Vienna 2019 Abstract Submission

Title
Measuring the Wine Market: Creating model-based market indices from vintage data

I want to submit an abstract for:
Conference Presentation

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Keywords
Wine, market index, age-period-cohort models, Bordeaux wine

Research Question
Can we create market indices for wines by specific regions and specific producers with more resolution and stability than traditional market indices?

Methods
Using age-period-cohort analysis, we create a range of market indices and compare them to market basket indices and to one another.

Results
The results show that for the top wines, sufficient data exists to produce wine-specific indices that are more stable and revealing than market basket indices.

Abstract
Several outlets provide wine indices based upon baskets of specific wine vintages. Those baskets are typically chosen by wine experts and the average observed price is reported as an index. This approach is common in the financial markets, but unlike stocks, bonds, and most commodities, the age of the wine is an important determinant of price. Therefore, wine markets as measured from a fixed basket of vintages will be biased toward appreciation.

The current research leverages previous work by (Breeden & Liang, 2017) to obtain a market environment measure that is independent of the age of the wine and popularity (price) of specific vintages. Previously a single market was measured for all Bordeaux wines. This study separately analyzes the top traded 25 Bordeaux wines in the auctionforecast.com database. From those 25 wine market measures, correlations between wines was explored and aggregate indices were constructed based upon observed dynamical similarities. These wine market measures were compared to simple price averages, showing that much more structure is revealed in a model-based approach to measuring the wine market. That structure was confirmed across the analysis, even with independently analyzed wines.

Method of Analysis
The analysis is based upon an Age-Period-Cohort approach, which has been used extensively in the social science for several decades (Holford, 1983) and recently achieved popularity in modeling consumer behavior (Breeden J. L., 2010) (Breeden & Canals-Cerda, 2016). APC models share the same basic concepts as survival and hazard models

(Cox & Oakes, 1984), but with specific treatment for the linear specification errors and nonparametric analysis.

APC models are a generic technique for analyzing performance data from separate vintages, decomposing the data into independent functions of vintage quality, lifecycle versus age, and environment versus time. For the current investigation, no further analysis of the drivers of either vintage quality or environmental drivers are required.

Since this application of the APC algorithm is being used to model constituent drivers of price sensitivity, it falls within the class of hedonic regression (Rosen, 1974) is also similar to Repeat Sales Regression (Bailey, Muth, & Nourse, 1963). Repeat sales regression assumes that the log appreciation rate equals the log appreciation rate of an environment plus an error term. Log differences of repeat sales are regressed on time dummies. Although similar in the concept of looking at recurring sales, because of the time nonuniformity of the auction data, the APC model is being applied directly to price values rather than price differences. We can model the individual auction results directly without any aggregation assumptions.

The APC approach also provides a specific estimate of all three dimensions of age, vintage and calendar date without the biases that come from omission and with proper treatment of long-term trends.

APC models can be expressed as
$\log(r(a=t-v,v,t)) \sim (F(a)+G(v)+H(t))$ (1)

Prices have a lognormal distribution, so the log of the price is modeled. F(a) is the wine lifecycle capturing the average price versus age of the wine for a typical vintage. G(v) is the vintage function measuring the scaling necessary to fit the average lifecycle to the price data for a specific vintage. On the scale of log-price, G(v) normally distributed about 0. H(t) is the environment for this wine segment versus calendar date, t. Again, H(t) is normally distributed about 0 capturing the increased or decreased prices observed at auction on certain calendar dates. It is a proportional adjustment across all wines and vintages within the same segment.

Each function in Equation 1, F(a), G(v), and H(t) is estimated nonparametrically (one coefficient for each observed age, vintage, and date) using a Bayesian APC algorithm as described by
Schmid and Held (Schmid & Held, 2007). Bayesian APC results look “noisier” than a spline estimation as one would obtain from standard APC implementations, but it has the potential to estimate nonlinearities and discontinuities prevalent in the vintage and environment functions.

Data
The analysis was conducted on a database provided by auctionforecast.com covering a 13-year time span from Jan 2016 through December 2018. The following auction houses were included: Acker Wines, Bidforwine, Bonhams, Chicago Wine Co., Christie's, Hart Davis Hart, Langton's, Skinner, Sotheby's, Spectrum Wine, Veiling Sylvie's, and Zachys. The provided data adjusted all currencies to US dollars according to the exchange rate on the date of the auction. Prices are in nominal dollars, without adjustment for inflation over time. All prices are hammer prices.

Only auction results for lots containing a single wine vintage were included, and all prices were converted to price per bottle. The full database contains more than two million auction prices, but only the 25 top traded Bordeaux wines were considered for the current study. Those wines are listed in Table 1 including the average price during the final three-year period.

For comparison, an analysis of all Bordeaux wine vintages with selling prices above $100 per bottle is included in Figure 5. That analysis included 158,000 auction prices for xxxx wines in 46 vintages.

Results
Each wine in Table 1 was analyzed independently according to Equation 1. The lifecycles from those analyses were, within estimation error, simple scalings of a common lifecycle obtained by modeling all Bordeaux wines with auction prices greater than US$100. Still, for the remaining analysis, the separate lifecycles were retained in order to provide an independent comparison of the wines.

