

Analytics for Fine Wine: Realistic Prices

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Earlier publications indicate that the price of young wines cannot be estimated accurately through weather conditions. Considering that a majority of wine trade occurs when the wine is young and even before it is bottled, determining realistic prices for these fine wines accurately is one of the most critical decisions. Surveys of leading wine merchants and industry experts exhibit significant departures from the realized market prices.

We develop a pricing model for fine wines using weather, market and expert reviews. The financial exchange for fine wines called Liv-ex has already adopted our estimated prices and tagged them as “realistic prices.” Our approach combines temperature, rainfall, market fluctuations and tasting expert scores and leads to accurate estimations that the wine industry has not seen before. Our study shows that higher temperatures, lower levels of precipitation, appreciation in the Liv-ex 100 index as a market indicator, and higher barrel scores increase market prices. We conduct a comprehensive set of robustness checks and show that the mean absolute deviation of actual market prices from our estimated prices is substantially smaller than any academic benchmark. Our realistic prices help create transparency in this highly opaque market. When compared with the realized prices, our realistic prices guide buyers (e.g., distributors, restaurateurs, merchants) in their purchase decisions as they can determine whether a wine is underpriced or overpriced.

Keywords: *wine futures, price, weather, barrel score*

1. Introduction

Economists have long tried to estimate wine prices through weather. In two most influential publications, Ashenfelter et al. (1995) and Ashenfelter (2008) provided remarkable insights regarding the impact of weather on *aged* Bordeaux wines. However, these scholars, as well as authors of similar publications, conclude that estimating *young* wine prices using weather information does not lead to accurate results. For brevity, we limit our definition of *young* wines to the wines that are still aging in the barrel but traded in the form of *en primeur*, i.e., financial contracts loosely translated into English as wine futures, before the wines are bottled. Our paper develops pricing models that estimate the appropriate prices for fine Bordeaux wines. It identifies the determinants of prices which include changes in weather (both the average of daily maximum temperatures and total precipitation), in market conditions described through an index, and in the barrel scores of tasting experts.

Wine is an important agricultural product with a growing global interest. The global wine market is expected to reach \$424 billion in 2023 from its \$302 billion in 2017. France is the leading wine exporting country with an estimated value of €13 billion in 2017. Bordeaux region of France, which is the motivating region of our study, produces the most sought-after wines around the world. Bordeaux wine prices often influence the prices of the wines produced in other regions of the world. Thus, Bordeaux wines are perceived as the pacesetter of worldwide trade in wine supply chains.

Figure 1 presents a timeline of events in the Bordeaux wine supply chain. Chateaus grow their grapes in their estate from May to August each summer. Grapes are harvested and pressed in September, and the wine (of vintage t) begins aging in barrels. Tasting experts visit chateaus approximately eight to nine months after the harvest and then release their barrel tasting scores in April of year $t + 1$. This is when chateaus begin to sell their wines to négociants. Négociants purchase the wine from chateaus at the *ex-chateau* price and serve as an unofficial bank for chateaus. These négociants then sell the wine in terms of futures contracts in the market at an *ex-négociant* price. A vast majority of Bordeaux wines, more than 80% and often 100%, are traded in the form of wine futures in the summer of year $t + 1$.

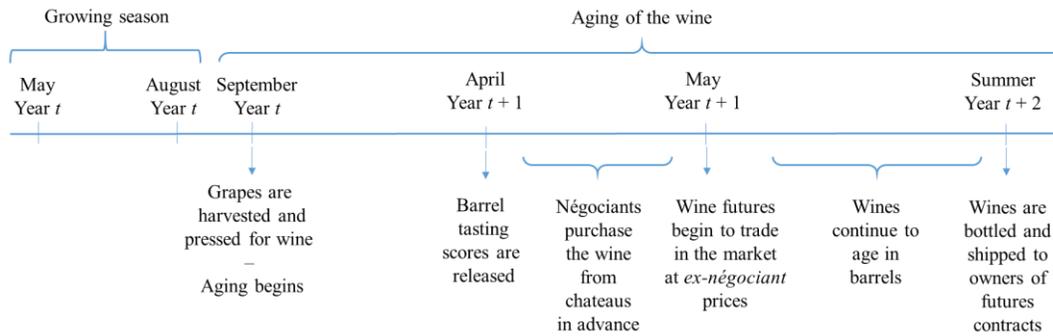


Figure 1. The sequence of events leading to the revelation of *ex-négociant* prices for vintage t wines.

