2015 EMPLOYMENT PROJECTIONS

Industries
Occupations
Growth Rates
Job Openings
Skill Projections
Occupations in Demand

Employment Security Department
WASHINGTON STATE

Labor Market and Performance Analysis

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About the employment, industry and occupational projections

Employment projections provide a general outlook for industry and occupational employment in Washington state. They provide job seekers, policy makers and training providers an idea of how much an industry or occupation is projected to change over time and show the future demand for workers.

On an annual basis, the Employment Security Department produces industry employment projections for two, five and 10 years from a base period. The base period for the two-year (short-term) projections is second quarter 2014. The base period for the five-year (medium-term) and 10-year (long-term) projections is 2013.

Staffing patterns for each industry are used to convert industry projections into occupational projections.

Industry classifications are based on the North American Industry Classification System (NAICS). However, they have been modified to match the industry definitions used by the U.S. Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES) program. These modified industry definitions are called Industry Control Totals (ICTs). The Standard Occupational Classification (SOC) system is used to group occupations. *Appendix 5* contains frequently asked questions relating to projections. *Appendix 6* provides a glossary of terms.

Data sets used to develop projections

The following data sets are used to produce projections:

1. Historical employment time series, in this case the U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW).
2. Employment not covered by the unemployment insurance system from the U.S. Bureau of Labor Statistics' Current Employment Statistics (CES) program.
3. Occupational employment by industries (staffing patterns) based on the OES survey.
4. Independent variables (predictive indicators), which help to project the future direction of the economy, from IHS Global Insight's national forecast.

Use of employment projections

Employment projections are intended for career development over time, not as the basis for budget or revenue projections, or for immediate corrective actions within the labor market.

Employment projections are the basis of the Occupations in Demand (OID) list covering Washington's 12 workforce development areas and the state as a whole. This list is used to determine eligibility for a variety of training and support programs, but was created to support the unemployment insurance Training Benefits Program. *Appendix 3* contains a technical description of the OID list.

The full OID list is accessible through the "Learn about an occupation" tool located at: **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/occupations-in-demand**.

Executive summary

This report highlights findings on specific aspects of Washington's employment outlook. In the first section, industry projections results, we describe changes in employment by industry from 2013 through 2023. In the next section, occupational projections results, we look at:

- Major occupational groups
- Specific occupations

Detailed information on the projected demand for industry and occupational employment is available in the Employment Projections data files at: **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/employment-projections**.

In addition, detailed skill projections information is available in *Appendix 4* of this report.

Key findings

The 10-year average annual growth rate for total nonfarm employment for the 2013 through 2023 period is projected to be 1.79 percent. This is an increase over the 1.62 percent average annual growth rate predicted last year for 2012 through 2022.[1]

Industry projections

- The largest increase by share of employment is projected for the professional and business services sector.
- The largest decreases by shares of employment are projected for manufacturing and government sectors.

Occupational projections

Major occupational groups

- The largest increases by shares of employment are projected for the construction and extraction occupations. It was stated in last year's report that during the Great Recession, construction dropped significantly and was partially regaining ground. This trend remains in this year's projections.
- The largest decreases by shares of employment are projected for the production and sales and related occupations.
- The largest employment shares in 2023 are projected for the office and administrative support occupations, sales and related occupations and food preparation and serving-related occupations. However, the first two occupational groups are projected to have declining employment shares.

[1] See: "2014 Employment Projections," Washington State Employment Security Department, Labor Market and Performance Analysis (LMPA), *Figure 2*, page 6.

Specific occupations

- The retail salespersons occupations are projected to have the largest number of average annual total openings.
- Only five of the 20 occupations with the largest numbers of total openings are projected to have a greater number of openings due to growth than to replacement. These occupations are software developers, applications; carpenters; construction laborers; janitors and cleaners, except maids and housekeeping cleaners; and sales representatives, wholesale and manufacturing, except technical and scientific products.
- Out of a total of 804 publishable state-level occupations, 189 are projected to have a greater number of openings due to growth than to replacement and 35 are projected to have equal numbers of openings due to growth and replacement.

2015 industry projections results

Figure 1 presents 2013 estimated employment, 2013, 2018 and 2023 employment shares, and changes in employment shares from 2013 through 2018 and 2018 through 2023 by industry for Washington state.

Through 2023, the three industry sectors with the largest increases in employment shares are projected to be professional and business services, health services and social assistance, and construction.

For this same time period, the two industry sectors with the largest decreases in employment shares are projected to be manufacturing and state and local government (including education).

A notable code change occurred in this year's industry data. The U.S. Bureau of Labor Statistics moved employment out of the private household NAICS classification and into the individual and family services classification. This change increased total nonfarm employment, since private households are not included in total nonfarm employment numbers. The change occurred in the middle of 2013 and affected half of the year's individual and family services employment totals. As a result, it increased employment by an estimated 23,400. In 2014, the full effect of the code change was realized when the change increased individual and family services employment by an estimated 49,400.

For detailed industry projections, the code change was interpreted as a break in series and published data excluded it for the period of 2013 through 2018.[2] The published growth rate for the industry is 3.71 percent. If the code change was incorporated into ICT calculations, the average annual growth rate for individual and family services for 2013 through 2018 would have been 9.01 percent.

Unlike published ICT data, the code change was incorporated into published aggregated industry projections. This had a ripple effect up through higher employment data aggregation levels until it finally affected total nonfarm employment. The employment increase change moved upwards through individual and family services, health services and social assistance, education and health services and finally into total nonfarm employment. *Figure 2* presents the effect of the code change on growth rates from 2013 through 2018.

[2] This reflects the fact that the occupational/industry staffing patterns for this round of projections reflected the old definition of private households.

Figure 1. Base and projected nonfarm industry employment
Washington state, 2013, 2018 and 2023
Source: Employment Security Department/LMPA; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages

Industry sector*	WA state est. empl. 2013	WA state est. empl. shares 2013	WA state proj. empl. shares 2018	WA state proj. empl. shares 2023	Washington state percentage point change in employment shares 2013 through 2018	Washington state percentage point change in employment shares 2018 through 2023	Washington state percentage point change in employment shares 2013 through 2023
Natural resources and mining	6,100	0.21%	0.19%	0.18%	-0.01%	-0.01%	-0.02%
Construction	149,000	5.02%	5.69%	5.85%	0.67%	0.16%	0.83%
Manufacturing	286,400	9.65%	8.94%	8.48%	-0.71%	-0.46%	-1.17%
Wholesale trade	127,200	4.28%	4.28%	4.21%	-0.01%	-0.07%	-0.08%
Retail trade	329,700	11.10%	10.94%	10.66%	-0.16%	-0.28%	-0.44%
Utilities	4,800	0.16%	0.15%	0.14%	-0.01%	-0.01%	-0.02%
Transportation and warehousing	89,200	3.00%	2.95%	2.86%	-0.06%	-0.08%	-0.14%
Information	106,200	3.58%	3.58%	3.64%	0.00%	0.06%	0.06%
Financial activities	150,600	5.07%	4.87%	4.74%	-0.21%	-0.13%	-0.33%
Professional and business services	361,000	12.16%	12.78%	13.56%	0.62%	0.78%	1.40%
Education services	51,900	1.75%	1.79%	1.83%	0.04%	0.05%	0.08%
Health services and social assistance	363,600	12.25%	13.12%	13.41%	0.87%	0.30%	1.17%
Leisure and hospitality	287,300	9.68%	9.58%	9.59%	-0.09%	0.01%	-0.08%
Other services	111,400	3.75%	3.69%	3.68%	-0.06%	-0.02%	-0.08%
Federal government	71,600	2.41%	2.13%	1.97%	-0.28%	-0.16%	-0.44%
State and local government (including education)	473,000	15.93%	15.33%	15.19%	-0.60%	-0.14%	-0.74%

*The sectors presented in the table are based on CES definitions.

The largest growth sectors are projected for professional and business services, health services and social assistance and construction. However, the growth in health services and social assistance from 2013 through 2018 is overstated due to a code change (see narrative). Without this code change, the estimated increase in employment shares from 2013 through 2018 for this sector would be just 0.22 percentage points, instead of 0.87 percentage points.

