation.
Kindergarten and elementary school teachers	6	Excellent immediate employment opportunities. Shortages of teachers for elementary grades will continue longer than at higher grade levels.
Signalmen and Signal Maintainers (Railroads)	6	Good prospects for skilled men and moderate number of openings for newcomers. Upward trend in employment expected in both short and long run.
Physicians	7	Excellent opportunities for those able to gain admission to medical school and complete requirements for practice.
Radio Announcers	7	The broadcasting industry is growing rapidly....Many hundreds of additional announcers will be needed in the near future to man new stations and those established stations which are expanding their facilities, as well as to fill vacancies due to turn-over.

Notes: This table shows predictions for several occupations in the occupational outlook. **Occupation** gives the name of the occupation (as given in the Outlook). **Forecast** is the numeric forecast, inferred using a large language model, where 1 = Rapid decline/obsolescence, 4 = Stable/no change, and 7 = Exceptional growth. **Text** is the raw excerpted text from the 1948 Outlook for that occupation.

- 1 = Rapid decline/obsolescence
- 2 = Moderate decline
- 3 = Slight decline

- 4 = Stable/no change
- 5 = Modest growth
- 6 = Strong growth
- 7 = Exceptional growth

The full prompt is given in Appendix B, and the middle column in Table 2 shows the example output for several of the occupations. I call this the growth score in the analysis below.

Embeddings-based predictions One limitation of the LLM-based approach is that, even if instructed not to, the model might incorporate occupation-specific contextual knowledge when generating numeric ratings rather than focusing solely on the growth language. Identical phrases like "the market will continue to grow" might receive different numeric ratings when applied to different occupations due to the model's pre-existing knowledge about these fields. For example, the model could be more skeptical that employment for welders will grow compared to that for teachers, and this could leak into its numeric score. If contextual clues make it clear that the sentence is about welders, the model may bake-in the decline of welding based on its historical knowledge.

To hedge against this risk, and to ensure that our results do not depend on any particular operationalization, I also construct quantifications of the Outlook predictions using embeddings. I first use an LLM to extract the context from the Outlook paragraphs, so that no occupation-specific language could tilt the embeddings. I give examples in Appendix C. Next, I encode the Outlook paragraphs for every job using the `all-mpnet-base-v2` sentence embeddings. Finally, I fit an XGBoost model predicting job growth using these embeddings. The out-of-sample predictions taken from this process form my core continuous Outlook prediction.

Occupations I use the harmonized `occ1950` variable from IPUMS (see "Occupation Codes and Income Scores" in the IPUMS User Guide IPUMS (2025)). As a robustness check, I also study results using only the occupations that appear in all Census decades.

Counterfactual predictions We will find that the Outlook predictions are highly predictive of occupation growth. However, to provide a benchmark, I simply rank the same occupations by their growth in the most recent decade for which data would have been available. So, for example, for the 1951 Outlook, its predictions are compared to a ranking of jobs based solely on their growth from 1940 to 1950. This is meant to approximate what an analyst would have had access to at the time.

5 Results

5.1 Raw data

I first show raw data tracking employment growth in the mentioned occupations in panel (a) of Figure 3. The build begins with an occupation from an Outlook in a specific Census year. Its normalized growth is its employment in the current Census year divided by its employment in the reference Census year, defined as the most recent Census as of the Outlook's publishing. Each of these observations is assigned an "event time", the difference between the Census and Outlook year, rounded to the nearest decade. Then, I take the average of normalized growth for all the decades since predictions for every tercile of optimism.

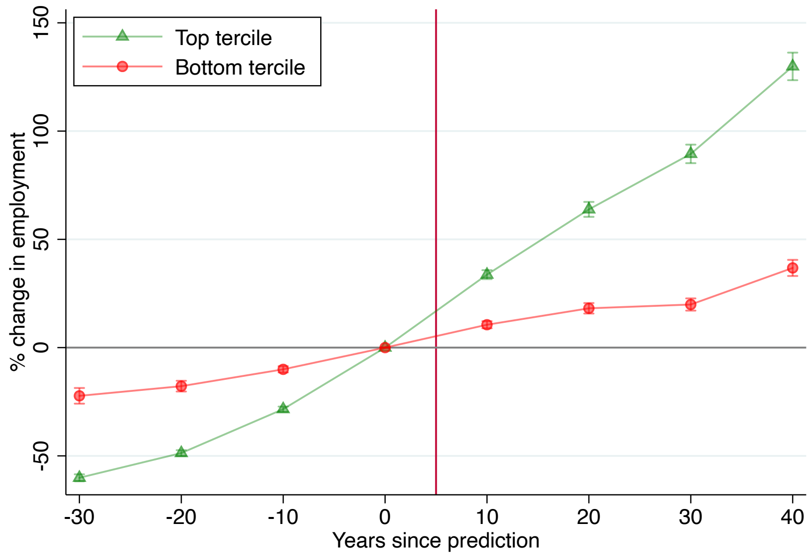
The results show that the Outlooks were highly effective at predicting job growth. Twenty years after the Outlook prediction, employment in the top tercile occupations has grown by 57 percent, compared to just 12 percent in the bottom tercile occupations. Also, this trend continues at year 60, where an almost 200 percentage point difference in growth opens up between the top and bottom tercile.

