Vineyard Financial Associates

Forecast for Oregon Average Wine Grape Price, 2018-2021

Table of Contents

[1 Introduction 1](#_Toc520813339)

[2 Forecast (Nominal and Inflation-Adjusted) 2](#_Toc520813340)

[2.1 Charts and Tables 2](#_Toc520813341)

[2.2 Possible Bias 4](#_Toc520813342)

[2.3 Assumptions 4](#_Toc520813343)

[2.4 Rule-of-Thumb Adjustments of Assumptions 5](#_Toc520813344)

[2.5 Discussion of Probability Distribution 5](#_Toc520813345)

[2.6 Strength of Model and Caveats 5](#_Toc520813346)

[3 Discussion 6](#_Toc520813347)

[4 Component Models 9](#_Toc520813348)

[5 Benchmark Models 9](#_Toc520813349)

[Endnotes 11](#_Toc520813350)

# 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 mitigate this and improve my understanding of the West Coast wine grape market, I have decided to methodically take a broader look at that 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/forecasting-investment-consulting-f). 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 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. On that note, this forecast, unfortunately, isn’t as thorough as the [forecast for Washington wine grape prices](https://www.vineyardfinancialassociates.com/single-post/2018/07/31/Three-Year-Forecast-of-Washington-Wine-Grape-Prices). That was due to a busy schedule. I hope to return to thorough forecasts in the future.

# 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 below, the Forecast column is bolded, while the columns that indicate the probability distribution are not. For help understanding the use, presentation and meaning of the probability distribution, see [2.4 Discussion of Probability Distribution](#_Discussion_of_Probability).

|  |  |  |  |
| --- | --- | --- | --- |
| Vintage | 2.5 Lower | Forecast | 97.5 Upper |
| 2018 | $1,847.29  | **$2,087.96**  | $2,332.19  |
| 2019 | $1,857.50  | **$2,081.05**  | $2,416.39  |
| 2020 | $1,867.79  | **$2,113.95**  | $2,473.65  |
| 2021 | $1,825.66  | **$2,101.76**  | $2,490.76  |

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Vintage | 2.5 Lower | Forecast | 97.5 Upper | Assumed CPI Factor[[2]](#endnote-2) |
| 2018 | $1,895.32 | **$2,142.25** | $2,392.83 | 1.026 |
| 2019 | $1,949.62 | **$2,184.26** | $2,536.24 | 1.050 |
| 2020 | $2,005.13 | **$2,269.38** | $2,655.53 | 1.074 |
| 2021 | $2,004.58 | **$2,307.75** | $2,734.87 | 1.098 |

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

## 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 2020/2021, respectively[[3]](#endnote-3).
* This model assumes that Oregon will see significant increases in bearing vineyard acreage[[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. See the endnotes for the statistical information needed to calculate such an adjustment.

## 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 97.5 Upper column figure 2.5% of the time.

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. In this case, unlike [my forecast for Washington grape prices](https://www.vineyardfinancialassociates.com/single-post/2018/07/31/Three-Year-Forecast-of-Washington-Wine-Grape-Prices), I only included the two bounds for the probability distribution, due to time constraints. I hope that these still have some use for my readers, in addition to their usefulness to me for judging the model’s success.

## 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. For instance, with Joe Wagner ditching his Oregon grape contracts, which constitute roughly 2% of the total Oregon market, prices may be lower for 2018 than expected. 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 uncertainty.

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, with links to definitions and explanations.

In addition to the following chart, note that no variables included in the price component models had a [p-value](https://en.wikipedia.org/wiki/P-value) exceeding 0.159, though the acreage-prediction model incorporated into Model 3 utilized a variable with a p-value of .286. In academia, variables are considered significant if their p-value =< .050. In business applications, p-values as high as .200 are considered great. No model used more than 4 parameters, of which no more than 1 was an independent variable. 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 1 | Model 2 | Model 3 | Link to Explanation |
| Sample size | 30 | 30 | 30 | <https://en.wikipedia.org/wiki/Sample_size_determination> |
| Mean | 1,906.06 | 1,906.06 | 1,906.06 | <https://en.wikipedia.org/wiki/Mean> |
| Adj. R-square | 0.9 | 0.9 | 0.91 | [https://en.wikipedia.org/wiki/Coefficient\_of\_determination#Adjusted\_R2](https://en.wikipedia.org/wiki/Coefficient_of_determination%23Adjusted_R2) |
| Durbin-Watson | 2.31 | 2.37 | 1.72 | <https://en.wikipedia.org/wiki/Durbin%E2%80%93Watson_statistic> |
| Forecast error | 111.65 | 110.97 | 103.11 | <https://en.wikipedia.org/wiki/Forecast_error> |
| MAPE | 4.22% | 4.16% | 4.41% | <https://en.wikipedia.org/wiki/Mean_absolute_percentage_error> |
| RMSE | 105.92 | 107.21 | 95.99 | <https://en.wikipedia.org/wiki/Root-mean-square_deviation> |
| MAD/Mean Ratio | 0.04 | 0.04 | 0.04 | MAD (see below), divided by mean, used for scaling purposes |
| Std. deviation | 348.32 | 348.32 | 348.32 | <https://en.wikipedia.org/wiki/Standard_deviation> |
| Ljung-Box(18) | 22.2 P=0.78 | 25.0 P=0.88 | 17.0 P=0.48 | <https://en.wikipedia.org/wiki/Ljung%E2%80%93Box_test> |
| BIC | 125.56 | 120.08 | 120.43 | <https://en.wikipedia.org/wiki/Bayesian_information_criterion> |
| MAD | 79.18 | 78.42 | 79.78 | <https://en.wikipedia.org/wiki/Average_absolute_deviation> |