The vintage functions from the wines were retained, but are not discussed further for the present analysis. The following analysis focuses on the 25 environment functions obtained from the Bayesian APC estimation.

Figure 1 shows the correlations between environment function by wine. The correlation estimates were weighted by √(n(t)), where n(t) is the number auctions for those two wines in month t. The colors range from bright green for a maximum value of 1.0 to bright red for the minimum observed value, which was -0.1. The dendrogram on the side shows a hierarchical clustering of the wines based upon the weighted correlation matrix.

Figure 2 shows the same analysis, but only for the environment functions observed from January 2016 through December 2018. This is done to test the stability of the observed correlations and to get a view using the part of the dataset with the greatest number of observations so that the weighting is relatively unimportant.

Figure 1 shows that the most frequently traded wines in Table 1 are also highly inter-correlated. Although not as highly correlated, the dendrogram also identifies a second cluster. Both clusters are listed in Table 2. For the period January 2016 through December 2018 the environment functions are less noisy so the second cluster is more pronounced. However, we also see that Chateau Margaux and Chateau Ausone could be members of both clusters, or that we really only have one cluster.

All of the correlations for the 2016 – 2018 time period are written out with their confidence intervals in Table 3. We see that none of the wines are actually anticorrelated when the confidence intervals are taken into account. We either have correlation or no significance.

Figure 3 and Figure 4 plot the individual wine environment functions for the two clusters. Cluster 1 looks quite tight, but Cluster 2 looks more diffuse. Nevertheless, when a 20% trimmed mean is applied to both graphs to create the lines in Figure 5, they look very similar, just with Cluster 1 being more dynamic.

In addition to the series for Clusters 1 and 2, Figure 5 includes an aggregate line for all top 25 Bordeaux wines, again with a 25% trimmed mean. Lastly, a line is included for the environment function for all Bordeaux wines in the database with sales price greater than US$100. That line follows the same trend as the other wines, but with much greater seasonality.

The last result is a comparison of the environment function for the Top 25 Bordeaux wines to the average price for that same basket of wines. We know from decades of theoretical work that APC models accurately isolate the environment (calendar based) effects from age and vintage effects. We also know from the preceding analysis that we have a surprisingly high amount of agreement across independently modeled wines. Considering both facts, the Top 25 Bordeaux Wine Environment shown is believable as real market moves, even when those can be sudden, such as the spikes in 2016. Consequently, that means that the simple average price time series is missing quite a lot of structure because of the effects of popular vintages entering the averages or aging.

Although we want to continue this analysis by comparing to popular published wine indices, the conclusion to date is that a model-based measure of the wine markets can provide a better view than the basket-based approaches without relying on expert judgment to create the baskets.

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Measuring the Wine Market: Creating model-based market indices from vintage data

By Joseph L. Breeden

Research Question: Can we create broad market indices for wines by specific regions and specific producers with more resolution and stability than traditional market indices?

Methods: Using age-period-cohort analysis, we create a range of market indices and compare them to market basket indices and to one another.

Results: The results show that for the top wines, sufficient data exists to produce wine-specific indices that are more stable and revealing than market basket indices.

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Prices have a lognormal distribution, so the log of the price is modeled. F(a) is the wine lifecycle capturing the average price versus age of the wine for a typical vintage. G(v) is the vintage function measuring the scaling necessary to fit the average lifecycle to the price data for a specific vintage. On the scale of log-price, G(v) normally distributed about 0. H(t) is the environment for this wine segment versus calendar date, t. Again, H(t) is normally distributed about 0 capturing the increased or decreased prices observed at auction on certain calendar dates. It is a proportional adjustment across all wines and vintages within the same segment.

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Table 1: Auction counts by wine.

Wine	**Total**	**Per Month, 2016 - 2018**
Chateau Lafite Rothschild	22,852	149.5
Chateau Mouton Rothschild	22,010	152.3
Chateau Latour	15,377	104.6
Chateau Margaux	13,910	88.6
Chateau Haut Brion	10,766	78.6
Chateau Petrus	10,212	70.0
Chateau Cheval Blanc	8,403	56.8
Chateau Leoville Las Cases	6,555	54.6
Chateau Lynch Bages	5,838	46.2
Chateau La Mission Haut Brion	5,636	52.7
Chateau Palmer	4,969	35.4
Chateau Cos Destournel	4,646	34.5
Chateau Ducru Beaucaillou	3,993	37.8
Chateau Pichon Longueville Lalande	3,562	28.1
Chateau Montrose	3,543	33.3
Chateau Leoville Barton	2,968	21.2
Chateau Pavie	2,904	25.5
Chateau Ausone	2,812	20.8
Carruades De Lafite	2,798	22.9
Chateau Pichon Longueville Comtesse De Lalande	2,746	26.3
Chateau Gruaud Larose	2,359	15.6
Chateau Lafleur	2,268	17.7
Chateau Angelus	2,246	24.0
Chateau Pichon Longueville Baron	1,938	19.1
Chateau Trotanoy	1,688	15.5
Total		