These are striking differences, but how do they compare to a naive straight-line prediction? Panel (b) of Figure 3 shows similar results except the terciles are chosen by ranking occupations based on their growth over the most recent two decades of Census data that would have been available to the Outlook authors. Observed growth is also strikingly predictive of long-run growth. At year twenty, for example the top tercile jobs have grown 50 percent compared to 11 percent in the bottom tercile. This suggests that the gains from consulting the Outlook's advice might have been fairly similar to consulting Census data.

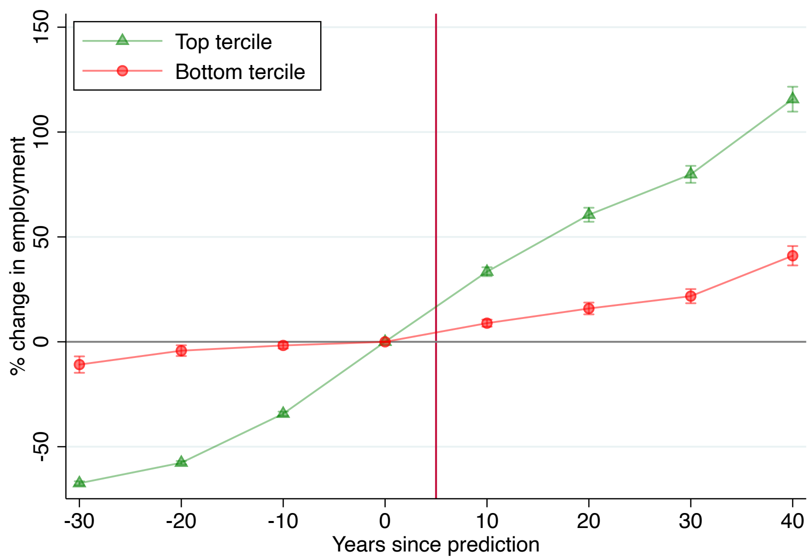
5.2 Regression analysis

In order to better understand the quality of the predictions, I use a regression framework. The unit of observation is an (occupation)-(Outlook year)-(Census year) combination, and I restrict to Census observations that are between 5 and 34 years since the prediction in order to approximate what would be useful to a prospective job seeker. Each observation is weighted by the number of workers in the reference year (i.e., the previous Census when the Outlook was published). Note that the same Census

Figure 3: Occupational outlook vs. naive predictions



(a) Ranked using *Occupational Outlook* text



(b) Ranked using growth over the previous decade

Notes: Panel (a) shows percent growth in occupational employment, split by whether it is in the highest or lowest tercile of Outlook employment sentiment. Year 0 is the year the prediction is made. So, for example, it is 1951 for the 1951 Outlook, and more recent Outlooks drop out of the sample as the years progress. The outcome is employment in that occupation divided by its employment in the reference year (the Census before the Outlook was produced). Panel (b) shows the same, except the terciles are based on the naive prediction using only employment growth over the previous decade.

year for a given occupation will be repeated for as many times as it appears in the Outlook. Standard errors are two-way clustered at the job level and Census level.

I estimate the following using ordinary least squares:

$$Y_{iot} = \alpha_t + \beta_1 * BottomTercile_{iot} + \beta_3 * TopTercile_{iot} + e_{iot}. \tag{1}$$

where Y_{iot} is some employment outcome like its normalized growth. This model says that the growth of job i from Outlook year o during Census year t is a function of Census year fixed effects (α_t) and dummies for being in the top and bottom tercile of expected growth. The core estimand of interest is

$$\beta_3 - \beta_1,$$

the additional "lift" in employment growth that a job seeker could expect if they chose a job in the top 33 percent of forecasts instead of one in the bottom 33 percent.

I estimate Equation 1 using three different ways to define terciles. The first two are based on Outlook optimism and the naive prediction, as in Figure 3. The third is the simplest possible combination of the two, taking the unweighted average of the two terciles.

In Table 3, I use log employment growth since the reference year as the outcome. Column (1) shows the results for the Outlook terciles. Jobs in the lowest tercile grew 5 log points less than jobs in the middle tercile. And jobs in the highest tercile grew 6 log points more. My estimate of the lift from leaving the bottom for the top tercile is the difference between these two, or 10 log points (in the row marked "Highest - Lowest"). This provides some of the first comprehensive evidence that prospective workers would do well by reading the Outlook's prognostications.