Figure 2. Estimated impact on growth rates of code change from personal household to individual and family services
Washington state, 2013 through 2018
Source: Employment Security Department/LMPA; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages

NAICS supersectors and total nonfarm	Growth rate without code change 2013 through 2018	Growth rate with code change 2013 through 2018
Healthcare and social assistance	2.34%	3.45%
Education and health services*	2.37%	3.42%
Total nonfarm	**1.97%**	**2.12%**

*Current Employment Statistics category not shown in *Figure 1*.

The BLS code change artificially increased the total nonfarm growth rate by 0.15 percentage points.

Historical and projected growth rates

Figure 3 shows the historical and projected growth rates for the state and Washington's 12 workforce development areas (WDAs).

The largest positive difference between historical growth rates and projected growth rates is in the Eastern Washington WDA. For this area, the difference between the historical and projected rate is 1.19 percent. The Olympic Consortium was a close second with a difference of 1.14 percent. Benton-Franklin's projected growth rate of 1.86 percent just edged out the previous 10 years' growth rate of 1.85 percent. The only area where projected growth is less than the previous 10 years is in the Snohomish County WDA.

Figure 3. Historical and projected total nonfarm employment growth
Washington state and workforce development areas, 1990 through 2013 and 2013 through 2023
Source: Employment Security Department/LMPA; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages

Workforce development area[1]	Historical growth[2] rate 2003 through 2013	Projected growth rate 2013 through 2023	Historical trend[3] growth 1990 through 2013
Olympic Consortium	0.29%	1.43%	1.16%
Pacific Mountain	0.56%	1.64%	1.28%
Northwest	0.92%	1.69%	1.83%
Snohomish County	2.49%	1.44%	2.06%
Seattle-King County	1.00%	1.94%	1.11%
Pierce County	1.10%	1.79%	1.67%
Southwest Washington	1.02%	1.96%	1.68%
North Central	0.94%	1.68%	1.27%
South Central	0.46%	1.58%	0.79%
Eastern Washington	0.39%	1.58%	1.02%
Benton-Franklin	1.85%	1.86%	2.16%
Spokane	0.62%	1.68%	1.29%
Statewide	**1.07%**	**1.79%**	**1.36%**

[1]Workforce development areas are regions within Washington state with economic and geographic similarities.

[2]Historical growth is based only on covered employment.

[3]Historical trend growth is defined as the growth rate of the linear trend line.

The Snohomish County WDA is the only area where the projected growth is less than the previous 10 years' growth.

2015 occupational projections results

The detailed state-level occupational projections cover 813 occupations, 804 of which are publishable. This publication, however, provides only a summary of the top occupations. For a complete list of occupations and projected employment, see the 2015 Employment Projections data files available at: **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/employment-projections**.

Major occupational groups

Figure 4 shows occupational employment estimates and employment shares for Washington state.

At the state level, two occupational groups stand out with increases in employment shares from 2013 through 2023. Construction and extraction occupations are projected to increase employment shares from 5.11 percent to 5.77 percent for an increase of 0.66 percentage points. The next highest increase in shares is projected for computer and mathematical occupations with an increase of 0.55 percentage points.

The largest decreases in employment shares at the state level are in production occupations, with a projected decrease of 0.36 percentage points, and in sales and related occupations, with a projected decrease of 0.31 percentage points.

By 2023, the top three occupational groups for shares of employment are projected to be:

1. Office and administrative support occupations (12.39 percent)
2. Sales and related occupations (9.86 percent)
3. Food preparation and serving-related occupations (7.41 percent)

By 2023, combined, these three major groups are projected to represent nearly 30 percent of total employment shares for the state.

Figure 4. Base and projected occupational employment
Washington state, 2013 through 2023
Source: Employment Security Department/LMPA; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages, Occupational Employment Statistics

2-digit SOC	Major occupational group	WA state est. empl. 2013	WA state est. empl. shares 2013	WA state proj. empl. shares 2018	WA state proj. empl. shares 2023	WA state percentage point change in empl. shares 2013 through 2018	WA state percentage point change in empl. shares 2018 through 2023
11-0000	Management	183,776	5.39%	5.42%	5.46%	0.04%	0.03%
13-0000	Business and financial operations	201,178	5.90%	5.90%	5.95%	0.01%	0.05%
15-0000	Computer and mathematical	150,917	4.42%	4.71%	4.97%	0.29%	0.26%
17-0000	Architecture and engineering	80,926	2.37%	2.25%	2.22%	-0.12%	-0.03%
19-0000	Life, physical and social sciences	36,119	1.06%	1.04%	1.04%	-0.02%	0.00%
21-0000	Community and social services	56,260	1.65%	1.66%	1.68%	0.01%	0.02%
23-0000	Legal	27,163	0.80%	0.78%	0.78%	-0.02%	0.00%
25-0000	Education, training and library	203,157	5.95%	5.86%	5.89%	-0.09%	0.03%
27-0000	Arts, design, entertainment, sports and media	68,736	2.01%	2.03%	2.07%	0.02%	0.04%
29-0000	Healthcare practitioners and technical	159,756	4.68%	4.72%	4.79%	0.04%	0.08%
31-0000	Healthcare support	84,102	2.46%	2.53%	2.62%	0.06%	0.09%
33-0000	Protective service	59,977	1.76%	1.72%	1.70%	-0.04%	-0.01%
35-0000	Food preparation and serving related	252,242	7.39%	7.38%	7.41%	-0.01%	0.03%
37-0000	Building and grounds cleaning and maintenance	136,853	4.01%	4.03%	4.05%	0.02%	0.02%
39-0000	Personal care and service	147,302	4.32%	4.34%	4.39%	0.02%	0.05%
41-0000	Sales and related	347,164	10.17%	10.04%	9.86%	-0.13%	-0.18%
43-0000	Office and administrative support	431,543	12.65%	12.50%	12.39%	-0.15%	-0.11%
45-0000	Farming, fishing and forestry	92,496	2.71%	2.58%	2.47%	-0.13%	-0.11%
47-0000	Construction and extraction	174,519	5.11%	5.67%	5.77%	0.55%	0.11%
49-0000	Installation, maintenance and repair	123,158	3.61%	3.55%	3.47%	-0.06%	-0.08%
51-0000	Production	183,304	5.37%	5.18%	5.01%	-0.20%	-0.16%
53-0000	Transportation and material moving	211,822	6.21%	6.12%	5.99%	-0.09%	-0.13%

Over the 2013 through 2023 period, the largest increases in employment shares are expected for the construction and extraction and computer and mathematical occupations.

The projected average annual growth rates for the major occupational groups in Washington state are presented in *Figure 5*. Construction and extraction occupations (2.96 percent), computer and mathematical occupations (2.91 percent) and healthcare support occupations (2.34 percent) are projected to grow faster than other occupational groups from 2013 through 2023. In the long term, only one occupational group is projected to fall below a 1 percent average annual growth rate: farming, fishing and forestry (0.77 percent).

Figure 5. Projected average annual growth rates for major occupational groups
Washington state, 2013 through 2023
Source: Employment Security Department/LMPA ; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages, Occupational Employment Statistics

Construction and extraction occupations, computer and mathematical and healthcare support occupations are projected to experience the largest growth rates through 2023 (2.96, 2.91 and 2.34 percent, respectively).