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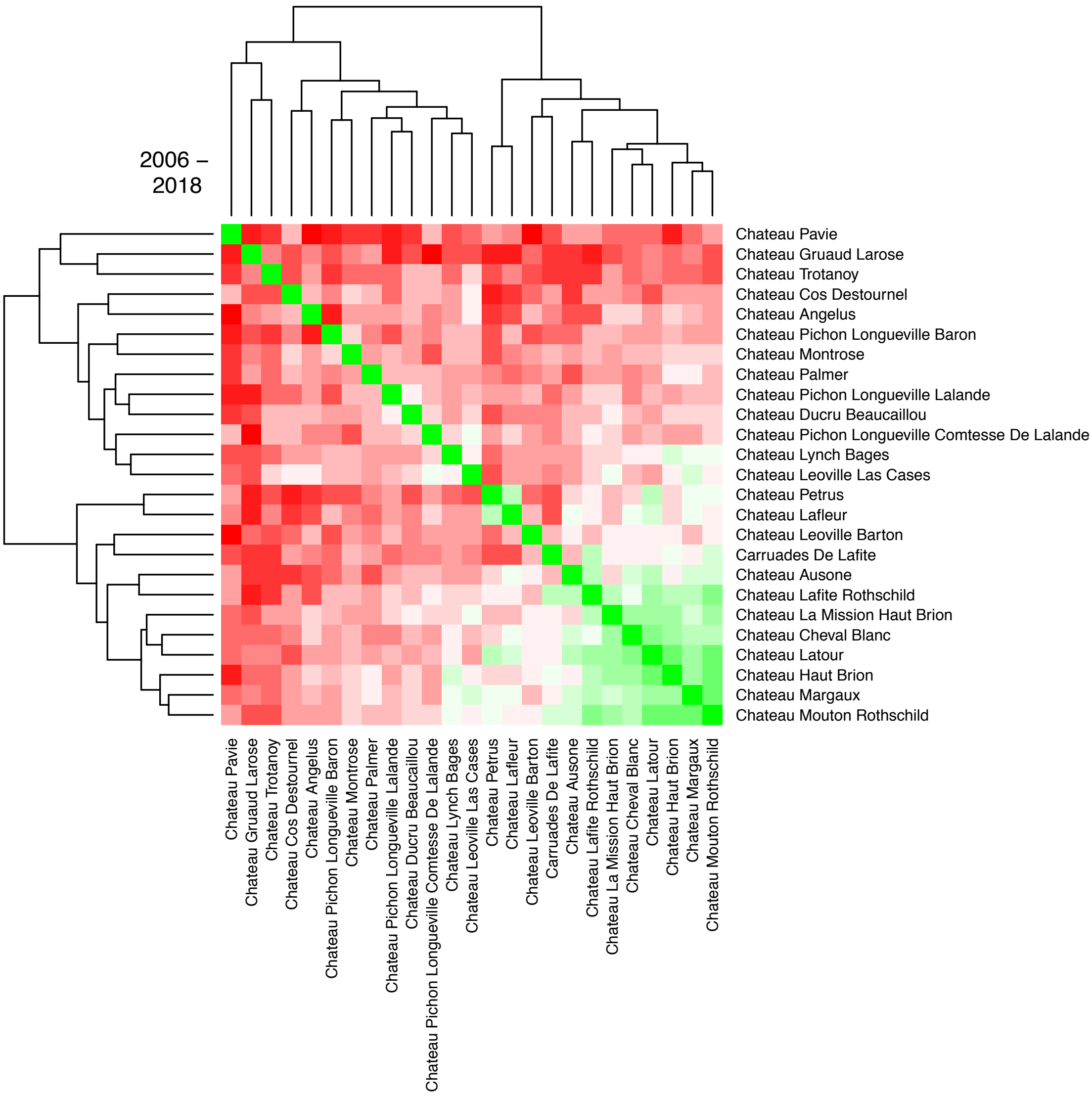

Figure 1: Correlation matrix and clustering dendrogram for the environment functions from Jan 2006 through Dec 2018.