How difficult was it to make these predictions? Column (2) shows the same results for observed growth, achieving a lift of 9 log points. The Outlook outperforms the observed terciles based on this measure, but almost all of the lift is attainable using this naive method. This result suggests that, in order to avoid a shrinking job, one could do quite well by merely avoiding jobs that shrank according to the most recent available data.

Finally, I combine Outlook and observed in column (3). This shows the biggest lift, 12 log points. This suggests that the Outlook left some predictive power on the table by not integrating information from the simple decadal growth numbers derived from the Census.

Table 3: Regression results

	(1) Outlook	(2) Naive	(3) Combined
Lowest Tercile	-0.052***	-0.055*	-0.074***
	(0.017)	(0.027)	(0.021)
Highest Tercile	0.055**	0.039*	0.045**
	(0.020)	(0.021)	(0.018)
Highest - Lowest	0.107	0.094	0.120
	(0.024)	(0.026)	(0.027)
R-squared	0.148	0.139	0.154
N	12,613	12,534	12,534

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table shows three separate regressions with measures of occupational growth as the outcome. The two independent variables are dummies for being in either the lowest or highest growth category according to the forecasting technique indicated in the columns. The Outlook forecasts slightly outperform a naive forecast based on based past data, but a forecast combining the two performs best.

Continuous predictions This provides evidence that the Outlook predictions were useful and would have provided job seekers with a leg up. However, most of the information captured in the Outlook was also in existing Census data. I next explore several robustness checks to help ensure that my data construction or parameterization is not driving the results.

First, I use the continuous predictions based on the XGBoost procedure described in Section 4. I fit a machine learning model with the same hyperparameters for the naive prediction as well in order to give both forecasts similar flexibility in functional form. The results of these estimates are given in Table 4.

Overall, this more flexible method for quantifying the Outlook predictions shows much higher predictive power. The r-squared based on the XGBoost predictions from the Outlook is 0.25 compared to just 0.16 for the naive predictions using past growth.

Robustness To probe the importance of my particular parameterization of growth, I show in Table A1 that I get the same qualitative results when I swap out my main growth outcome for the normalized growth in the worker share of the labor force, also measured using the Census. Another potential concern is that some occupation codes get merged with others or otherwise drift in and out

Table 4: Regression results, Continuous predictions

	(1)	(2)	(3)
ML pred based on Outlook embeddings	2.207^{***}		1.913^{***}
	(0.256)		(0.255)
ML pred based on past growth		2.418^{***}	1.338^{***}
		(0.356)	(0.240)
Outlook and Census fixed effects	X	X	X
R-squared	0.299	0.156	0.332
Observations	9,526	9,526	9,526

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table shows regressions using the Outlook, past employment growth, and the both to predict log employment growth. The ML predictions are from XGBoost with basic hyperparameter tuning.

of the sample. In Table A2, I also find the same results restricting to the 132 occupations that are observed during each of the seven decades of my analysis.

In all cases, the core takeaways are quite similar. The Outlook forecasts identify a large difference in growth over the subsequent three decades (column 1). The ranking based only on observed growth is close behind (column 2). And the measure combining both growth predictions exceeds them both in predictive power (column 3).

5.3 Decade-specific estimates

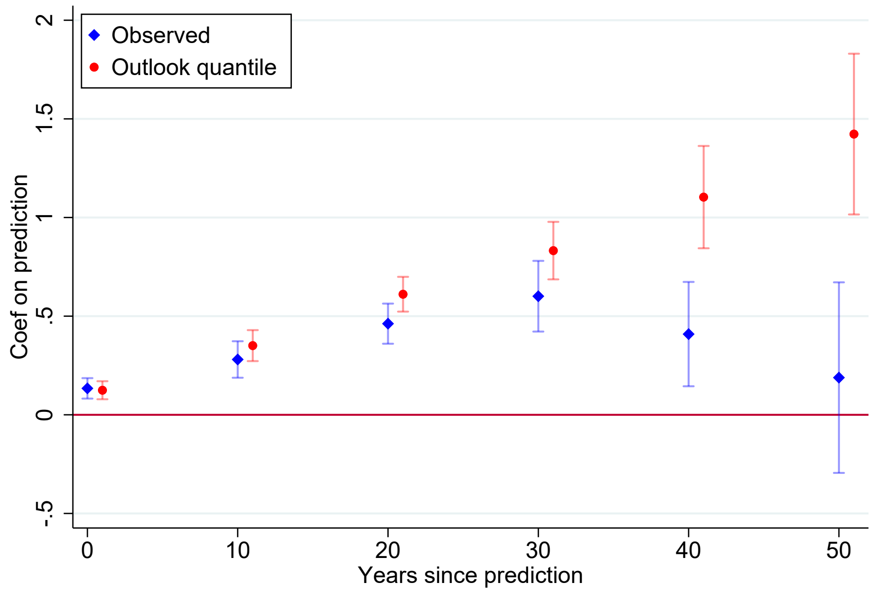
These regressions summarize the overall growth differences attained by the forecasts over three decades. Next, I look at the estimates five decades following the forecast, allowing the difference in terciles to depend on the number of decades since the prediction. The difference between β_3 and β_1 is plotted along with its confidence intervals.