Specific occupations

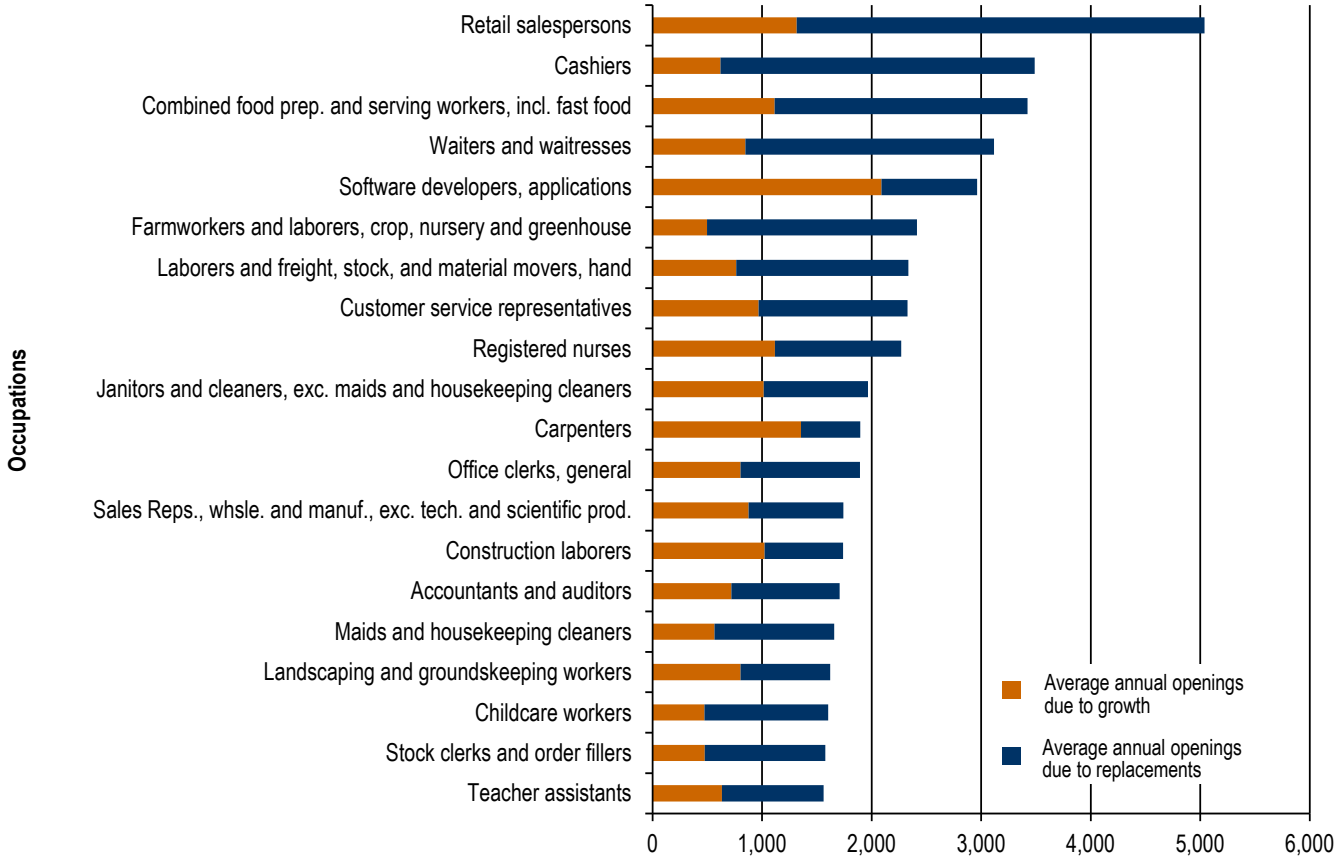
The top 20 specific occupations by total openings are presented in *Figure 6*. At the detailed occupational level (six-digit SOC), the retail salespersons occupation is projected to have the largest number of total openings. Openings can be due to net replacement (workers must exit an occupation entirely in order to create a net replacement

need) or due to growth (a newly created position). On average at the state level, the total number of openings due to replacement is about 1.35 times greater than the number of openings due to growth.

The number of openings due to job growth is greater than the number of openings due to replacement in five of the top 20 occupations:

- Software developers, applications
- Carpenters
- Construction laborers
- Janitors and cleaners, except maids and housekeeping cleaners
- Sales representatives, wholesale and manufacturing, except technical and scientific products

Figure 6. Top 20 specific occupations by average annual total openings
Washington state, 2013 through 2023
Source: Employment Security Department/LMPA; U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages, Occupational Employment Statistics



The number of openings due to growth is greater than the number of openings due to replacement needs in five of the top 20 occupations.

Appendices

Appendix 1. Use and misuse of employment projections

Employment projections provide a general outlook for industries and occupations in Washington state. Occupational projections show how many job openings are projected due to occupational employment growth and replacement needs.[3]

Replacement includes openings created by retirements and separations. It does not include normal turnover as workers go from one employer to another or from one area to another without changing their occupations. Total openings from occupational projections do not represent the total demand, but can be used as an indicator of demand.

Occupational details for employment (with at least 10 jobs) are presented for the state and all workforce development areas in our employment projections data files available online at: **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/employment-projections**.

Observed and predicted extremes in employment growth and other indicators, such as fastest-growing occupations and shortage of skills, can be used for placement and short-term training decisions. However, these should be limited for use when developing long-term education programs. There are two main reasons for this limitation:

1. First, with more education targeting occupations with skill shortages, there is a higher probability that this will cause an oversupply in those occupations and skill sets.[4]
2. Second, the general development of transferable skills is much more productive than trying to catch up with a skill shortage.

The U.S. Bureau of Labor Statistics cautions: "The 2010 SOC was designed solely for statistical purposes. Although it is likely that the 2010 SOC also will be used for various non-statistical purposes (e.g., for administrative, regulatory, or taxation functions), the requirements of government agencies or private users that choose to use the 2010 SOC for non-statistical purposes have played no role in its development, nor will OMB modify the classification to meet the requirements of any non-statistical program.

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[3] As we discuss in the technical description in *Appendix 2,* due to the non-additive formula for calculating total openings, in this round of projections we calculated total openings for aggregated occupations as a total for detailed occupations. As a result, the aggregated level of total openings might not equal the total of growth plus replacement.

[4] Occupational projections are the basis of the Occupations in Demand list (also referred to as the Training Benefits list). See https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/occupations-in-demand

Consequently, the 2010 SOC is not to be used in any administrative, regulatory, or tax program unless the head of the agency administering that program has first determined that the use of such occupational definitions is appropriate to the implementation of the program's objectives."[5]

Different programs use different SOC coding systems. Combining the employment projections with other data sources generally requires a case-by-case analysis; an understanding of the differences of each program should be clearly explained and properly handled.

Occupations in Demand list

The methodology for determining whether an occupation is "in demand," "not in demand" or "balanced" is based on industry and occupational projections. Specific levels of job growth and job openings are used to designate an occupation as "in demand," "not in demand" or "balanced." For more details and methodology, see *Appendix 3* in this report and refer to **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/occupations-in-demand/determine-demand**.

[5] See: **www.bls.gov/soc/soc_2010_user_guide.pdf**, pages xxv-xxvi.

Appendix 2. Technical description

Introduction

The Projections Managing Partnership[6] (PMP) methodologies advise forecasters to combine alternative econometric forecasting methods and to choose the best fitting model in order to produce reliable forecasts. The "fit" of a model is based on performance measures for the observed time periods. PMP's advice was followed for the production of state and regional forecasts.

Two major sets of data are required for making a forecast:

1. An employment time series.
2. Independent variables (predictive indicators).

Autoregressive models only use historical employment time series to forecast employment. The more complex models incorporate dependent and independent variables. Structural changes in employment are incorporated in the complex models through independent leading indicators.

Projection accuracy is measured by the variance between predicted and actual observed results (in-sample and out-of-sample). Typically, time series models produce accurate results for industries, areas and occupations when smooth patterns of economic development exist. However, such models cannot reliably predict unexpected changes. No econometric tools exist that can predict structural changes. However, such predictions are highly valued by forecast consumers. Current forecast models are based on the assumption of smooth economic development.

High statistical accuracy may not indicate the achievement of significant results. For example, a one-day-ahead weather forecast which predicts tomorrow's weather will be the same as today has a high measure of statistical reliability, but is of no real value. Predicting significant economic change carries the risk of increasing statistical errors, but raises the value of the prediction for those who plan for future events. Such predictions often require the use of subjective judgment. Subjective judgment can differ significantly between individuals.[7]

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[6] PMP partnership is between (1) the U.S. Department of Labor, Employment and Training Administration (ETA); (2) the U.S. Department of Labor, Bureau of Labor Statistics (BLS); (3) the National Association of State Workforce Agencies (NASWA); and (4) the State Projections Consortium. The PMP operates an integrated, nationwide program of state and local projections.

[7] For example, two individuals observe a car driving well above the speed limit. One of them is thinking that the car will reach its destination faster; the other thinks there is a higher probability that the car will be stopped by a police officer or cause a traffic accident. The same is true for extremely fast growing industries and occupations.

Nonetheless, subjective judgments are often used to adjust initial results. The need for adjustment increases as the level of detail increases.

The main biases in employment projections come from:

- Applying ongoing trends.
- Using opinions or anecdotes rather than data-based expectations.
- Ignoring the possible effects of actions taken by consumers because of projection results. For example, assume a scenario in which a forecast states that registered nurses will be in demand. Prospective students and college planners read the nursing forecast. A large influx of nursing students occurs and colleges graduate a large number of registered nurses. With the resulting oversupply of registered nurses in the market, a sizeable number of applicants for nursing jobs find that their skills are no longer in demand.