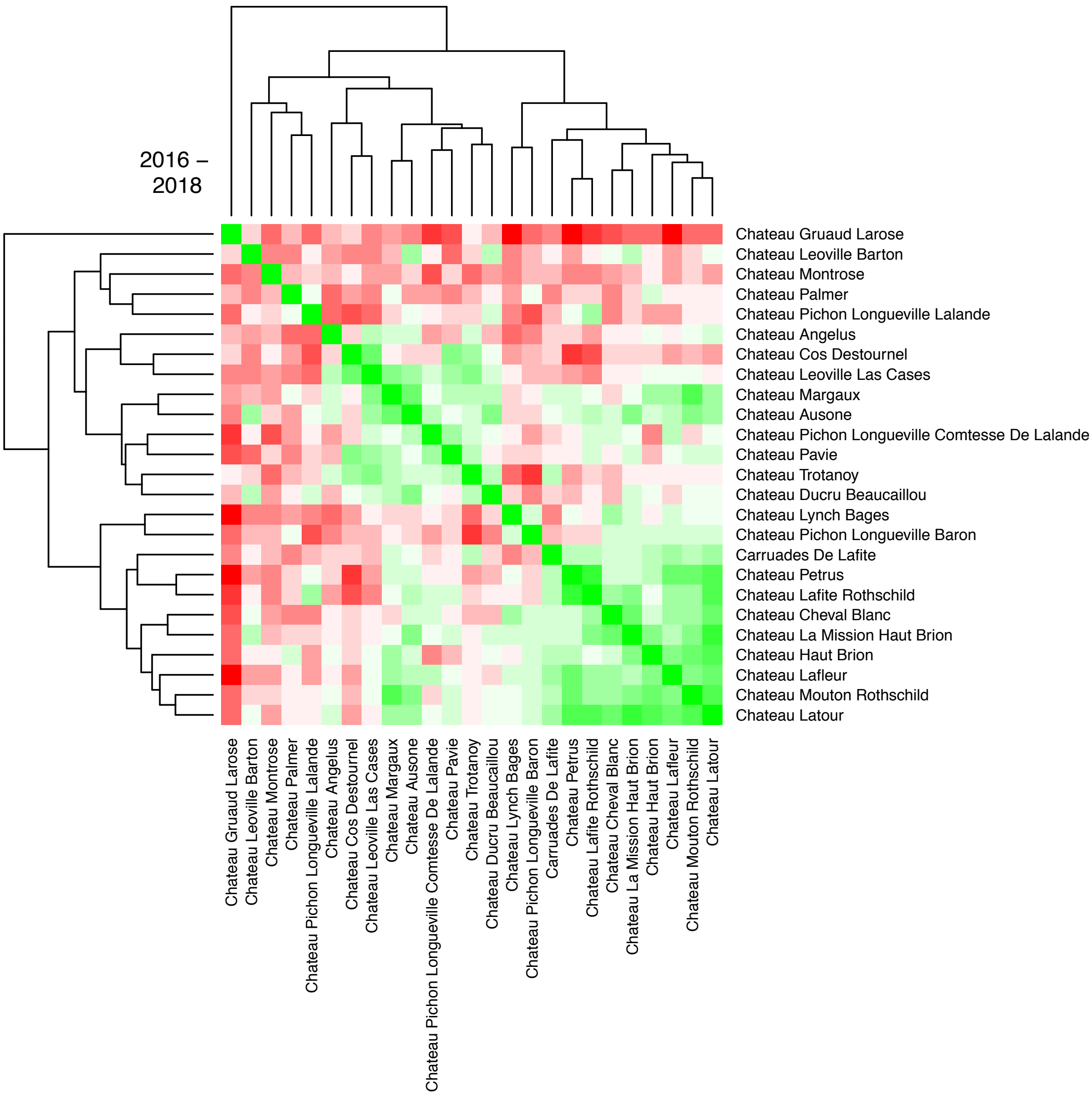

Figure 2: Correlation matrix and clustering dendrogram for the environment functions from Jan 2016 through Dec 2018.

Table 2: Cluster membership

Cluster 1			**Cluster 2**	
2006 - 2018	*2016 - 2018*		*2006 - 2018*	*2016 - 2018*
Chateau Petrus	Chateau Lynch Bages		Chateau Cos Destournel	Chateau Angelus
Chateau Lafleur	Chateau Pichon Longueville Baron		Chateau Angelus	Chateau Cos Destournel Chateau Leoville Las Cases
Chateau Leoville Barton	Carruades De Lafite		Chateau Pichon Longueville Baron	Chateau Margaux

Carruades De Lafite	Chateau Petrus		Chateau Montrose	Chateau Ausone
Chateau Ausone	Chateau Lafite Rothschild		Chateau Palmer	Chateau Pichon Longueville Comtesse De Lalande
Chateau Lafite Rothschild	Chateau Cheval Blanc		Chateau Pichon Longueville Lalande	Chateau Pavie
Chateau La Mission Haut Brion	Chateau La Mission Haut Brion		Chateau Ducru Beaucaillou	Chateau Trotanoy
Chateau Cheval Blanc	Chateau Haut Brion		Chateau Pichon Longueville Comtesse De Lalande	Chateau Ducru Beaucaillou
Chateau Latour	Chateau Lafleur		Chateau Lynch Bages	
Chateau Haut Brion	Chateau Mouton Rothschild		Chateau Leoville Las Cases	
Chateau Margaux	Chateau Latour			
Chateau Mouton Rothschild				

All of the correlations for the 2016 – 2018 time period are written out with their confidence intervals in Table 3. We see that none of the wines are actually anticorrelated when the confidence intervals are taken into account. We either have correlation or no significance.

Table 3: Correlation statistics with confidence intervals for the market indices from Jan 2006 through Dec 2018.