Figure 4 shows the results. Between zero and thirty years after the prediction, the Outlook performs similarly to the predictions based on observed growth. For example, both achieve a 50 percentage point growth difference two decades after the prediction. But at 40 years after, the series diverge, with the Outlook predictions become more informative and the observed growth predictions less so.

5.4 Topic analysis

Were the Outlook forecasts particularly accurate or inaccurate when they drew evidence from certain areas? The Outlook sections were wide ranging, often covering industry growth, replacement and turnover, technological changes, educational requirements, demographic shifts, government spend-

Figure 4: Predictive lift by years since prediction



Notes: This figure shows decade-specific estimates of the predictive accuracy of the Occupational Outlooks (red circles) compared to a naive prediction based on the most recent 10 years of occupation growth (blue diamonds). Each of the two series is based on a single regression like Equation 1, except the forecasts are interacted with the time horizon. The whiskers give the 95% confidence intervals. The x-axis shows years since the prediction. For example, the red circles at year 20 show that jobs in the top tercile of optimism based on the Outlook assessments grew just over 50 percentage points more than those in the bottom tercile. All specifications include Outlook and Census fixed effects, so this compares jobs in the same Outlook issue and the same Census. The blue diamonds show a similar but smaller lift for forecasts using the observed growth in the most recent decade.

ing and regulations, geographic factors, changes in business models, and consumer tastes.

For example, this sentence from the 1946 Outlook for optical mechanics mentions both technological and demographic shifts: "Technological improvements, based on wartime-gained experience in precision optics, will tend to reduce labor requirements; but an offsetting factor is the likelihood of a continued increase in number of eyeglass wearers." And this passage on dietitians from the 1951 Outlook cites government spending: "[T]he Federal Government's hospital construction program is creating many new jobs for dietitians in communities which formerly had no hospital or only a small one."

To examine the connection of topics and accuracy, I estimate the following:

$$Y_{iot} = \alpha_{ot} + \beta_1 Outlook_{iot} + \beta_2 Topic_{io} + \beta_3 Outlook_{iot} * Topic_{io} + e_{iot}, \quad (2)$$

where Y_{iot} is the growth of job i from Outlook year o in Census year t, $Outlook_{iot}$ is the 1-7 optimism score and $Topic_{io}$ is an indicator for whether the Outlook covering job i in edition o mentioned a particular topic. α_{ot} denotes Outlook by Census year fixed effects. The coefficient of interest is β_3, which measures whether mentions that topic tighten or loosen the connection between the forecast and actual growth. I use the same 5 to 34 year prediction window. For the Outlook variable, I use the equally-weighted average of the normalized growth score and the XGBoost prediction from the embeddings. This increases power by strengthening the relationship between the outcome and the Outlook.

Table 5: Topic regressions

	(1) Industry	(2) Technological	(3) Demographics	(4) Government	(5) Geography	(6) Business	(7) Consumers
Outlook	0.102	0.303^{***}	0.222^{***}	0.221^{***}	0.252^{***}	0.185^{***}	0.240^{***}
	(0.081)	(0.038)	(0.031)	(0.033)	(0.034)	(0.033)	(0.031)
Topic	0.249	-0.171	-0.067	0.071	-0.049	0.198^{**}	-0.309^{***}
	(0.196)	(0.095)	(0.084)	(0.095)	(0.087)	(0.087)	(0.097)
Outlook × Topic	0.145	-0.110^{**}	0.068^{*}	0.069	-0.041	0.094^{*}	-0.033
	(0.098)	(0.037)	(0.034)	(0.043)	(0.062)	(0.045)	(0.044)
Share mentioning	0.951	0.561	0.378	0.283	0.182	0.325	0.188
R-squared	0.316	0.330	0.319	0.318	0.315	0.332	0.327
Observations	9143.000	9143.000	9143.000	9143.000	9143.000	9143.000	9143.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Notes: This table shows estimates of Equation 2, where the forecast is interacted with an indicator for the presence of a certain topic. For example, in column (2), I study how predictions of employment growth depend on the mention on technology. The interaction is negative, suggesting that Outlooks that mentioned technology were less predictive than those that did not. In the third row from the bottom, I report the share of Outlooks mentioning the topic. In column (2), this figure is 56% for technology. All regressions contain Outlook and Census fixed effects.

I show results in Table 5. The table shows the main effect and interaction of the Outlook and topic dummies for seven different topics, each estimated in a separate regression. The row labeled "share mentioning" gives the fraction of Outlooks in the sample covering that topic. This is highest for Industry (96%) and lowest for Geography (21%).