Projection output is put to multiple uses. Therefore, the application of various methodological treatments to projections is warranted. In some cases, projection results are used for developing fast corrective actions. For example, employment projections used for budget forecasting and contingency budget planning should receive priority attention from forecasters. Employment projections for budgetary planning require the use of adaptive controls. Consequently, forecasts should be updated often to reflect the best and most current data. In such cases, up-to-date data takes priority over long, stable forecasting time periods.

Other consumers use forecasts for career development. Prospective students need forecasts that are stable for medium-range time periods. Frequent updates of forecasts in such cases would be disruptive. In other words, for prospective students, frequently updated forecasts lose practical value.

The compromise between statistical accuracy and the ability to predict sharp economic changes can be achieved by developing a relatively smooth baseline forecast (i.e., what happens if nothing changes) and introducing a few alternative scenarios, which address the possibility of positive and negative shocks. Some well-known forecasting companies, including Global Insight, successfully use such an approach.

Industry projections

The principal source for industry employment projections is a detailed, covered employment time series of four-digit NAICS data for all Washington counties. These data are aggregated to WDA levels.

The PMP advised analysts to use quarterly data frequencies for short-term projections and annual frequencies for long-term projections. The PMP has the software for producing short- and long-term projections, but no software for producing medium-term projections.

We found it to be more effective to combine elements of these two programs and then to supplement them with medium-term projections. It should be noted that medium-term projections are required by Washington state law. We also found that the best results can be achieved by using models with monthly data frequencies. These data frequencies are better suited for incorporating seasonality into the forecasting model.

There are two options for reflecting seasonality:

1. Use an independently adjusted series as an input in the model, or
2. Incorporate seasonal dummy variables as part of the projection model.

In our special study, "Seasonality in Employment Time Series,"[8] we demonstrated that the best model for seasonal adjustment might not be the best autoregressive model for forecasting and vice versa. Consequently, in the majority of cases it is preferable to incorporate seasonal adjustments in the forecasting model, rather than use an independently adjusted series as an input to the model.

Short-term projections have a two-year time horizon from the latest available quarter of covered employment data. For this round of short-term projections, second-quarter 2014 was the latest available data; the target point was second-quarter 2016. For the current round of long-term projections, the latest available data was for 2013 and target point was 2023. The medium-term projection target is the middle point of the long-term horizon. In this case, it is the year 2018.

Due to some differences in noncovered employment (which are used for benchmarking) and the way noneconomic code changes are handled, the base numbers used for projections can be slightly different from those published in the Current Employment Statistics (CES) estimates.

Projection process

The first step was to develop aggregated statewide industry projections. Initial covered employment at the county level was aggregated into 34 industry groups (cells) for nonfarm employment. These groups were used in the Global Insight model and then rolled up to the statewide series.

The technique called ex-post projections, or hold-out sample, was used to estimate out-of-sample errors. The main idea behind this approach was to estimate a model on a sample that covered a shorter period of time than the available historical time series. Then, we made forecasts and calculated errors for observations that were available, but not included in the sample. The following illustration shows the main idea of this technique:

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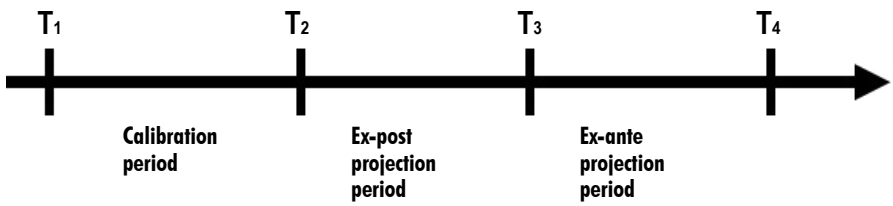
[8] Available from the Employment Security Department Labor Market Information Center, 800-215-1617.

Ex-post projection tests



T_3 = Base year (for ex-ante projections)
T_4 = Projection year (for ex-ante projections)
T_2 = Base year (for ex-post projection tests)
T_3 = Projection year (for ex-post projection tests)
T_1 = Beginning year of calibration period

The historical data were available for period **T_1 – T_3**, but the model was estimated on a shorter interval of **T_1 – T_2** and then a forecast was produced for the interval **T_2 – T_3**. Since we have observed data for this period, we calculated the forecasting errors for the out-of-sample forecasts.

The mean absolute percent error (MAPE) commonly used for error estimations and defined as:

$$\mathbf{MAPE} = \frac{1}{\mathrm{T}} \sum \left| \frac{P_t - A_t}{A_t} * 100 \right|$$

Where:

P_t is the predicted value at time t.

A_t is the actual value at time t.

T is the number of time periods for which the model is tested.

The other useful measure of errors, which reflects the ability of models to pick up variances, is the Theil U-statistic, which is built into the PMP long-term projection software.

$$\mathbf{U} = \left(\left(\frac{1}{\mathrm{T}} \sum_{t=2}^{T} (p_t - a_t)^2 / \left(\frac{1}{T} \sum_{t=2}^{T} a_t^{\,2}\right)\right)\right)^{1/2}$$

Where: P_t = Predicted, or Projected Value at Time t

A_t = Actual Value at Time t

$$p_t = \frac{P_t - A_{t-1}}{A_{t-1}} \qquad a_t = \frac{A_t - A_{t-1}}{A_{t-1}}$$

T = Number of time periods for which projections are developed within the projection horizon.

A lower value of U is desirable. The extreme negative case, which is an eventual death sentence for the model and forecast, is when U>1. It means that a straight-line (i.e., no change) forecast would serve better in terms of reflecting the variance. Even with a possible lower MAPE, such a forecast is worthless.

To meet state employment projections requirements and Occupational Employment Statistic (OES) definitional requirements, we transformed codes from the Global Insight model in order to match them with codes used in state projections. For example, we disaggregated transportation equipment to aerospace and other transportation equipment. State and local government were disaggregated to government education, hospitals and other government. Two industries related to the information sector were disaggregated. Forecasts for these industries were produced mainly by the same means, excluding Global Insight forecasts as regressors.

This year, we transitioned from using SAS to using R software in developing our projections. R software is an open-source, object-oriented language (software) with advanced statistical and optimization procedures. It also allows direct operations with matrices and vectors. This ability provides significant advantages, when used for occupational projections, over sequel-based statistical software like SAS.

Two major procedures were used for industry projections:

1) Not indexed, for all series
2) Indexed by series.

Two specialized R-code libraries were used for industry forecasts:

1) "forecast"
2) "dynlm" – dynamic linear model.

The "not indexed" procedure included:

- The import of all data.
- The definition of necessary subsets and all necessary objects (for later use for each series-indexed procedure and cross-indexed procedures).
- Seasonal dummies and time variables for differing time intervals.

First indexed procedure included:

Creating time series for dependent variables and regressors.

Within the main indexed procedure (in-sample and 24 month out-of-sample testing):

a) The following 4 classes of models were tested:

- Exponential smoothing – state-space autoregressive model with optimized selection of smoothing parameters (criteria minimum: Mean Absolute Percent Error (MAPE))

- Auto ARIMA (Autoregressive Integrated Moving Average) – optimized selection of parameters of ARIMA, seasonal ARIMA, period of seasonality, etc. with regressors (criteria: AIC (Akaike's information criterion)) – most sophisticated single equation model available.
- Naïve regression model with only seasonal dummies and time (linear trend) as regressors.
- Dynamic linear regression model, which include regressors (the same as for Auto ARIMA), seasonal dummies and linear trend.

b) *An optimization model was used for creating combined forecasts:*

- "In-sample" and "out-of-sample" forecasts for each model class and actual initial series were used for parameters.
- Weights for each of the four model classes were subject to optimization.
- Eight calculated variables (two for each model class) were used to define objective functions, subject to minimization. For each of the models the following were used: MAPE for testing "in full sample" and MAPE for testing for 24 month "out-of-sample" (hold-out sample).
- The average between averages of four MAPEs, for "in-sample" and "out-of-sample" testing, was subject to minimization.
- Output from the procedure was subjected to optimum weights for each model class to produce the best combined forecast.

c) *Producing and combining the forecasts:*

Based on the best-fitted equations for the full sample and forecasting regressors (independent forecasts), the forecasts for each class of model were produced and combined with optimum weights obtained from the previous step.

d) *Combining and exporting all of the results from the cross index procedure (based on R-code "data.frame" objects)*

All of the main projections results were combined and exported into default directories as CSV files. The exported results included: 1) fitted statistics for each model class of "in-sample" and "out-of-sample;" 2) forecasts for each class of models with 90 and 95 percent confidence intervals (created with 5,000 replications bootstrap for state-space and Auto ARIMA models); 3) optimum weights for each series; 4) optimization status (0 for converged); and 5) combined optimum forecasts. Optionally, fitted regression parameters can be exported for specific models as text files, but are too complex to include in data.frame objects.

