Vineyard Financial Associates

Forecast for Washington Average Wine Grape Price, 2018-2020

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# Introduction

I am continually creating forecasts for clients: land prices, expenses, acreage numbers, labor rates, revenue and, especially, grape prices. But those forecasts can be narrowly focused. For instance, a client may want a forecast for the 80th percentile price for Pinot Noir in Sonoma County. That means I spend a great deal of time looking at specific segments of the West Coast wine grape market.

As [I have discussed before](https://www.vineyardfinancialassociates.com/blog/tag/cognitive%20biases), we humans have a huge design flaw: our tendency to let cognitive biases dictate our views and decisions. To avoid this, I have decided to methodically take a broader look at the West Coast wine grape market. I plan to forecast the overall, average price of wine grapes grown across many, if not all, wine grape-producing regions of California, Oregon and Washington. I also plan to make these forecasts public.

My goals in making these forecasts public are three-fold. First, I hope the industry makes use of them and this leads to greater use of quantitative analysis for decision-making. Second, I hope that some of my readers are prompted to get in touch and see [how my forecasting skills can benefit their businesses](https://www.vineyardfinancialassociates.com/blog/tag/cognitive%20biases). Finally, while I keep detailed, internal records of my forecasting results and accuracy, nothing is as transparent and useful as a public record. I have made many public forecasts and review them each year. I have not kept great public records, however. This project will present a good starting point for creating such a record. I believe that I am the best forecaster of wine grape prices and intend to provide proof.

I have put the forecasts near the top of this document, since I know that is the most interesting part. I would strongly recommend that, if you intend to make any use of these forecasts, that you read the whole document. Understand what these forecasts mean, a bit about how they were created and also how to adjust them as the future unfolds.

I invite you to make requests. Whichever region(s) get the most requests will be published first. I cannot promise any timeline, as I must prioritize client work. The forecasts I may generate are only for all wine grapes (no specific variety and not including table grapes crushed for wine.) In addition to this forecast of Washington prices, I will consider Oregon’s statewide prices, any of USDA’s 17 California Grape Pricing Districts and California’s statewide price.

Finally, let me ask for your pardon in advance if proof-reading or presentation are a bit lacking. As this is not a paying client project, I have emphasized content, but not presentation, to reduce the work involved in making this public.

# Forecast (Nominal and Inflation-Adjusted)

Before I jump into the forecasts I want to reiterate that you should read more than just the forecasts. At the very least, read the rest of this section for some explanation of the forecasts. I would also strongly recommend the next section, which contains some concise discussion of the forecast. Finally, if you’re interested in the forecasting process or understanding how to judge the forecast, read sections [4 Component Models](#_Component_Models) and [5 Benchmark Models](#_Benchmark_Models).

## Charts and Tables

I have presented the forecasts in two forms: inflation-adjusted into constant, 2017 dollars and non-adjusted, nominal dollars[[1]](#endnote-1). In the tables, the Forecast column is bolded, while the columns that indicate the probability distribution are not. The charts are presented with point forecasts in white and probability distributions in gradient colors. For help understanding the use, presentation and meaning of the probability distribution, see [2.5 Discussion of Probability Distribution](#_Discussion_of_Probability).

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Year | 2.5 Lower | 5.0 Lower | 10.0 Lower | 20.0 Lower | Forecast | 80.0 Upper | 90.0 Upper | 95.0 Upper | 97.5 Upper |
| 2018 | $871.16  | $923.03  | $982.84  | $1,055.25  | **$1,176.60**  | $1,332.33  | $1,404.75  | $1,464.55  | $1,516.42  |
| 2019 | $785.65  | $850.75  | $925.82  | $1,016.71  | **$1,165.20**  | $1,364.49  | $1,455.39  | $1,530.45  | $1,595.56  |
| 2020 | $742.69  | $814.32  | $896.89  | $996.89  | **$1,158.39**  | $1,379.47  | $1,479.47  | $1,562.04  | $1,633.67  |