The factor most associated with improved predictions is Business, referring to shifts in how services are provided. Some examples:

- Dentists, 1978: "Employment of dentists is expected to grow about as fast as the average for all occupations due to population growth, increased awareness that regular dental care helps prevent and control dental diseases, and the expansion of prepayment arrangements, which make it easier for people to afford dental services."

- Truck drivers, 1974: "[T]he trend to large shopping centers rather than many small stores will reduce the number of deliveries required."

- Firefighters, 1974: "Many jobs also will be created as smaller communities replace volunteer fire companies with official departments. In addition, more firemen will be required as city fire departments continue to shorten the hours that their men work."

Interestingly, mentions of technology are associated with worse predictive performance. Column (2) of Table 5 shows that the link between the forecast and job growth was weakest when the Outlook mentioned technology. Over half (56%) of the forecasts mention technology. Some excerpts from assorted occupation Outlooks tagged as technological are below:

- Civil Aviation Occupations, 1963: "Over the longer run, the rate of airline employment growth is likely to slow down because the introduction of a supersonic transport plane will enable the airlines to fly more traffic without corresponding expansion in the number of airline planes and workers...[M]ore widespread installation of mechanical equipment, such as conveyors, will permit airlines to move greatly increased amounts of baggage and cargo without comparable growth in employment of baggage and cargo handlers."

- Power truck operators, 1968: "[T]he increasing use of containers and pallets for moving goods will increase the need for power truck operators. The favorable effects of these two factors on employment, however, will be partially offset by improved plant design and the continued development of more efficient power trucks and other mechanized materials handling equipment."

- Telephone operators, 1988: "Employment of switchboard operators is expected to grow about as fast as the average for all occupations as businesses expand to meet the changing needs of the population. On the other hand, employment of directory assistance operators and central office operators is expected to decline as automation continues to increase these workers' productivity."

- Bakers, 1980: "[A] continuation of the trend toward larger and fewer baking plants will allow these larger bakeries to make more use of labor-saving technology and thus meet the demand with fewer employees. Pneumatic handling systems and pumps quickly and easily transfer ingredients from trucks or railroad cars to storage containers. The "continuous mix" process eliminates doughmixing and proofing operations, and conveyor systems move panned dough from ovens to labeling machines in one continuous process."

Table 6: The role of technology in the Outlook accuracy

	(1) Growth score	(2) Actual job growth
Mentions technology	-0.562***	-0.306**
	(0.110)	(0.101)
Growth score		0.183***
		(0.026)
Year $\times$ Outlook Year FEs	X	X
Outcome mean	4.861	1.551
Outcome SD	1.335	1.243
R-squared	0.098	0.157
Observations	11,212	11,212

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Why did the forecasts mentioning technology fare so much worse? I use two simple regressions in Table 6 to shed light on this. In Column (1) of Table 6, I regress the 1-7 optimism score on the indicator for mentioning technology and Census year by Outlook year fixed effects. The coefficient suggests that forecasts mentioning technology tended to be gloomy, with on average 0.56 fewer points on the 7-point scale. Column (2) shows, however, that these predictions were not pessimistic enough. The outcome in column (2) is actual growth (relative to the reference year), as in Equation 1 and Table 3, and I include both the growth score and the technology dummy. The coefficient on the indicator for technology is large and negative, suggesting that those predictions were overly optimistic. In summary, although technology-imbued predictions were already more pessimistic than average, the predictions improve when an additional growth discount on the order of 30 percentage points is added to forecasts mentioning technology. Note though that this does not mean that technological innovations tended to be bad for employment growth—it could be that the Outlook's authors only thought to mention technological shocks that would displace labor.

6 Discussion

These results suggest that, at least historically, occupational employment has been predictable. Using only the qualitative forecasts offered by the Bureau of Labor Statistics's *Occupational Outlook* from 1946 to 1996, I find large differences in growth outcomes for the most and least optimistic assessments. Interestingly, this contrasts with other macroeconomic predictions (see, e.g., Timmermann, 2007), although what counts as good can depend on the context. Notably, though, these predictions were not that much better than a naive forecast based only on growth over the previous decade. One implication is that, in general, jobs go away slowly: over decades rather than years. Historically, job seekers have been able to get a good sense of the future growth of a job by looking at what's been growing in the past.

Since the predictions have been useful on average, it might help policymakers to study the occupations predicted to be impacted. The most recent Outlook (U.S. Bureau of Labor Statistics, 2023) mentions artificial intelligence for about twenty occupations. It predicts that information technology jobs such as computer network architects and database administrators will grow faster than average, while demand for paralegals and graphic designers will be curbed somewhat by automation.