For final selection, we used optimum forecast as well as forecasts from specific models.

Aggregated statewide employment projections from the Economic and Revenue Forecast Council (ERFC) and the Office of Financial Management (OFM) were used as important guides in the projection process.

Selected projections results were rolled up to create multi-level tables that are somewhat comparable to Current Employment Statistics (CES) tables.

Industry projections follow a step-down approach, from aggregated statewide projections down to detailed WDA-level projections.

Upper-level forecasts are used as regressors for lower-level forecasts.

Adjusted statewide projections were disaggregated down to WDA levels of industry employment projections. This occurred at the same level of industry detail as state forecasts, and with the same complex of models. State forecasts were used as independent variables for the same industries as WDA forecasts. The forecasts also incorporated the effects of special events.

For detailed forecasts, there were limited options for manually evaluating each model and each forecasting result. At the same time, the direct use of model results can produce extreme results. To smooth the results, we used the concept of stability controls for dynamic systems. The variance of historical employment was used to define confidence intervals for projected employment variances. To avoid the impact of seasonality, we used 12-month differences in employment at this stage in the process. We also arbitrarily established the upper and lower confidence limits. Confidence limits are used to prevent variance for time series, which incorporates structural changes or have short duration. The default value of four percent was used, but some alternative scenarios were considered. The intervals represented the lower number between the historical confidence and the established limit.

For each time point, if the projected numbers fell within the used intervals, it stayed. Otherwise, the proper limit was applied. This process was used as the main mechanism for model adjustments.

In the current projection cycle, we used two adjustment models, which were based on more conservative and relaxed established limits, respectively. Adjustments were applied only to optimum forecasts and created two more options for final selection (bringing the total to six different forecasts). In addition, some other limited manual adjustments may be used. These other limited adjustments are mainly used for targeting the variances between areas.

Finally, the totals of smoothed projections for each industry and/or state totals were adjusted to meet each other.

Industry inputs for occupational employment projections (industry control totals)

The industry inputs for occupational projections are called industry control totals (ICTs). ICTs act as a bridge between industry and occupational projections. To create such inputs, the following steps were followed:

- Forecasts for employment other than nonfarm (e.g., private households, agriculture, forestry and fishing) were developed at the WDA level.
- Industry projections for nonfarm employment were disaggregated according to OES definitions (mainly to the four-digit NAICS level).

Forecasts for private households, agricultural, forestry and fishing employment were based on the covered employment time series and on the same techniques used for aggregated industry projections with the exclusion of regressors from the models.

Occupational projections also account for self-employment and unpaid family member workers. However regular historical data does not exist for these worker types. To estimate the base numbers for the year 2013, we used the American Community Survey (ACS) five-year data estimation (2009 through 2013). (See **www.census.gov/acs/www/**).

There is no direct industry forecast for self-employed and unpaid family member workers. The growth of self-employment was defined by national occupational self-employment ratios. These ratios were applied to occupational forecasts. Then, these growth rates were applied to base-year estimations adjusted to American Community Survey totals.

To provide industry input for occupational projections, the industry inputs were disaggregated and then rolled up according to the definitions used in OES surveys. Stability controls and adjustments were important for the smoothing of results. Regressors for detailed industry projections at the state level were the aggregated state projections. For detailed workforce development area (WDA) projections regressors were excluded and, consequently, only three types of model were used:

1. Exponential smoothing – state-space autoregressive model
2. Auto ARIMA
3. Naïve regression model with only seasonal dummies and time (linear trend).

Optimum selection was conducted to select from these three model types.

For private employment, industry control totals (ICTs) were mainly at the four-digit NAICS level. Both agriculture and educational employment were aggregated separately. Federal government employment, excluding post offices, was a separately aggregated cell.

Employment for educational sectors and hospitals were separated from state and local government employment and then combined with private employment for these industries. After education and hospital employment were removed, the remaining employment was dispersed between state and local government.

Due to the combination of private and government employment for education and hospitals, industry control totals could not be directly aggregated to conventional industry sectors. In addition, it is not advisable to use them as detailed industry projections due to the very low statistical reliability of forecasts for the detailed industry cells.

The goal of these processes was to provide input for occupational projections.

Occupational estimations and projections

Occupational employment projections result from the conversion of industry employment to occupations. These conversions are based on occupation/industry ratios (i.e., staffing patterns) from the OES survey. This survey is conducted by the Labor Market and Performance Analysis (LMPA) branch of the Employment Security Department (ESD) in cooperation with the U.S. Bureau of Labor Statistics (BLS). The full OES survey has a three-year cycle. One-third of the survey is completed each year. Occupational estimations and projections are subject to the limitations of the OES survey, which include nonfarm employment and agriculture services, but exclude noncovered employment, self-employment and unpaid family members, major agriculture employment, except services, and private households.

The sample for the OES survey is designed for metropolitan statistical areas (MSA). From the perspective of statistical accuracy for occupational projections, this level of aggregation is most appropriate. However, for different applications like the Training Benefits Program, we used the WDA aggregation levels for regional details. The direct use of OES staffing patterns for WDAs can create significant bias for a variety of reasons.

For instance, in cases where the OES survey has weak or missing cells for geographic areas, a substituted staffing pattern was used. These substitutions come from other similar in-state areas or from other states. Such imputations can have a significant influence on staffing patterns from the OES survey. In addition, the imputations were based on wage statistics and may not properly reflect employment structures. Direct use of OES staffing patterns can also create significant bias for industries with high shares of noncovered employment, which were not part of the survey (e.g., religious organizations).

For a few industries, a combined staffing pattern was used between areas. This mainly occurred for the King County and Snohomish County WDAs. This was a necessary step because King and Snohomish counties were combined in the OES survey sample. The national staffing pattern was only used as a last resort. We had to use national staffing patterns for private households.

Some problems, however, were unavoidable and significantly influenced the final occupational estimations and projections. For example, doctors are not always employed by clinics or hospitals, but rather may be employees of independent associations or may be self-employed. For this reason, staffing patterns for medical institutions were bound to be biased.

Occupational projections use the following national inputs:

- Self-employment and unpaid family worker ratios.
- Net replacement rates for each occupation.
- Change factors, which we modify.

Also noteworthy this year was the limited use of some of the results from the 2012 OES green supplemental survey for agriculture industries. The green supplemental survey allowed us to create staffing patterns for agriculture, based on weighted sample responses.

Once staffing patterns are developed, the national methodology advises the application of change factors. Change factors are developed nationally. Change factors predict the expected changes in the occupational shares for each industry over time. The reliability of change factors tend to be low because unlike for industry employment, there are no historical time series for occupational employment. With the lack of historical trends upon which to base future expectations, BLS uses researchers' expectations about structural changes for occupations inside industries. Within this BLS process, there is a high degree of subjective judgment. This is especially true since change factors must be developed for each occupation in an industry. Occupational outputs are very sensitive to these change factors. It is very important to evaluate the adequacy of the change factors before use. Incorrect change factors can drastically increase the errors in projections.

Some testing in Washington and Oregon demonstrated that the quality of projections was better without using the full file of change factors. We created change factors for a very limited numbers of cells. This was done where the national historical series and the state historical series were available and consistent with the suggested change factors in the national file. For such cases, we used the most conservative estimation as a change factor.

Introducing change factors in occupational estimations created a difference between staffing patterns for base and projected periods. After applying change factors to each projected staffing pattern, the shares of occupational employment for each industry were readjusted (normalized). The total of occupational shares for all industries in the projected and base staffing pattern should be equal to one.

Multiplying occupational/industry matrices for each time period of industry control totals produced initial occupational employment estimations.

We used national self-employment ratios to produce unadjusted estimations of self-employment. Self-employment estimations for the base periods were adjusted to totals from the ACS and then projected based on growth rates from unadjusted self-employment estimations. Finally, the adjusted and projected estimations of the self-employed were added to initial employment estimations. The results represented the total estimations and projections of occupational employment.