Table 1: Forecasted Average Price for Washington Wine Grapes, in 2017 Dollars

Chart 1: Forecasted Average Price, 2017 Dollars, for Washington Wine Grapes

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Date | 2.5 Lower | 5.0 Lower | 10.0 Lower | 20.0 Lower | Forecast | 80.0 Upper | 90.0 Upper | 95.0 Upper | 97.5 Upper |
| 2018 | $893.81  | $947.03  | $1,008.39  | $1,082.69  | **$1,207.19**  | $1,366.97  | $1,441.27  | $1,502.63  | $1,555.85  |
| 2019 | $824.62  | $892.95  | $971.74  | $1,067.14  | **$1,222.99**  | $1,432.17  | $1,527.57  | $1,606.36  | $1,674.70  |
| 2020 | $797.30  | $874.20  | $962.84  | $1,070.19  | **$1,243.57**  | $1,480.90  | $1,588.25  | $1,676.89  | $1,753.79  |

Table 2: Forecasted Average Price for Washington Wine Grapes, in Nominal Dollars

Chart 2: Forecasted Average Price, in Nominal Dollars, for Washington Wine Grapes

## Possible Bias

To estimate the model’s future performance, it was tested against a rolling hold-out sample. In this case, I withheld the last three years of data, recalculated the formulae used to produce the forecast, using only that reduced sample set, and tested it against the withheld data. I repeated this while withholding only two years of data and again, withholding only one year. This yielded three one-year ahead forecasts, two two-year ahead forecasts and one three-year ahead forecast.

All these forecasts were slightly lower than the actual outcome, by an average of 1.61%. One might argue that it would be appropriate to adjust the forecasts upward by 1.61%. This is legitimate and you may want to do this. I chose not to. It is a small error and based on a relatively small hold-out sample.

## Assumptions

This model depends upon the following assumptions:

* Inflation is equal to the consumer price index, which will be 2.60%, 2.30% and 2.28% in 2018, 2019 and 2020, respectively[[2]](#endnote-2).
* This model assumes that California will see no change in bearing vineyard acreage[[3]](#endnote-3).
* The model assumes that Washington bearing acreage will increase to 48,142, 60,409 and 61,253 in 2018, 2019 and 2020, respectively[[4]](#endnote-4).

## Rule-of-Thumb Adjustments of Assumptions

If the assumptions above turn out to be wrong, we can adjust to understand how that might influence the model. This also allows us to score the model separately of the assumptions. In the case of inflation, one can simply use different inflation adjustments to create a new estimate. This can be done retroactively, to see what the forecast would look like had the inflation numbers been correct. It can also be proactive, in the case that you want to use different estimates of inflation going forward.

If the assumptions regarding acreage are incorrect, this can be adjusted for, too, though not as easily. Based on the formula used for estimating the forecast, every bearing acre in excess of my assumptions should, as a rule of thumb, reduce the price by roughly .024¢ and vice-versa. If, as an example, acreage numbers turn out to be 1,000 acres below the assumed level, the price forecast would be expected to be roughly 24¢ higher.

## Discussion of Probability Distribution

Generally, people want to use forecasts almost exclusively for the point forecast. The point forecast is, roughly speaking, the outcome that the forecast predicts as most likely. This is certainly useful information, but using it in a vacuum is a mis-use of forecasting. Forecasting is not fortune-telling. A forecast is always wrong by some amount. To properly use a forecast, you should understand the probability distribution (also known as a confidence interval or prediction interval.) This is an estimate of how likely the forecast is to be off, by how much, and in which direction.

First, an explanation of the charts and tables above. The bounds are given as a number, followed by the words ‘Lower’ or ‘Upper’. In either case, the number given is the percent chance that the actual outcome will fall below this number. The actual outcome is expected to be lower than the 2.5 Lower column figure only 2.5% of the time. The actual outcome is expected to exceed the 80.0 Upper column figure 20% of the time. This is depicted visually in Chart 1 and Chart 2.