If these findings are a good guide for what will unfold over the coming decades from AI-induced changes, the organic or government-prompted dissemination of occupational forecasts could limit the economic harms. But there are key reasons why this time could be different. A recent estimate found that 37 percent of jobs in the US could be done fully remotely (Dingel and Neiman, 2020), and some AI observers think that all of these jobs could be performed by "drop-in remote workers" (Aschenbrenner, 2024). If this is true, the coming economic changes could dwarf the slow displacement that once sidelined teamsters, elevator operators, and farmers.

References

Acemoglu, Daron, "The simple macroeconomics of AI," *Economic Policy*, 2025, *40* (121), 13–58.

Aschenbrenner, Leopold, "Situational awareness," *The decade ahead. situational-awareness. ai*, 2024.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum, "The evolution of work in the United States," *American Economic Journal: Applied Economics*, 2020, *12* (2), 1–34.

Autor, David H, David Dorn, and Gordon H Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American economic review*, 2013, *103* (6), 2121–2168.

_ , Frank Levy, and Richard J Murnane, "The skill content of recent technological change: An empirical exploration," *The Quarterly journal of economics*, 2003, *118* (4), 1279–1333.

Ben-David, Itzhak, John R Graham, and Campbell R Harvey, "Managerial miscalibration," *The Quarterly journal of economics*, 2013, *128* (4), 1547–1584.

Boren, Zach, "How Government Can Embrace AI and Workers," 2024.

Cattaneo, Maria A, Christian Gschwendt, and Stefan C Wolter, "How scary is the risk of automation? evidence from a large-scale survey experiment," *Journal of Economic Behavior & Organization*, 2025, *235*, 107034.

Cavounidis, Costas, Qingyuan Chai, Kevin Lang, and Raghav Malhotra, "Obsolescence Rents: Teamsters, Truckers, and Impending Innovations," Technical Report, National Bureau of Economic Research 2023.

Cederlöf, Jonas, Peter Fredriksson, Arash Nekoei, and David Seim, "Mandatory Notice of Layoff, Job Search, and Efficiency," *The Quarterly Journal of Economics*, 2025, *140* (1), 585–633.

DellaVigna, Stefano and Devin Pope, "Predicting experimental results: who knows what?," *Journal of Political Economy*, 2018, *126* (6), 2410–2456.

Dingel, Jonathan I and Brent Neiman, "How many jobs can be done at home?," *Journal of public economics*, 2020, *189*, 104235.

Edin, Per-Anders, Tiernan Evans, Georg Graetz, Sofia Hernnäs, and Guy Michaels, "Individual consequences of occupational decline," *The Economic Journal*, 2023, *133* (654), 2178–2209.

Fama, Eugene F., "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 1970.

Fama, Eugene F and Robert R Bliss, "The information in long-maturity forward rates," *The American Economic Review*, 1987, pp. 680–692.

Faust, Jon and Jonathan H Wright, "Forecasting inflation," in "Handbook of economic forecasting," Vol. 2, Elsevier, 2013, pp. 2–56.

Fortin, Nicole M and Thomas Lemieux, "Institutional changes and rising wage inequality: Is there a linkage?," *Journal of economic perspectives*, 1997, *11* (2), 75–96.

Frey, Carl Benedikt and Michael A Osborne, "The future of employment: How susceptible are jobs to computerisation?," *Technological forecasting and social change*, 2017, *114*, 254–280.

Goldin, Claudia Dale and Lawrence F Katz, *The race between education and technology*, harvard university press, 2008.

Goldstein, Harold, "The early history of the Occupational Outlook Handbook," *Monthly Labor Review*, May 1999, *122* (5), 3–7. Harold Goldstein is a former Associate Commissioner of the Bureau of Labor Statistics.

Hughes, Gerard, "An overview of occupational forecasting in OECD countries," *International Contributions to Labour Studies*, 1994, *4*, 129–144.

Humlum, Anders and Emilie Vestergaard, "Large Language Models, Small Labor Market Effects," Technical Report, National Bureau of Economic Research 2025.

IPUMS, "User Guide," 2025. Accessed on March 21, 2025.

Morisi, Teresa L, "70 years of the Occupational Outlook Handbook," *Monthly Labor Review*, 2019, pp. 1–16.

Pilot, Michael J, "Occupational Outlook Handbook: a review of 50 years of change," *Monthly Lab. Rev.*, 1999, *122*, 8.

Rock, D, T Elondou, S Manning, and P Mishkin, "GPTs are GPTs: An early Look at the labor market impact potential of large language models," *Retrieved from Cornell University: https://arxiv.org/abs/2303.10130*, 2023.

Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rodgers, Jonathan Schroeder, and Kari C.W. Williams, "IPUMS USA: Version 16.0 [dataset]," 2025.

Tetlock, Philip E, *Expert Political Judgment: How Good Is It? How Can We Know?-New Edition*, Princeton University Press, 2017.

Timmermann, Allan, "An evaluation of the World Economic Outlook forecasts," *IMF Staff Papers*, 2007, *54* (1), 1–33.