To calculate openings due to replacement for detailed occupations, we applied national net replacement rates to annual employment on a compound basis. Then, average annual openings due to replacement were calculated.

Total openings for each detailed occupation are equal to the openings due to replacement and growth, but they cannot be negative. So if the numbers are negative, they are replaced with zero. If a projected decline in occupational employment is greater than the projected replacement, the negative totals are replaced with zeroes. This creates non additive results for total openings. In other words, if we apply the same calculations of total openings for aggregated occupations as for detailed occupations, total openings for aggregated levels would be less than total openings for detailed levels.

There is no perfect solution for this problem. Our solution was to aggregate the total openings from the detailed levels. In this way, the aggregated numbers of total openings are equal to the totals for detailed occupations. However, on the aggregate level, the total openings might not be equal to the total of growth plus replacement. The differences were not significant for this round of projections, especially at the state level.

The formal description of occupational projections

Here is a fragment of a hypothetical staffing pattern matrix:

Occupations across rows

SOC	NAICS 1	NAICS 2	NAICS....n
11-1011	0.30	0.20	0.05
15-1143	0.10	0.50	0.10
35-3022	0.05	0.00	0.08
41-2031	0.25	0.08	0.08
47-2031	0.00	0.00	0.10
51-4041	0.30	0.22	0.59
Totals	**1.0**	**1.0**	**1.0**

Industries across columns

Shares of employment estimates across industries by occupation in percentage

Columns sum to 1.0

(100% of industry employment)

The calculations of occupational outputs are based on staffing pattern matrices and ICT vectors.

Let's define:

Indexes:

i = 1,2, …, m - for occupations

j = 1,2, …, n - for industries

Vectors:

known $X = \begin{bmatrix} x_1 \\ . \\ . \\ . \\ . \\ x_n \end{bmatrix}$ – base year ICT vector (without self-employed and unpaid family members)

$\underline{X} = \begin{bmatrix} \underline{x}_1 \\ . \\ . \\ . \\ . \\ \underline{x}_n \end{bmatrix}$ – projected year ICT vector

$S = \begin{bmatrix} s_1 \\ . \\ . \\ . \\ . \\ s_m \end{bmatrix}$ – self-employed and unpaid family members ratios (could be combined or separate)

Unknown

$Y = \begin{bmatrix} y_1 \\ . \\ . \\ . \\ . \\ y_m \end{bmatrix}$ – base year occupational employment

$\underline{Y} = \begin{bmatrix} \underline{y}_1 \\ . \\ . \\ . \\ . \\ \underline{y}_m \end{bmatrix}$ – projected year occupation employment

Matrices:

Known $A = [a_{ij}]$ i = 1,…,m; j = 1, …,n – base year staffing pattern

$C = [c_{ij}]$ i = 1,…,m; j = 1, …,n – change factors

Unknown $\underline{A} = [a_{ij}]$ i = 1,…,m; j = 1, …,n – projected year staffing pattern

The basic calculations

Each column of matrix A should be normalized, so $\Sigma_j a_{ij} = 1$ for all i = 1, …,n.

$Y = A^*X$ or $y_i = \Sigma_j a_{ij}^*x_j$ i=1, …,m (1)

$\breve{a}_{ij} = a_{ij} * c_{ij}$ for each i = 1, …,n, j=1,…,m

normalized $\underline{a}_{ij} = \breve{a}_{ij} / \Sigma_i \breve{a}_{ij}$ for each i = 1, …,n, j=1,…,m (2)

$\underline{Y} = \underline{A}^*\underline{X}$ or $\underline{y}_i = \Sigma_j \underline{a}_{ij}^*\underline{x}_j$ i=1, …,m (3)

Due to $\Sigma_j a_{ij} = 1$ and $\Sigma_j a_{ij} = 1$ we will have $\Sigma_j x_j = \Sigma_i y_i$ and $\Sigma_j x_j = \Sigma_i y_i$

If base year employment $x_j = 0$ and projected $\underline{x}_j > 0$ we can add the column in projected matrix.

Calculations of self-employment and unpaid family members

The non-adjusted vector of self-employed (m,1) $\Delta = \{\Delta_i\}$ i =1,…, m for the base year will be:

$\Delta = (S,Y)$ or $\Delta_i = s_i * y_i$, i =1,…, m (4)

If Δ' is a control total

$\Delta(i)a_{dj} = \Delta_i * (\Delta' / \Sigma_i \Delta_i)$

The final outputs

$Y(i)$ final $= Y(i) + \Delta(i)a_{dj}$

$\underline{Y}(i)$ final $= \underline{Y}(i) + \underline{\Delta}(i)a_{dj}$

The final results could be rounded to the integers and this will not create any significant differences between ICT totals and occupational employment totals.

Supplementary calculations of openings due to growth and replacement

To calculate the annual openings due to replacement, the net replacement rates r_i should be applied to the annual employment on a compound basis. Let's define average annual growth rates as:

$g_i = (\underline{Y}(i)\text{ final}/ Y(i)\text{ final})\text{^}(1/T)-1$ i=1, …,m ,

where T – number of projected years.

The average annual openings Ri due to replacement were calculated as:

$$R_i = \left(\sum_{t=0}^{T-1} r_i * Y^t_i (1+ g_i)\right)^t / T \qquad i=1, \ldots, m ,$$

The average annual openings due to growth

$$OG(i) = (Y(i) \text{ final} - Y(i) \text{ final})/T$$

Finally average annual total openings are:

$$TO(i) = \max(0, (OG(i) + R_i)).$$

The Projections Managing Partnership projections software applies replacement rates to base-year employment. Because of this approach, openings due to replacement are unrelated to projected employment changes.

To illustrate the possible differences between the compound and the base-year calculation of replacement rates, let's suppose we have a base-year occupational employment of 100, an annual growth rate of 20 percent and a replacement rate of 5 percent. The number of average annual opening due to replacement will be 11.6 for the 10-year projection and 5.5 for the two-year projection under the compound approach.

The same number for the base-year calculations will be 5 percent for any period in spite of significant differences in annual average employment. The ratio of openings due to replacement compared to openings due to growth under the compound approach is equal to the proportion of replacement and growth rates (5/20 = 25 percent) and does not depend on the projection period.

Under the base-year calculations, this ratio will be 22.7 percent for the two-year projections and 10.8 percent for the 10-year projections. Most importantly, the replacement rate calculated under the base-year approach is not the average annual rate of openings due to replacement.

BLS used the same approach in the past, but recently changed to applying the replacement rates to the first and last years and then taking averages. This is a significant improvement compared to applying the replacement rates to the base-year only, but is still not quite an accurate approach. This most recent BLS approach assumes a fixed absolute change in employment for the projected period. Our approach assumes a fixed growth rate.

Appendix 3. Occupations in Demand (OID)

Employment Projections are intended for career development over time, not as the basis for budget or revenue projections, or for immediate corrective actions within the labor market.

Employment projections are the basis of the Occupations in Demand (OID) list covering Washington's 12 workforce development areas and the state as a whole. This list is used to determine eligibility for a variety of training and support programs, but was created to support the unemployment insurance Training Benefits Program.

The full OID list is accessible through the "Learn about an occupation" tool located at: **https://fortress.wa.gov/esd/employmentdata/reports-publications/occupational-reports/occupations-in-demand**.

All occupations in the list have demand indication definitions. The definitions come in three forms: "in demand," "not in demand" or "balanced." These definitions indicate the probability of a job seeker gaining employment in a given occupation. The term "in demand" indicates a greater probability of gaining employment. The term "not in demand" indicates a lesser probability and "balanced" indicates an uncertain probability between success and failure in gaining employment. The definitions are created through a four-step process as follows:

The data sources for the OID list:

The 2015 list is based on projections:

- Five-year projections for 2013 through 2018, using average annual growth rates and total job openings.
- Ten-year projections for 2013 through 2023, using average annual growth rates and total job openings.
- A combination of two-year (second quarter 2014 through second quarter 2016) and ten-year (2013 through 2023) projections, using average annual growth rates and total job openings.

All of these time frames use unsuppressed occupations with employment in a base year (2013), consisting of 50 or more employees, for the state and Workforce Development Areas (WDAs).