Table : Within-Sample Statistics for Component Models

# Discussion

Though the forecast indicates a continual rise in nominal prices, the forecasted change, in inflation-adjusted terms, is small, uncertain and unsteady. Essentially, the forecast is just a bit better for growers than a flat one and prices are not expected to move a great deal. No big surprise there, but hopefully useful.

I would encourage buyers and sellers of grapes to look at the 2.5 and 97.5 percent probability levels, too. Considering how wide of a probability range that is, the numbers indicate relatively low volatility. These worst-best case scenarios do not look too extreme.

As shown in Chart 2, Oregon’s wine grapes saw a great deal of price growth 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.

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 Oregon, where producers exercise a great deal of control, prices are dictated more by what budget a grower needs in order to continue to operate. 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 Oregon, I certainly cannot say for sure, as I have limited 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, Oregon 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 2 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.

To be clear, a recession would, of course, reduce grape prices and one of my component models considers this. But the scale is, assuming a recession like the Great Recession, along the lines of a couple dozen dollars, not a couple hundred dollars.

On the other hand, we have seen how price growth has begun to stagnate (in inflation-adjusted terms), in the past 10-20 years. This, despite increasing popularity and growing scores. One explanation can be found in Chart 1. That period of stagnation in prices has seen rapid growth in vineyard plantings. My models assume this will continue. If last year’s slow growth in new plantings continues, we may see higher prices.

Chart : Historical Acreage, Oregon Vineyards

Chart 2: Historical Prices, Inflation-Adjusted, Oregon 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. In this case, for technical reasons, I will be tracking only one-year ahead performance for the three component models.

**Model 1** has three parameters, one of which is an independent variable measuring wine industry indications. Model 1 estimates that each acre of vineyard reduces inflation-adjusted grape prices per ton by $0.029.

**Model 2** has only two parameters, one of which is an independent variable measuring macroeconomic indications. Both Models 1 and 2 have excellent in-sample and hold-out sample indications for one-year out predictive capacity and, when combined, allow me to consider macroeconomic and industry indications. Model 2 estimates that each $1.00 of per-capita GDP lifts inflation-adjusted grape prices per ton by $0.006741.

**Model 3** has four parameters, one of which is acreage and, therefore, relies on an iterative, companion model for estimating future acreage. Though Model 3 is strong and improves longer-term forecasts, the companion model is weaker and increases uncertainty. Model 3 estimates that each acre of vineyard reduces inflation-adjusted grape prices per ton by $0.05375, a greater effect than in Model 1.

|  |  |
| --- | --- |
| Model | Forecast for 2018 |
| Model 1 | $2,054.90  |
| Model 2 | $2,064.95 |
| Model 3 | $2,144.04  |

Table : Component Model Forecasts for 2018

# 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 Oregon wine grapes. Note that, 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 is relatively stable. 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. Note that these very simple models are likely to be considerably less effective for forecasting smaller data sets, such as Rogue Valley Pinot Noir prices or any other specific grape category.

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,072.78 |
| 2019 | $2,072.78 |
| 2020 | $2,072.78 |

Table 5: 3-Year, Simple Moving Average

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,157.71 |
| 2019 | $2,157.71 |
| 2020 | $2,157.71 |

Table 6: 5-Year, Simple Moving Average

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,056.00 |
| 2019 | $2,056.00 |
| 2020 | $2,056.00 |

Table 7: Same as Last Year

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,090.34 |
| 2019 | $2,125.24 |
| 2020 | $2,160.74 |

Table : Same as Last Year, Increasing by Long-Term CAGR of 1.67%

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,082.89 |
| 2019 | $2,109.78 |
| 2020 | $2,136.67 |

Table 9: Same as Last Year, Increasing by Average Increment of $26.89

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,016.48 |
| 2019 | $1,977.72 |
| 2020 | $1,939.71 |

Table 10: Same Percentage Increase as Last Year Over Previous

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,015.71 |
| 2019 | $1,975.41 |
| 2020 | $1,935.12 |

Table 11: Same Incremental Increase as Last Year Over Previous

|  |  |
| --- | --- |
| Year | Forecast |
| 2018 | $2,454.56 |
| 2019 | $2,490.16 |
| 2020 | $2,525.77 |

Table 12: Linear Regression

# 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 “Total” line for the “Price per Ton” column of the relevant report. [↑](#endnote-ref-1)
2. This is the adjustment made to the inflation-agnostic numbers to estimate nominal prices. These are derived from an assumption of 2.6% inflation for 2018, 2.3% for 2019 and 2.28% for 2020 and 2021, 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. 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-3)
4. See this chart for acreage assumptions , which are derived from a formula based on the following parameters: . See the following statistical analysis of the model: . [↑](#endnote-ref-4)