It is important to highlight that the *ex-négociant* price is the “market price” for wine futures. Our study estimates the market price, or the true value of the wine in the wine market, designated as the *ex-négociant* price. Determining the appropriate *ex-négociant* price is critical in the wine supply chain because it sets the pace in the downstream and influences the trade significantly. In the remaining part of the manuscript, we will use the term “market price” referring to the *ex-négociant* price. Figure 2 provides a visual depiction of the wine supply chain. The wine continues to age in barrels for another year after wine futures are offered; the wine is bottled during the summer of year $t + 2$; thus, the total aging after harvest is 18 to 24 months. After bottling, the wine gets delivered to the buyers who purchased the wine in the market from the négociants.

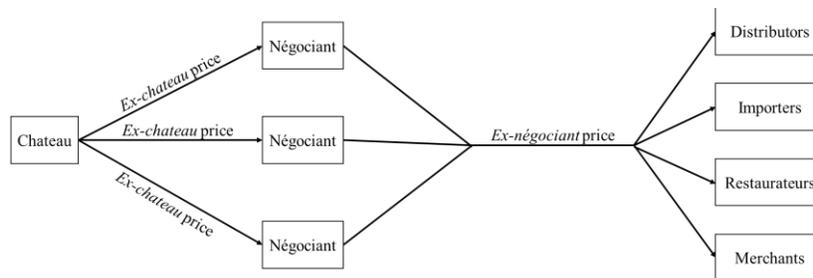


Figure 2. The Bordeaux wine supply chain.

What is the right market price for a wine? Can it be determined accurately before the *en primeur* campaign, i.e., before the wine futures begin to be sold in the market? As pointed out by the abovementioned academic publications, it turns out that estimating the appropriate *ex-négociant* prices is an incredibly challenging task even for industry experts. The challenge is evident in the surveys of the London International Vintner's Exchange (Liv-ex) which serves as the financial exchange where all fine wines are traded. A 2016 Liv-ex survey involving 440 of the world's leading wine merchants sheds light on the difficulty of estimating the *ex-négociant* prices of the 2015 vintage wines (<https://www.liv-ex.com/2016/06/merchants-underestimated-bordeaux-2015-release-prices/>). The survey constructs a basket where bottles of wine are included from Cheval Blanc, Cos d'Estournel, Leoville Las Cases, Mission Haut Brion, Montrose, Mouton Rothschild, Pavie, Pichon Lalande, Pontet Canet and Talbot – all 2015 vintage wines. The 2016 survey results reveal that these 440 leading wine merchants predicted the above basket of wines to have a value of €1,607.80. After *ex-négociant* prices are established, the basket had an actual value of €2,054.40 – corresponding to a 21% estimation error. The survey also showed that, when these leading wine merchants estimated the *ex-négociant* prices, they expected a 17.8% increase in 2015 from the *ex-négociant* prices of the 2014 vintage; however, the actual market prices increased by a whopping 45.8% from 2014. How can the leading merchants and the industry experts be so inaccurate in their expectations? Is there an empirical way to estimate the true value of these wines? Our study fills the void in developing benchmark *ex-négociant* prices based on weather information, market fluctuations and tasting expert scores.

From a buyer's perspective, the lack of a reliable benchmark *ex-négociant* price for these fine wines creates an inertia to invest in wine futures. In the absence of an accurate estimation of the *ex-négociant* price, a buyer (e.g., importer, distributor, merchant, etc.) cannot tell whether a wine is appropriately priced in the market. Our conversations with the executives of the largest wine distributors in the US point to the same need for establishing a benchmark price so that they can determine in confidence whether a wine is overpriced or underpriced. While there is plenty of expert opinion with tasting scores, these scores do not immediately translate to appropriate prices for these wines. Our study responds to this need by establishing a benchmark price estimate that provides guidance for buyers in this industry. Collectively, our study brings transparency into an otherwise highly opaque market.