In addition to projections, the OID list is created using supply and demand data:

- **Supply data**: average annual counts of WorkSource registered job seekers and unemployment claimants for WDAs for the most recent full year (April 2015 and the preceding 11 months).
- **Demand data**: average annual counts of job announcements from Help Wanted OnLine (HWOL) mid-monthly time series (April 2015 and the preceding 11 months).

Step one: Identify initial "in demand" and "not in demand" categories for each period.

- For each time frame, occupations with average annual growth rates of at least 90 percent of their respective geographic areas (statewide or workforce development area) total average annual growth rates *and* a share of total openings of at least .08 percent are defined as "in demand."
- Occupations with average annual growth rates less than 70 percent of their respective geographic areas total growth rates and a share of total openings of less than 1 percent are defined as "not in demand."

Step two: Identify provisional occupational categories.

- If within any of the three projection time frames (five-year, 10-year and two-/10-years combined), an occupation is categorized as being "in demand," it receives the first provisional identification as "in demand."
- If within any of the three projection time frames, an occupation is categorized as "not in demand," it receives a second provisional identification of "not in demand."

Step three: Create final projections definitions.

- If an occupation has only one provisional definition, it equals the final projections definition.
- If an occupation has two provisional definitions of "in demand" and "not in demand," it gets identified as "balanced."
- All other occupations, without provisional definitions (i.e., not meeting the thresholds from step one), are identified as "balanced."

Step four: Create final adjustment definitions.

The projections definitions are now put through an adjustment process, using current labor market supply/demand data, which compares online job postings to information on unemployment claimants and WorkSource job seekers. An adjustment is applied when current supply/demand data significantly contradicts the model-based projections definitions.

The adjustment methodology

- If the projections definition is "in demand" or "balanced" but the ratio of supply to demand is more than 2, then the adjusted definition is "not in demand."
- If the projections definition is "in demand" and the ratio of supply to demand is not larger than 2, but more than 1.5, then the adjusted definition is "balanced."

- If the projections definition is “not in demand” or “balanced,” but the ratio of supply to demand is less than 0.5, then the adjusted definition is “in demand.”
- If the projections definition is “not in demand” and the ratio is at least 0.5, but less than 0.75, then the adjusted definition is “balanced.”
- If the number of new job announcements for a current month is at least 10 and supply data are not available, the adjusted definition is “in demand.”

The final list: Local adjustments

The Employment Security’s Labor Market and Performance Analysis division uses the methodology outlined above to prepare the initial lists for the state as a whole and by workforce development area. Those lists are then given to local workforce development councils to review, adjust and approve on the basis of their local, on-the-ground experience.

Appendix 4. Skill projections

Our skill projections process is a new attempt to convert occupational projections into skill projections. We rely on the content of employers' job postings rather than the predefined, general O*NET skills. While the results of this attempt should be considered as preliminary, we believe that the attempt to use skills identified by employers in their job postings deserves some attention.

Data sources

The main source for this analysis was a download of the top 100 hard skills for each detailed (six-digit SOC) occupation for Washington state from WANTED Analytics. The downloaded files represent the extracted hard skills from online job announcements posted in the first four months of 2015 (January through April). Each skill is displayed with the number of job announcements from which it was extracted. This skill-announcement(s) pairing permits every occupation to display the relative importance of each skill. Theoretically, each occupation could contain a vector of up to 100 components with announcement numbers indicating the relative importance of each skill. A skill drawn from a greater number of job announcements is relatively more important. A vector is a single entity (i.e., a column) consisting of an ordered collection of numbers. The number of job announcements is summed for each occupation. Only vectors with a summation value of at least five and not less than 1 percent of base-year employment were used. Some occupations contain very limited (if any) numbers of components and skills.

Each of the used vectors was normalized (i.e., scaled) to totals of one. With this type of normalization, we created skill–to-occupation matrices. These matrices were used to convert occupational estimations and projections into comparable numbers expressed as hard skills.

The skill matrices are similar in structure and function to normalized matrices used for occupational-industrial staffing patterns. The skill matrices were based on statewide data and were used to convert occupational projections for the state and all areas into skill projections.[9]

After conversion, we deleted all records where estimated or projected employment numbers were below five since we consider estimations below five as unreliable. As a result of filtering out missing skill/occupation vectors and removing results below five, only a portion of the occupational employment estimates were converted into skills.

[9] WANTED Analytics data includes duplicated job announcements. Normalization of the matrices eliminates these inflated totals, but bias is still possible.

The converted portion (calculated on base year employment) varies between about 66 percent for Seattle-King County, 60 percent for the state, Snohomish County and Spokane WDAs, 58 percent for Pierce County and 56 percent for the Olympic Consortium, Pacific Mountain and Southwest Washington WDAs. The lowest portion of occupational employment converted to skills was for the North Central Washington WDA (just under 41 percent).

Some results

The skill–to-occupation matrices have different dimensions for the state's areas based on data availability. As a result, the largest number of detailed skills were 1,283 for Washington state, followed by King County at 1,273. The lowest number was for Eastern Washington at 645 skills.

The top three detailed hard skills, based on projected numbers of openings as well as available number of jobs were: food preparation, bilingual and quality assurance. It is no surprise these three skills are the same for all areas since the same statewide matrix was used for all areas. The top detailed hard skills were not the same when we increased the number to the top five. This is due to differences in occupational employment structure by area. The numbers of total annual projected openings from 2013 through 2023 associated with these three skills for Washington state, in corresponding order, are 5,523, 4,088 and 3,204. Combined they represent 14.6 percent of total openings represented in the skill projections. However, the skills with the largest number of openings do not have high growth rates.

The fastest growth is projected for skills related to information technology (IT). The IT skills are very specific, vary from area to area, and the majority, individually, are not large in terms of employment and job openings. The largest average annual growth rates for 2013 through 2023, are expected to be for JavaScript, Amazon Web Services and Object-oriented design. However, the combined totals for these three detailed occupations represented an insignificant share (just under 0.2 percent) of total openings represented in the skill projections.

The top 20 detailed skills for Washington state based on a combined rank of average annual openings and growth for 2013 through 2023 are presented in *Appendix Figure A4-1*.

Appendix Figure A4-1. Top 20 skills ranked by combined growth and openings
Washington state, 2013 through 2023
Source: Employment Security Department/LMPA; WANTED Analytics

Combined rank	Hard skill titles	Estimated hard skill employment numbers 2013	Projected hard skill employment numbers 2023	Average annual growth rate 2013 through 2023	Total average annual openings 2013 through 2023
1	C-sharp	4,111	5,482	2.92%	222
2	JavaScript	2,898	3,916	3.05%	155
3	Java	8,058	10,512	2.69%	408
4	C/C++	3,345	4,428	2.84%	171
5	Amazon Web Services	2,106	2,833	3.01%	109
6	Distributed system	2,267	3,045	3.00%	117
7	Systems Development Life Cycle	3,084	4,078	2.83%	160
8	Object-oriented design	1,474	2,017	3.19%	80
9	Linux	5,280	6,853	2.64%	256
10	Cascading Style Sheets	2,151	2,874	2.94%	117
11	Microsoft SQL Server	2,934	3,877	2.83%	156
12	Microsoft .NET Framework	1,897	2,542	2.97%	105
13	Software development	15,129	19,151	2.39%	712
14	Relational Database Management System	1,993	2,644	2.87%	104
15	Ruby	1,524	2,058	3.05%	80
16	Autodesk Maya	926	1,278	3.28%	61
17	Python	4,211	5,429	2.57%	205
18	Extensible markup language	1,685	2,240	2.88%	90
19	Adobe LifeCycle ES	2,075	2,740	2.82%	107
20	Hypertext markup language	3,220	4,172	2.62%	165

All of the top 20 skills are related to information technology.

The top 20 occupations still represented just slightly over 4 percent of total openings represented in the skill projections. All of them are related to information technology (IT). In the entire list of skills, some skills are quite general and represent a significant share of total numbers and openings. Examples are the top three skills based on openings: food preparation, bilingual and quality assurance. The majority of the skills, especially related to IT and high-tech, are very specific and their numbers are dispersed among all occupations. As a result, such detailed skills normally do not represent a significant share of the total numbers.

Results change significantly if we group all detailed skills together, based on their primary fields. This type of grouping is quite challenging since a significant number of skills are a combination of specific fields and IT skills. A good example of this is the grouping of CAD software with the field of architectural drawing.