2016 - 2018	Chateau Lafite Rothschild	Chateau Mouton Rothschild	Chateau Latour	Chateau Haut Brion	Chateau Cheval Blanc	Chateau Petrus	Chateau Lynch Bages	Chateau La Mission Haut Brion	Carruades De Lafite	Chateau Lafleur	Chateau Pichon Longueville Baron	Chateau Margaux	Chateau Leoville Las Cases	Chateau Cos Destournel	Chateau Ducru Beaucaillou	Chateau Pavie	Chateau Ausone	Chateau Pichon Longueville Comtesse De Lalande	Chateau Angelus	Chateau Trotanoy	Chateau Palmer	Chateau Pichon Longueville Lalande	Chateau Montrose	Chateau Leoville Barton	Chateau Gruaud Larose
Chateau Lafite Rothschild	1.00	0.59	0.79	0.39	0.53	0.84	0.31	0.60	0.50	0.58	0.22	0.37	0.03	-0.14	0.31	0.40	0.52	0.42	0.10	0.20	0.19	0.54	-0.02	0.31	-0.20
	(0.00)	(0.14)	(0.11)	(0.16)	(0.14)	(0.09)	(0.16)	(0.14)	(0.15)	(0.14)	(0.17)	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.15)	(0.16)	(0.17)	(0.17)	(0.17)	(0.14)	(0.17)	(0.16)	(0.17)
Chateau Mouton Rothschild	0.59	1.00	0.79	0.67	0.53	0.67	0.38	0.60	0.51	0.65	0.42	0.79	0.36	0.15	0.33	0.43	0.61	0.24	0.34	0.26	0.29	0.30	0.23	0.22	-0.07
	(0.14)	(0.00)	(0.10)	(0.13)	(0.15)	(0.13)	(0.16)	(0.14)	(0.15)	(0.13)	(0.16)	(0.10)	(0.16)	(0.17)	(0.16)	(0.16)	(0.14)	(0.17)	(0.16)	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)
Chateau Latour	0.79	0.79	1.00	0.75	0.67	0.77	0.38	0.80	0.54	0.68	0.41	0.55	0.26	0.08	0.33	0.40	0.57	0.34	0.40	0.30	0.31	0.28	0.07	0.37	-0.06
	(0.11)	(0.10)	(0.00)	(0.11)	(0.13)	(0.11)	(0.16)	(0.10)	(0.14)	(0.13)	(0.16)	(0.14)	(0.17)	(0.17)	(0.16)	(0.16)	(0.14)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)
Chateau Haut Brion	0.39	0.67	0.75	1.00	0.46	0.51	0.31	0.63	0.49	0.63	0.43	0.54	0.33	0.20	0.36	0.15	0.41	0.04	0.36	0.31	0.42	0.08	0.27	0.29	-0.03
	(0.16)	(0.13)	(0.11)	(0.00)	(0.15)	(0.15)	(0.16)	(0.13)	(0.15)	(0.13)	(0.15)	(0.14)	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	(0.17)
Chateau Cheval Blanc	0.53	0.53	0.67	0.46	1.00	0.43	0.56	0.72	0.41	0.55	0.44	0.25	0.27	0.23	0.16	0.28	0.42	0.39	0.27	0.14	-0.01	0.03	0.10	0.35	-0.15
	(0.14)	(0.15)	(0.13)	(0.15)	(0.00)	(0.16)	(0.14)	(0.12)	(0.16)	(0.15)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)
Chateau Petrus	0.84	0.67	0.77	0.51	0.43	1.00	0.33	0.45	0.50	0.69	0.20	0.44	0.07	-0.18	0.13	0.27	0.44	0.27	0.19	0.07	0.24	0.34	0.03	0.10	-0.33
	(0.09)	(0.13)	(0.11)	(0.15)	(0.16)	(0.00)	(0.16)	(0.16)	(0.15)	(0.13)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.16)
Chateau Lynch Bages	0.31	0.38	0.38	0.31	0.56	0.33	1.00	0.41	0.03	0.44	0.40	0.23	0.29	0.07	0.20	0.19	0.22	0.31	-0.03	-0.03	0.07	-0.01	0.02	0.02	-0.34
	(0.16)	(0.16)	(0.16)	(0.16)	(0.14)	(0.16)	(0.00)	(0.16)	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)
Chateau La Mission Haut Brion	0.60	0.60	0.80	0.63	0.72	0.45	0.41	1.00	0.39	0.49	0.42	0.38	0.29	0.20	0.46	0.40	0.60	0.34	0.30	0.25	0.19	0.22	0.14	0.47	-0.04
	(0.14)	(0.14)	(0.10)	(0.13)	(0.12)	(0.16)	(0.16)	(0.00)	(0.16)	(0.15)	(0.16)	(0.16)	(0.16)	(0.17)	(0.15)	(0.16)	(0.14)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)
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	(0.15)	(0.15)	(0.14)	(0.15)	(0.16)	(0.15)	(0.17)	(0.16)	(0.00)	(0.14)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)
Chateau Lafleur	0.58	0.65	0.68	0.63	0.55	0.69	0.44	0.49	0.58	1.00	0.44	0.58	0.33	0.09	0.25	0.36	0.48	0.49	0.29	0.31	0.26	0.07	0.06	0.07	-0.36
	(0.14)	(0.13)	(0.13)	(0.13)	(0.15)	(0.13)	(0.16)	(0.15)	(0.14)	(0.00)	(0.16)	(0.14)	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)
Chateau Pichon Longueville Baron	0.22	0.42	0.41	0.43	0.44	0.20	0.40	0.42	0.14	0.44	1.00	0.32	0.13	0.17	0.04	0.20	0.20	0.11	-0.01	-0.19	0.33	-0.11	0.18	0.16	-0.03
	(0.17)	(0.16)	(0.16)	(0.15)	(0.15)	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)	(0.00)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Margaux	0.37	0.79	0.55	0.54	0.25	0.44	0.23	0.38	0.40	0.58	0.32	1.00	0.61	0.27	0.46	0.46	0.67	0.36	0.39	0.48	0.33	0.21	0.09	0.16	0.10