You can use these numbers to roughly estimate, for instance, the likelihood that prices would adequately cover costs or to understand how likely an indexed contract is to be a better deal than specific, nominal prices. For clients, I even use these probability distributions to run computerized simulations that can capture the relationship between various aspects of a business, such as multiple variety types, expenses, yields, etc. Such simulations can provide the most realistic financial forecasts possible.

## Strength of Model and Caveats

As stated earlier, forecasters are not fortune-tellers. This is a strictly quantitative forecast that integrates no knowledge from the field. Someone who is buying large amounts of varied grapes from diverse sources may be a better source of forecasts, at least one year out, if they are also applying quantitative rigor to integrating their knowledge. In general, however, quantitative forecasts outperform expert judgment.

More importantly, quantitative forecasts lack true prescience – they cannot anticipate changes in the world that have no historical precedent. Since 2008, these have widely come to be known as “black swans,” which you can look up on Wikipedia for more information. For this reason, I do not produce prediction intervals above the 95% range (corresponding to the probability distribution bounds Lower 2.5 and Higher 97.5). I simply assume there is a 5% chance of black swans or mistakes shattering the usefulness of a forecast. I consider this to be a conservative assumption, based on the empirical results of my forecasts. Still, it is a useful threshold for assumptions about forecasts.

On the other hand, forecasters can do a great job of measuring the accuracy and uncertainty of their forecasts. For one, I test my forecasts against hold-out data, which is integrated into the probability distribution. This creates a realistic assessment of uncertaintyvi.

Often people use historical fit as a measure of uncertainty. That is, if a model’s error produced an average 5% error during the historical period, they assume that the average error will be 5% going forward. That is wrong (and either lazy or ignorant.) In general, future periods do not look exactly like the periods studied and, therefore, models based on history generally have larger future errors than their historical, fitted error. By using hold-out data, I avoid this issue and accurately estimate future model error.

On the other hand, within-sample statistics can be useful for understanding a model’s likelihood to be valid. In some ways, hold-out data is still a better measure of validity, but the within-sample statistics are still useful. They are presented below, followed by some explanation.

In addition to the following chart, note that no variables included in the component models had a [p-value](https://en.wikipedia.org/wiki/P-value) exceeding 0.003. In academia, variables are considered significant if their p-value =< .050. All models were parsimonious, with no more than 3 parameters. In general, less complex models are superior, as each parameter introduces additional uncertainty and error. Finally, note that the final forecast relied upon 3 component models and all were built to predict prices in constant dollars, which were then adjusted for the nominal forecast.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Metric | Model 0 | Model 4 | Model 1 | Link to Explanation |
| Sample size[[5]](#endnote-5) | 47 | 21 | 21 | <https://en.wikipedia.org/wiki/Sample_size_determination> |
| Mean | 1,180.57 | 1,206.23 | 1,206.23 | <https://en.wikipedia.org/wiki/Mean> |
| Adj. R-square | 0.54 | 0.90 | 0.90 | [https://en.wikipedia.org/wiki/Coefficient\_of\_determination#Adjusted\_R2](https://en.wikipedia.org/wiki/Coefficient_of_determination%23Adjusted_R2) |
| Durbin-Watson | 1.91 | 2.52 | 2.58 | <https://en.wikipedia.org/wiki/Durbin%E2%80%93Watson_statistic> |
| Forecast error | 166.39 | 30.07 | 29.99 | <https://en.wikipedia.org/wiki/Forecast_error> |
| MAPE | 9.06% | 1.76% | 1.74% | <https://en.wikipedia.org/wiki/Mean_absolute_percentage_error> |
| RMSE | 164.61 | 27.84 | 27.77 | <https://en.wikipedia.org/wiki/Root-mean-square_deviation> |
| MAD/Mean Ratio | 0.09 | 0.02 | 0.02 | MAD (see below), divided by mean, used for scaling purposes |
| Std. deviation | 245.75 | 96.53 | 96.53 | <https://en.wikipedia.org/wiki/Standard_deviation> |
| Ljung-Box(18) | 22.6 P=0.79 | 17.0 P=0.80 | 17.5 P=0.82 | <https://en.wikipedia.org/wiki/Ljung%E2%80%93Box_test> |
| BIC | 171.49 | 34.6 | 34.52 | <https://en.wikipedia.org/wiki/Bayesian_information_criterion> |
| MAD | 105.51 | 20.61 | 20.34 | <https://en.wikipedia.org/wiki/Average_absolute_deviation> |