In the skill projections, by far the largest group of skills are IT related. They represent almost one-third of estimated skill numbers and openings. With the exclusion of an insignificant number of skills related to art, the IT group is projected to be the fastest growing with an average annual growth rate of 2.02 percent. The second largest group of skills is related to healthcare, which accounts for almost 11 percent of all skill numbers and openings. This group has the third largest projected growth rate of 1.91 percent, just slightly lower than IT and construction-related skills. Construction accounts for only about 1.5 percent of all skill numbers and openings. The third largest group of skills is related to quality control and lean manufacturing principles. The third largest group accounts for about 8 percent of all skill numbers and openings, but is projected to have a below average annual growth rate of 1.6 percent. The average annual growth rate for all skill numbers is 1.77 percent.

It is interesting to note that out of a total of 384 occupations, IT skills are present in 362 occupations. For 202 of these occupations, IT skills comprise more than one-quarter of total numbers and for 98 more, they comprise one-half of total numbers.

The IT skills naturally dominated shares in computer-related occupations, but also have a very high share in occupations whose primary occupational focus is not computers. The top 10 occupations with high computer skill requirements, based on IT shares (with IT skill numbers more than 100) are presented in *Appendix Figure A4-2*.

Appendix Figure A4-2. Occupations, not primarily computer related, with the largest shares of computer skill requirements
Washington state, 2013 occupational estimations (2015 first quarter skills/occupations matrices)
Source: Employment Security Department/LMPA; WANTED Analytics

SOC	Title	Share of skills that are IT
271025	Interior designers	91.6%
193011	Economists	87.7%
171011	Architects, except landscape and naval	85.3%
173011	Architectural and civil drafters	82.5%
271014	Multimedia artists and animators	82.1%
131111	Management analysts	79.8%
271021	Commercial and industrial designers	77.8%
271024	Graphic designers	77.3%
152031	Operations research analysts	75.7%
131161	Market research analysts and marketing specialists	74.7%
132051	Financial analysts	73.2%
152041	Statisticians	73.2%
259031	Instructional coordinators	67.3%
131051	Cost estimators	66.4%
131151	Training and development specialists	65.9%

IT skills are present in 362 occupations out of 384.

Conclusions

Some significant data limitations were encountered converting occupational data into skills from job announcements. In spite of these limitations, useful results were produced. It is our conclusion that it is more important to connect education and training programs with real world skill requirements than with generic skill definitions for occupations.

Some skills with large projected numbers of openings are well defined and can be linked to different levels of training. Examples of skills with the largest numbers of projected openings are: food preparation, bilingual (with a separate skill in bilingual Spanish), customer relationship management, pediatrics, behavioral health, etc.

A second significant group of skills which for the most part are well defined in terms of primary activities, but which require significant secondary skills related to IT, are: quality control, risk assessment, lean and different engineering skills. These types of skills are much more dispersed than the first group. Relating this second skill group to training is more complicated. While primary fields are relatively stable and well defined, the IT skill sets are ever changing. The IT skills are concentrated mainly in software, algorithms, some hardware and in web applications. Since required IT skill sets change frequently, specific software applications should be given a secondary emphasis in training.

Though the IT skills are a very large group, they are highly dispersed amongst detailed skills and are subject to frequent changes. Some specific skills, like those in *Figure 6,* are important and help graduates enter the labor market or move to higher paid jobs. However, in the long run, priority should be given to foundational academic subjects like math and formal logic, multidimensional design, and foundational concepts in object-oriented programming. In other words, foundational abilities to learn, develop and implement new knowledge and technology in the long run should take priority for career preparation. Specific IT skills should receive secondary emphasis.

Future possibilities

Our skill projections process used limited data and relied on downloading files from an internet site. Gaining direct access to a database containing real world skills and using longer time frames will significantly improve results. Also, it will be important to establish a direct connection between specific skills required by employers and education and training programs.

Appendix 5. Frequently asked questions

Q: What are the steps in industry projections?

A: There are two steps to industry projections. The first step is developing aggregated statewide industry projections using the Global Insight model. The second step produces detailed industry projections. The principal data source for industry projections is a detailed covered employment time series of four-digit NAICS data for all Washington counties, specifically, the U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages (QCEW).

Q: Why are the detailed industry projections not comparable with U.S. Bureau of Labor Statistics, Current Employment Statistics (CES) definitions?

A: Industry projections are disaggregated according to U.S. Bureau of Labor Statistics, Occupational Employment Statistics (OES) definitions, which are somewhat different from CES.

Q: What is the source for occupational/industry ratios?

A: The primary source for occupational/industry ratios is the OES survey. However, this survey uses different area designations than the state's workforce development areas (WDAs) and has limited industry coverage (agriculture, non-covered employment, private households and self-employment are excluded) necessitating the use of other staffing patterns as well.

Q: Why can the ratio for industry and occupational projections differ from the OES survey outputs?

A: The ratios can be different from the OES survey outputs due to the reasons stated above and the use of substituted or combined staffing patterns or raw sample.

Q: Why can occupational/industry ratios differ between the base year and projected years?

A: This is due to the use of change factors, which predict changes in the occupational shares for each industry over time.

Q: Why can't projections be benchmarked or verified?

A: There are no administrative records for employment by occupation; therefore, the data cannot be reliably benchmarked or verified by non-survey means.

Q: How are occupational projections used?

A: Occupational projections are the only data source for the statewide and WDA-specific occupational outlook. Projections are also the foundation for developing the Occupations in Demand list, which is used to determine eligibility for a variety of training and support programs, but was created to support the unemployment insurance Training Benefits Program.

Q: How are industry projections used?

A: Industry projections can be used by policy makers, job seekers, job counselors and economic analysts. For any policy decisions, the projections should be supplemented with other available data sources (e.g., unemployment insurance claims, educational data, job announcements, etc.).

Q: Which occupational codes are used?

A: The 2010 Standard Occupational Classification (SOC) system was used for this round of projections.

Q: Can the SOC be used for administrative purposes?

A: According to BLS, the 2010 SOC was designed solely for statistical purposes. To use SOC for administrative programs, the head of an agency considering using SOC must first determine if the use of SOC definitions is appropriate for a program's objectives.

Q: Why don't the occupational totals by WDA equal the state total?

A: The totals are not additive due to the use of local staffing patterns for projections by WDA, which differ from the statewide staffing pattern.

Appendix 6. Glossary of terms

American Community Survey (ACS)

The American Community Survey (ACS) is an ongoing survey providing vital information on yearly basis about our nation. It helps local officials, community leaders and businesses understand the changes taking place in their communities, assess the past and plan the future.

ARIMA

This model type is generally referred to as ARIMA (p,d,q), with the integers referring to the autoregressive, integrated and moving average parts of the data set, respectively. ARIMA modeling can take into account trends, seasonality, cycles, errors and non-stationary aspects of a data set when making forecasts.

Industries

A classification of business establishments based on their specific economic activity.

Job openings due to growth and net replacement

Job openings due to growth and net replacement (calculated on a compound basis) represent the total projected number of openings available for new entrances into the occupation. This does not include openings that result when workers change jobs but stay in the same occupation.

Net replacement

Net replacement includes openings created by retirements and separations. It does not include normal turnover as workers go from one employer to another or from one area to another without changing their occupations.

North American Industry Classification System (NAICS)

North American Industry Classification System (NAICS) is the system used by federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing and publishing statistical data related to the U.S. business economy. NAICS was developed under the authority of the U.S. Office of Management and Budget.

Occupation

A job or profession, a category of jobs that are similar with respect to the work performed and the skills possessed by the workers.

Occupational projections

Industry projections converted to occupations, based on occupational/industry ratios.

Standard Occupational Codes (SOC)

Standard Occupational Classification (SOC) is the system used by federal statistical agencies in classifying workers into occupational categories for the purpose of collecting, calculating or disseminating data. All workers are classified into one of 840 detailed occupations according to their occupational definition. SOC was developed under the authority of the U.S. Office of Management and Budget.

Total occupational estimations and projections

Total occupational estimations and projections are calculated to describe employment in the base year and future time periods.

Workforce development area (WDA)

Workforce Development Councils (WDCs) assure quality services to customers in the implementation of the Workforce Investment Act (WIA). The WDCs provide workforce development planning and promote coordination between education, training and employment efforts in their communities. They operate in 12 workforce development areas (WDAs) in Washington state. Each area contains one or more counties Workforce Development Area.