US BLS, *Occupational Outlook Handbook* number 940. In 'Issue.', Bureau of Labor Statistics, 1948. Describes 250 occupations which cover approximately 107 million jobs.

U.S. BLS, "Projections Evaluations," August 2024. Employment Projections Publication.

U.S. Bureau of Labor Statistics, "Employment Projections," *U.S. Bureau of Labor Statistics*, 2021. https://www.bls.gov/opub/hom/emp/pdf/emp.pdf.

—, "Occupational Outlook Handbook," 2023. U.S. Department of Labor, continuously updated. Accessed 20 Jul 2025.

Veneri, Carolyn M, "Evaluating the 1995 occupational employment projections," *Monthly Lab. Rev.*, 1997, *120*, 15.

Webb, Michael, "The impact of artificial intelligence on the labor market," *Available at SSRN 3482150*, 2019.

Wiswall, Matthew and Basit Zafar, "Determinants of college major choice: Identification using an information experiment," *The Review of Economic Studies*, 2015, *82* (2), 791–824.

Yucesoy, Burcu, Xindi Wang, Junming Huang, and Albert-László Barabási, "Success in books: a big data approach to bestsellers," *EPJ Data Science*, 2018, *7*, 1–25.

Additional Tables

Table A1: Regression results using normalized worker share as the outcome

	(1) Outlook	(2) Naive	(3) Combined
Lowest Tercile	-0.154**	-0.147*	-0.261***
	(0.050)	(0.072)	(0.046)
Highest Tercile	0.231***	0.193***	0.180**
	(0.061)	(0.059)	(0.062)
Highest - Lowest	0.384	0.340	0.441
	(0.071)	(0.068)	(0.073)
R-squared	0.136	0.113	0.154
N	12,613	12,534	12,534

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table shows three separate regressions with normalized worker share as the outcome.

Table A2: Regression results using balanced panel of jobs

	(1) Outlook	(2) Naive	(3) Combined
Lowest Tercile	-0.051**	-0.055*	-0.074***
	(0.018)	(0.028)	(0.021)
Highest Tercile	0.056**	0.029	0.036*
	(0.022)	(0.021)	(0.018)
Highest - Lowest	0.106	0.084	0.110
	(0.024)	(0.026)	(0.025)
R-squared	0.156	0.141	0.157
N	9,254	9,254	9,254

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table shows three separate regressions with measures of occupational growth as the outcome.

A Outlook examples

A.1 Entry for Physicians in the 1948 Occupational Outlook

This is an excerpt from the 1948 Occupational Outlook, Pages 43-45.

Physicians (D.O.T. 0-26.10)

Outlook Summary

Excellent opportunities for those able to gain admission to medical school and complete requirements for practice.

Nature of Work

Most physicians are engaged in private practice, either as individuals or in a group of doctors. Others have full-time positions on hospital staffs, with private firms, or in governmental agencies such as the United States Public Health Service, the armed forces, and the Veterans Administration—caring for patients or giving medical examinations. Some combine private practice with a part-time position in a hospital or industry. Physicians also teach in medical schools; do research on causes of disease and development of new methods of treatment; hold administrative positions in hospitals, clinics, laboratories, and other organizations; and write and edit medical books and magazines. A few devote their full time to these activities, but most care for patients as well.

Of the 165,000 employed physicians reported by the census in 1940, about a half were general practitioners; nearly a third were general practitioners with an interest or training in a specialty; the remainder (slightly over one-fifth) limited their practice to their specialty. The recognized specialties are, in descending order of numbers practicing: otolaryngology, internal medicine, surgery, ophthalmology, pediatrics, radiology, obstetrics and gynecology, neurology and psychiatry, pathology, urology, orthopedic surgery, dermatology and syphilology, anesthesiology, plastic surgery, neurosurgery, public health, industrial medicine, and physical medicine.

Training and Qualifications

For practice as a physician in any State or the District of Columbia, one must be licensed by a State board of medical examiners and register annually with this board. With rare exceptions, it takes 7 to 9 years after high school to complete the educational and experience requirements for licensure. Candidates must be graduates of approved medical schools, which give 4-year courses and require students to have completed 3 or more years of premedical study in college. A few schools require only 2 years of premedical study, whereas others require a bachelor's degree. At all schools, this degree is an advantage in competing for admission—an important consideration in view of the present waiting list for entrance into most schools. After completing medical school, graduates generally serve at least a year's internship in a hospital; 1 year is legally required in about half of the States. Finally, they have to pass a licensing examination given by the State board of medical examiners.

To be recognized as a specialist, a doctor must meet standards established by one of the 16 specialty boards set up by the American medical profession (except for public health or industrial medicine, for which there are no specialty boards as yet). These standards include: graduation from an approved medical school, completion of an approved internship, and generally 5 years of specialized training and practice in the selected field. Residencies of varying lengths in approved institutions are required for most specialties as part of the training. In addition, physicians intending to become general practitioners often serve as residents for a year or two after completing their internship to obtain additional training and experience.