	(0.16)	(0.10)	(0.14)	(0.14)	(0.17)	(0.16)	(0.17)	(0.16)	(0.16)	(0.14)	(0.16)	(0.00)	(0.14)	(0.17)	(0.15)	(0.15)	(0.13)	(0.16)	(0.16)	(0.15)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Leoville Las Cases	0.03	0.36	0.26	0.33	0.27	0.07	0.29	0.29	0.13	0.33	0.13	0.61	1.00	0.71	0.44	0.56	0.53	0.43	0.46	0.65	0.02	-0.09	0.06	0.03	0.04
	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)	(0.14)	(0.00)	(0.12)	(0.15)	(0.14)	(0.15)	(0.16)	(0.15)	(0.13)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Cos Destournel	-0.14	0.15	0.08	0.20	0.23	-0.18	0.07	0.20	0.21	0.09	0.17	0.27	0.71	1.00	0.34	0.62	0.21	0.24	0.24	0.53	0.05	-0.09	0.25	0.01	0.21
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.12)	(0.00)	(0.16)	(0.13)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Ducru Beaucaillou	0.31	0.33	0.33	0.36	0.16	0.13	0.20	0.46	0.20	0.25	0.04	0.46	0.44	0.34	1.00	0.29	0.62	0.37	0.15	0.46	0.31	0.43	0.06	0.46	0.14
	(0.16)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)	(0.15)	(0.15)	(0.16)	(0.00)	(0.16)	(0.14)	(0.16)	(0.17)	(0.15)	(0.16)	(0.15)	(0.17)	(0.15)	(0.17)
Chateau Pavie	0.40	0.43	0.40	0.15	0.28	0.27	0.19	0.40	0.32	0.36	0.20	0.46	0.56	0.62	0.29	1.00	0.37	0.53	0.14	0.47	0.03	0.23	0.21	-0.08	-0.13
	(0.16)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.15)	(0.14)	(0.13)	(0.16)	(0.00)	(0.16)	(0.15)	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Ausone	0.52	0.61	0.57	0.41	0.42	0.44	0.22	0.60	0.33	0.48	0.20	0.67	0.53	0.21	0.62	0.37	1.00	0.51	0.41	0.44	0.10	0.34	0.20	0.58	0.00
	(0.15)	(0.14)	(0.14)	(0.16)	(0.16)	(0.16)	(0.17)	(0.14)	(0.16)	(0.16)	(0.17)	(0.13)	(0.15)	(0.17)	(0.14)	(0.16)	(0.00)	(0.15)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)	(0.14)	(0.17)
Chateau Pichon Longueville Comtesse De Lalande	0.42	0.24	0.34	0.04	0.39	0.27	0.31	0.34	0.21	0.49	0.11	0.36	0.43	0.24	0.37	0.53	0.51	1.00	0.05	0.44	0.11	0.25	-0.15	0.27	-0.22
	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.16)	(0.17)	(0.15)	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)	(0.15)	(0.15)	(0.00)	(0.17)	(0.15)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Angelus	0.10	0.34	0.40	0.36	0.27	0.19	-0.03	0.30	0.25	0.29	-0.01	0.39	0.46	0.24	0.15	0.14	0.41	0.05	1.00	0.41	-0.07	-0.05	0.16	0.10	0.15
	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.15)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.00)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Chateau Trotanoy	0.20	0.26	0.30	0.31	0.14	0.07	-0.03	0.25	0.49	0.31	-0.19	0.48	0.65	0.53	0.46	0.47	0.44	0.44	0.41	1.00	0.13	0.21	-0.06	0.22	0.30
	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)	(0.17)	(0.15)	(0.13)	(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.16)	(0.00)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)
Chateau Palmer	0.19	0.29	0.31	0.42	-0.01	0.24	0.07	0.19	0.05	0.26	0.33	0.33	0.02	0.05	0.31	0.03	0.10	0.11	-0.07	0.13	1.00	0.36	0.15	0.04	0.12
	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.00)	(0.16)	(0.17)	(0.17)	(0.17)
Chateau Pichon Longueville Lalande	0.54	0.30	0.28	0.08	0.03	0.34	-0.01	0.22	0.16	0.07	-0.11	0.21	-0.09	-0.09	0.43	0.23	0.34	0.25	-0.05	0.21	0.36	1.00	0.19	0.27	-0.06
	(0.14)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.16)	(0.00)	(0.17)	(0.17)	(0.17)
Chateau Montrose	-0.02	0.23	0.07	0.27	0.10	0.03	0.02	0.14	0.15	0.06	0.18	0.09	0.06	0.25	0.06	0.21	0.20	-0.15	0.16	-0.06	0.15	0.19	1.00	0.03	-0.04
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.00)	(0.17)	(0.17)
Chateau Leoville Barton	0.31	0.22	0.37	0.29	0.35	0.10	0.02	0.47	0.30	0.07	0.16	0.16	0.03	0.01	0.46	-0.08	0.58	0.27	0.10	0.22	0.04	0.27	0.03	1.00	0.23
	(0.16)	(0.17)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.15)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	(0.17)	(0.14)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.00)	(0.17)
Chateau Gruaud Larose	-0.20	-0.07	-0.06	-0.03	-0.15	-0.33	-0.34	-0.04	0.01	-0.36	-0.03	0.10	0.04	0.21	0.14	-0.13	0.00	-0.22	0.15	0.30	0.12	-0.06	-0.04	0.23	1.00
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.00)