Table 3: Within-Sample Statistics for Component Models

# Discussion

Though the forecast indicates a slight rise in nominal prices, it also indicates that this will happen at a slower rate than inflation. Washington growers can expect to see some very slight compression of margins. This likelihood, however, is not much greater than a coin flip, as one might assume after viewing Chart 1 and Chart 2. Essentially, the forecast is flat and prices are not expected to move a great deal. For this reason, I would recommend that growers pay attention to the probability distribution: what are the chances that prices hit certain highs or lows?

As shown in Chart 3, Washington’s wine grapes saw a great deal of fluctuation in its earlier history. For the past 10-20 years, however, inflation-adjusted prices have been far more stable, through periods of recession and of great volatility in the California wine grape market. The forecast presented indicates that this stability will continue. Recent, minor gains, however, will probably be reversed.

In my experience, this pattern is typical of regions where grape prices are cost-driven. In regions where price is dictated by willingness to pay, like Sonoma County or Napa Valley, prices can shift rapidly to adjust to the market. In regions like Washington, where producers – most notably Altria, in this case – largely control the market, prices are dictated more by what budget a grower needs to continue to produce. Producers capture a great deal of the economic profit, while growers fight to maintain their narrow margins. Whether or not this is the case in Washington, I certainly cannot say for sure, as I have no front-line experience in the region. What I can say for sure is that, even if my theory is broadly correct, it applies only to the market in aggregate, and not to any specific operation.

I often add in scenario analysis to my forecasts. Lately, I have been looking into alternate scenarios that consider recessions at various points in the next several years, (touched upon in [this blog post](https://www.vineyardfinancialassociates.com/single-post/2018/07/09/Some-Big-Picture-Thoughts-on-Where-Our-Industry-is-Heading-in-the-Next-Few-Years).) I chose not to do so for this case. For one, that requires additional work. More importantly, as a region where grape price is (a) cost-driven and (b) offers great value, Washington should only see prices dip in a recession if the whole US wine market implodes or experiences a major, unanticipated shift. You can look at Chart 3 and see that prices held quite steady during the Great Recession. I would guess that growers had little room to give and the price point for the wines these grapes are going into offered good value to premium wine drinkers who needed to spend less on each bottle.

Chart 3: Historical Prices, Inflation-Adjusted, Washington Wine Grapes, All Varieties



# Component Models

In addition to tracking the final forecast, I also track the component forecasts. In most cases, my final forecasts include multiple models. In this case, three models are included. Tracking the component forecasts allows greater model improvement over time, as the components’ importance can be properly weighted to increase forecasting accuracy.

**Model 0** is by far the weakest model included, per the within-sample statistics, although hold-out testing results were excellent[[6]](#endnote-6). The forecast for this model actually went 7 years out, though I only used the first three years of that forecast. Despite the relative weakness of the model, I decided to include it for various reasons. For one, the method was significantly different and simpler than the other included models. More importantly, it relied on the whole available history of data, while the other two models only used the last 21 years. See the forecast results in Table 4. Furthermore, the accurate hold-out testing results also justified inclusion of the model.