Outlook

The demand for physicians' services is much greater now than before the war. The rise in national income and the development of prepayment plans for medical care and hospitalization are making it possible for many more people to obtain doctors' services. Among the other factors which will tend to increase the demand for their services are the increase in population (particularly of older persons); Government provision of medical care for veterans and for members of the armed forces and their families; and the planned large-scale program for construction of hospitals in areas which have no modern facilities. Underlying these factors is the general trend toward higher standards of medical care and public health. In addition, about 4,000 new physicians are needed

B Large language model prompt

```
prompt_instructions = '''You are an expert analyst reviewing labor market
    predictions from the US Department of Labor's Occupational Outlook.

Your task is to extract and analyze ALL occupational predictions from the
    following text. For each occupation mentioned with a prediction, provide the
    following in a strict format:

OCCUPATION: [exact occupation title]
PREDICTION_TEXT: [summary of the relevant prediction text, including time
    horizons]
CONTEXT: [any relevant context about requirements, conditions, or caveats]
GROWTH_SCORE: [integer 1-7 where:
   1 = Rapid decline/obsolescence
   2 = Moderate decline
   3 = Slight decline
   4 = Stable/no change
   5 = Modest growth
   6 = Strong growth
   7 = Exceptional growth]
CONFIDENCE: ["HIGH"/"MEDIUM"/"LOW" based on specificity of prediction]
REASONING: [brief explanation of why you assigned this growth score]

Format each occupation as a JSON object. Output an array of all occupations.

After your analysis:
1. Cross-reference with any index or summary sections
2. Add any missed occupations with the same structured format
3. Verify all scores follow the 1-7 scale strictly
4. Ensure predictions are based only on explicit statements in the text

Input text:
```

C Examples of Context Removal in Outlook Paragraphs

This appendix provides examples of how outlook paragraphs are transformed from their original form to context-free versions for embedding generation.

C.1 Example 1: Accountants (1946)

Original Text:

> Employment opportunities for accountants have increased considerably in recent years because of such factors as complex tax systems, government regulation of business and a growing emphasis on scientific management in industry for better control of production costs, etc. The war greatly increased the demand for accounting services, especially in the government. It is expected that this trend will continue. Reduced number of graduates during the war will probably make it possible for returning veterans to find employment, if they have experience in the field. New entrants, without training equivalent to the professional level, may find difficulty in entering the field. Jobs are found in all industries and in all locations, but most opportunities are in industrial centers. Federal civil service is an important source of employment for veterans who can qualify.

Context-Free Version:

> Employment opportunities for the occupation have increased considerably in recent years because of such factors as complex [things], government regulation of [things], and a growing emphasis on scientific management in the industry for better control of [process], etc. The [event] greatly increased the demand for services, especially in the government. It is expected that this trend will continue. Reduced number of graduates during the [event] will probably make it possible for returning [people] to find employment, if they have experience in this field. New entrants, without training equivalent to the professional level, may find difficulty in entering this field. Jobs are found in all industries and in all locations, but most opportunities are in industrial centers. Federal civil service is an important source of employment for [people] who can qualify.

C.2 Example 2: Architects (1946)

Original Text:

> During the war enrollments in schools of architecture dropped considerably below the prewar level. Supply of graduate architects during the immediate postwar years will be smaller than before the war. Demand for architects' services will be larger in postwar 5-year period, because of

expected increase in housing and commercial construction and construction of hospitals, schools, and other public and private institutional buildings. Cumulative wartime deficit of enrollments, coupled with a larger prospective demand, point to a more promising outlook in the profession in postwar 5 year period than before the war. This refers particularly to numerous experienced architects returning from the armed services. Employment opportunities for well-trained and qualified new entrants will also be more promising during the immediate postwar years than prior to war. Men entering schools of architecture now and expecting to enter the profession 4 years hence may still find good employment opportunities. In the long run, there will be opportunity only for a limited number of new entrants needed to meet replacement needs.

Context-Free Version:

During the [event] enrollments in schools dropped considerably below the pre-[event] level. Supply of graduate [occupation] during the immediate post-[event] years will be smaller than before the [event]. Demand for services will be larger in post-[event] period, because of expected increase in housing and commercial construction and construction of hospitals, schools, and other public and private institutional buildings. Cumulative [event]-time deficit of enrollments, coupled with a larger prospective demand, point to a more promising outlook in the profession in post-[event] period than before the [event]. This refers particularly to numerous experienced [occupation] returning from the armed services. Employment opportunities for well-trained and qualified new entrants will also be more promising during the immediate post-[event] years than prior to [event]. [People] entering schools now and expecting to enter the profession [number] years hence may still find good employment opportunities. In the long run, there will be opportunity only for a limited number of new entrants needed to meet replacement needs.