Figure 3 and Figure 4 plot the individual wine environment functions for the two clusters. Cluster 1 looks quite tight, but Cluster 2 looks more diffuse. Nevertheless, when a 20% trimmed mean is applied to both graphs to create the lines in Figure 5, they look very similar, just with Cluster 1 being more dynamic.

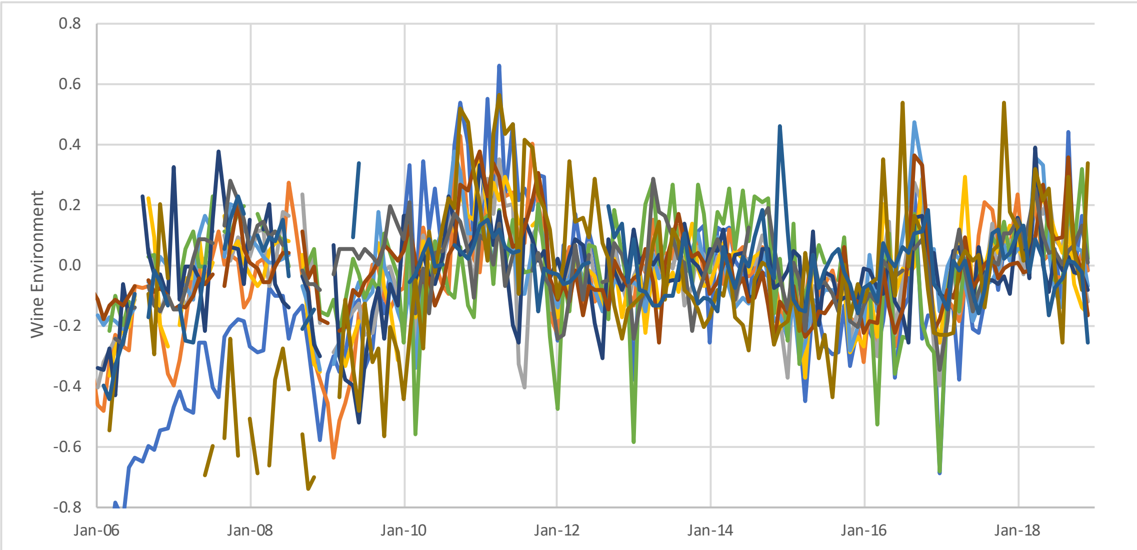

Figure 3: Wine environment measures for the wines in Cluster 1, 2016 – 2018.

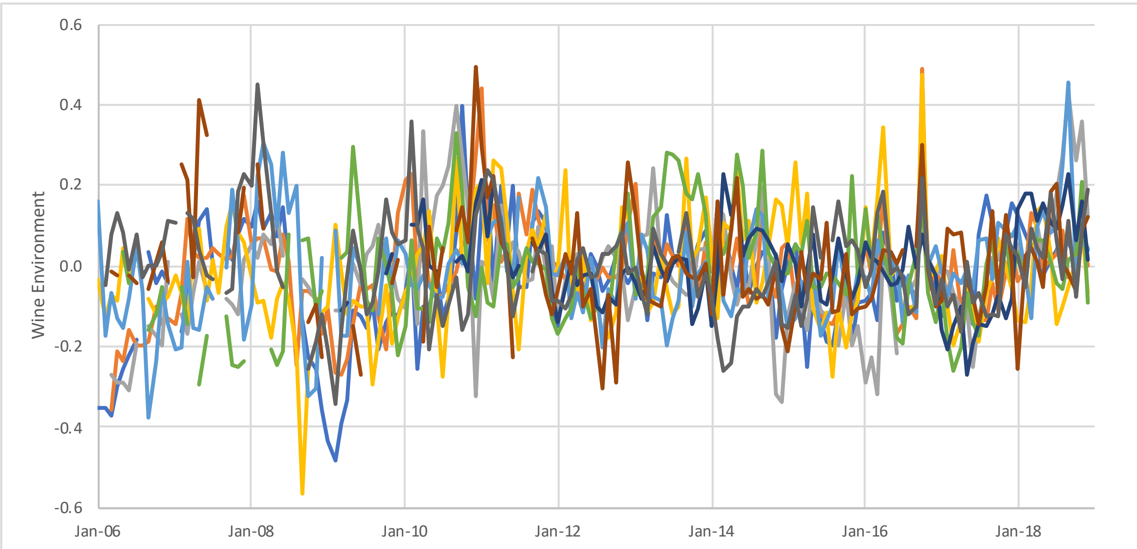

Figure 4: Wine environment measures for the wines in Cluster 2, 2016 - 2018.

In addition to the series for Clusters 1 and 2, Figure 5 includes an aggregate line for all top 25 Bordeaux wines, again with a 25% trimmed mean. Lastly, a line is included for the environment function for all Bordeaux wines in the database with sales price greater than US$100. That line follows the same trend as the other wines, but with much greater seasonality.