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,193.79  |
| 2019 | $1,190.60  |
| 2020 | $1,188.18  |

Table 4: Model 0 Results

**Model 1** and **Model 4** are similar in that they each have three parameters, of which they share two. These models have very similar coefficients for those shared parameters. Both show highly promising within-sample statistics and hold-out testing results. See the forecast results in Table 5 and Table 6.

|  |  |
| --- | --- |
| Date | Forecast |
| 2018 | $1,170.00  |
| 2019 | $1,155.00  |
| 2020 | $1,147.00  |

Table 5: Model 1 Results

|  |  |
| --- | --- |
| Date | Forecast |
| 2018 | $1,166.00  |
| 2019 | $1,150.00  |
| 2020 | $1,140.00  |

Table 6: Model 4 Results

# Benchmark Models

I have included benchmark models that rely upon very simple forecasting methods. These models can be used as a scalable metric for the usefulness of the forecast. If any one of these models consistently outperforms my forecast, it would call into question the usefulness of the forecast for Washington wine grapes. Note that, simply due to the number of benchmark models, at least one is likely to outperform the forecast in any given year, simply as a result of randomness. In this case, a benchmark model outperforming the primary model is not unrealistic, since inflation-adjusted price looks to be nearly static. In such a case, this model may serve only to confirm the validity of very simple models. On the other hand, since this forecast uses explanatory variables it should likely anticipate shifts in the market that the very simple models cannot.

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,198.00  |
| 2019 | $1,198.00  |
| 2020 | $1,198.00  |

Table 7: Exponential Smoothing Model, No Seasonality, No Trend[[7]](#endnote-7)

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,187.91  |
| 2019 | $1,187.91  |
| 2020 | $1,187.91  |

Table 8: 3-Year Moving Average

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,176.15  |
| 2019 | $1,176.15  |
| 2020 | $1,176.15  |

Table 9: 5-Year Moving Average

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,213.26  |
| 2019 | $1,213.26  |
| 2020 | $1,213.26  |

Table 10: Growth Curve[[8]](#endnote-8)

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,188.66  |
| 2019 | $1,189.00  |
| 2020 | $1,189.34  |

Table 11: Linear Extrapolation[[9]](#endnote-9)

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,214.64  |
| 2019 | $1,231.51  |
| 2020 | $1,248.62  |

Table 12: Same Percentage Increase as Last Year Over Previous[[10]](#endnote-10)

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,214.41  |
| 2019 | $1,230.83  |
| 2020 | $1,247.24  |

Table 13: Same Incremental Increase as Last Year Over Previous[[11]](#endnote-11)

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $1,216.45  |
| 2019 | $1,235.19  |
| 2020 | $1,254.21  |

Table 14: Historical Compounded Annual Growth Rate[[12]](#endnote-12)

# Endnotes

1. Technically, the real-world price cannot realistically be known with absolute precision. Throughout this document, when I refer to price, I am referring to the “All Varieties” line of the relevant reports put out by the USDA, Washington State Wine Commission and other organizations. [↑](#endnote-ref-1)
2. My estimates are derived from the most recent [Philadelphia Federal Reserve’s Livingston Survey](https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey). [↑](#endnote-ref-2)
3. This assumption is based off information provided by [Allied Grape Growers](http://www.alliedgrapegrowers.org/present.html), who I consider to be the most authoritative source. [↑](#endnote-ref-3)
4. Technically, the real-world acreage figure cannot realistically be known with absolute precision. Throughout this document, when I refer to acreage, I am referring to the “All Varieties” line, or similar figure, of the relevant reports put out by the USDA, Washington State Wine Commission and other organizations. [↑](#endnote-ref-4)
5. Predictive variables for Models 1 and 4 had a shorter available history. [↑](#endnote-ref-5)
6. Hold-out testing for Model 0 showed MAPEs of 2.69%, 2.29% and 1.47% for horizons of 1, 2 and 3 years respectively. For Model 4, the figures are 1.28%, 1.53% and 2.43%. For Model 4, the MAPEs are 1.50%, 1.89% and 2.85% at those respective horizons. [↑](#endnote-ref-6)
7. This forecast is identical to the Random Walk naïve model and, for these purposes, the Same As Last Year model. [↑](#endnote-ref-7)
8. y = a(1+exp(-b(t-c))); a = 1213.26, b = .6964, c = .02125. [↑](#endnote-ref-8)
9. Y = a + bt; a = 1172.82, b = .3372. [↑](#endnote-ref-9)
10. 1.4% [↑](#endnote-ref-10)
11. $16.42 [↑](#endnote-ref-11)
12. 1.54%

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