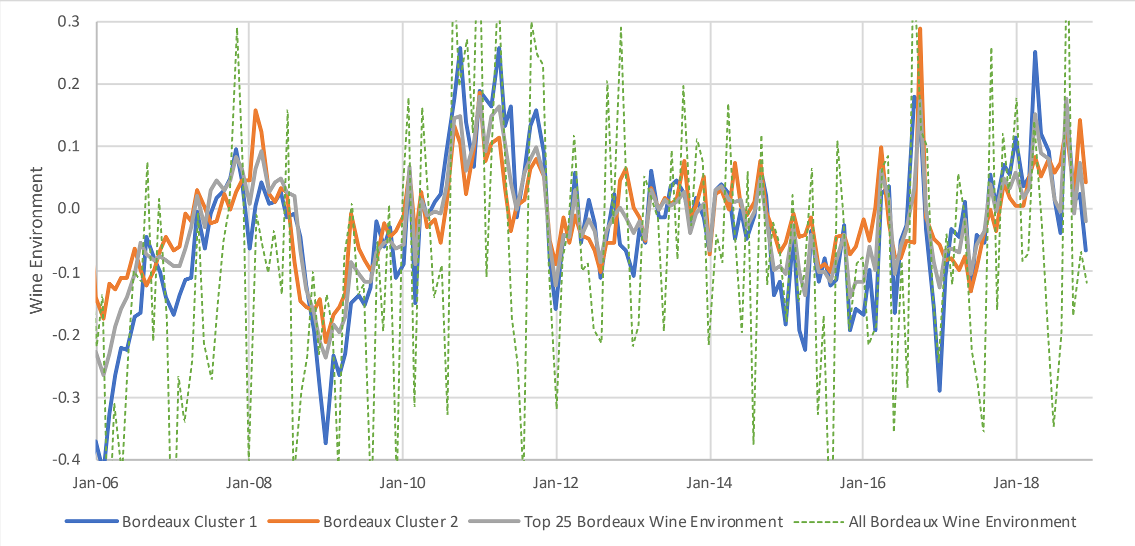

Figure 5: Aggregate wine environments for Cluster 1 & 2, 2016 - 2018 and the total environment for the top 25 Bordeaux wines and for the top xxxx Bordeaux wines.

The last result is a comparison of the environment function for the Top 25 Bordeaux wines to the average price for that same basket of wines. We know from decades of theoretical work that APC models accurately isolate the environment (calendar based) effects from age and vintage effects. We also know from the preceding analysis that we have a surprisingly high amount of agreement across independently modeled wines. Considering both facts, the Top 25 Bordeaux Wine Environment shown is believable as real market moves, even when those can be sudden, such as the spikes in 2016. Consequently, that means that the simple average price time series is missing quite a lot of structure because of the effects of popular vintages entering the averages or aging.

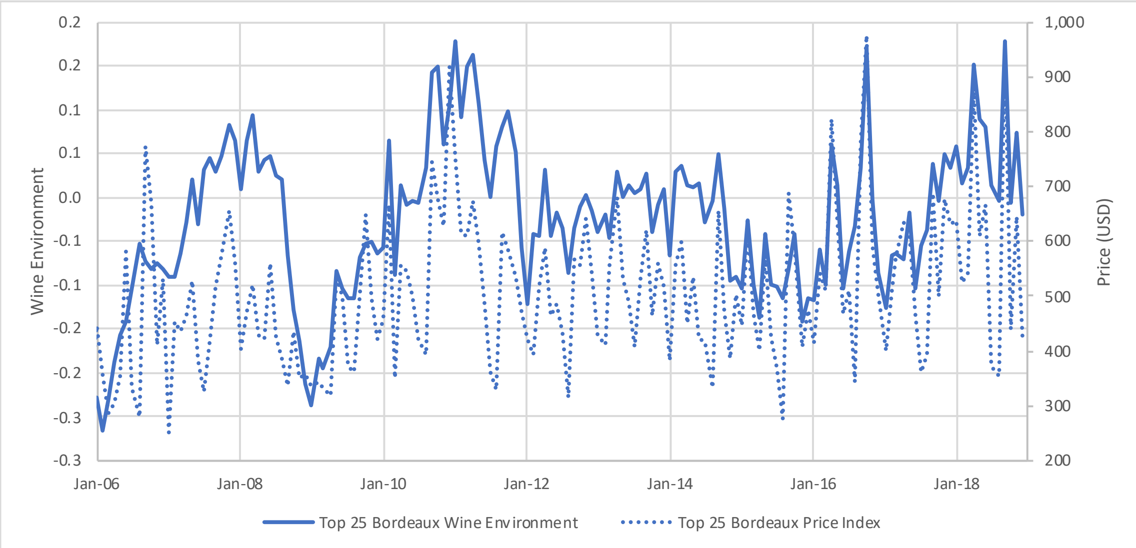

Figure 6: Comparison between the wine environment measure for the Top 25 Bordeaux Wines and the average price measured from the same data.

Although we want to continue this analysis by comparing to popular published wine indices, the conclusion to date is that a model-based measure of the wine markets can provide a better view than the basket-based approaches without relying on expert judgment to create the baskets.

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