While our study is motivated by the fine wine industry, our approach is general, and it applies to other industries where prices are influenced by quality perceptions and weather fluctuations. Examples include olive oil, wagyu beef and iron ore where prices are influenced by quality and weather, and technology products where prices are impacted by quality perceptions.

Market prices for Bordeaux wines show similar reactions when they change from one vintage to another. This is exemplified in Figure 3 which depicts the change in the *ex-négociant* price of a vintage

from the previous vintage for the 40 chateaus included in our study. One can immediately draw the conclusion that the adjustments in market prices from the previous vintage exhibit a highly similar behavior. Figure 3 demonstrates that vintages 2003, 2005 and 2009 are deemed as phenomenal vintages by the industry and their *ex-négociant* prices soared with respect to previous vintage *ex-négociant* prices. Our study identifies the factors that influence the price adjustments from the previous vintage.

One might wonder why the new vintage *ex-négociant* prices rely on the prior vintage’s *ex-négociant* prices. The reason for this behavior is operational. Chateaus have to remove the wine from barrels, bottle the liquid and replace the cellar with new barrels before the new vintage grapes arrive. Similarly, négociants have to move the inventory of the wine they purchased from chateaus to the market so that they can recover their cash investment and their money is not tied into unsold wines. Thus, this one-year planning effort creates a coordinated financial and physical flow that influences the price adjustments from the prior vintage’s *ex-négociant* prices. This operational planning phenomenon justifies the similar behavior observed in adjusting *ex-négociant* prices in Figure 3.

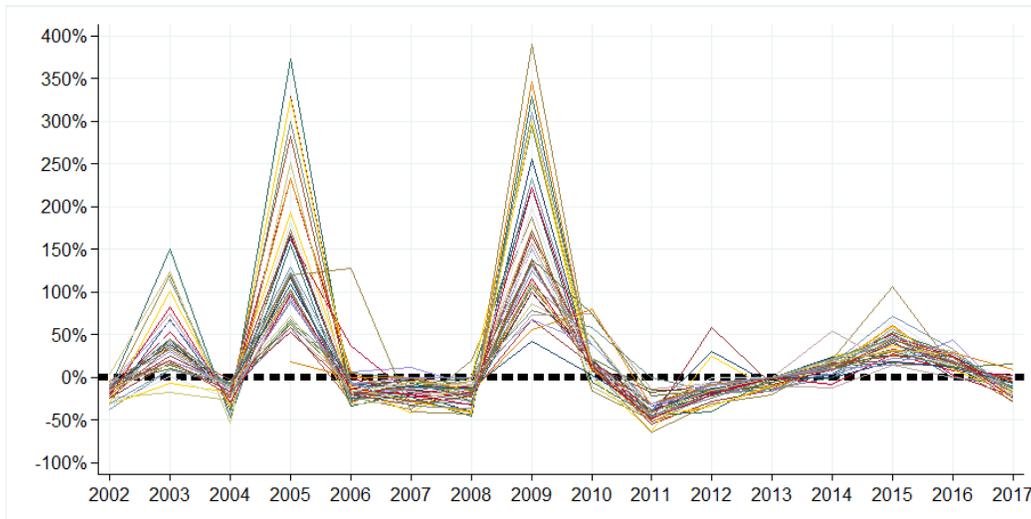


Figure 3: Percentage change in the *ex-négociant* prices in each vintage (between 2002 and 2017) in comparison to previous vintage for the 40 chateaus included in the study.

Our study makes several contributions. First, it identifies four primary factors that are influential in estimating the market prices for fine wines with significant accuracy: Temperature, rainfall, market conditions (e.g., the Liv-ex 100 index representing the value of the 100 most sought-after wines), and tasting expert reviews (e.g., barrel scores). Furthermore, for these factors, we develop unique variable definitions by comparing two consecutive vintages that account for the one-year planning phenomenon described above. Academically, our results provide significant improvements over earlier publications that estimate wine prices. In practice, Neil Taylor, vice president of data at Liv-ex, describes that “this

kind of accuracy is not seen in the wine industry for young wines.” To further test our model, we provided Liv-ex confidentially with our *ex-négociant* price estimations for the 2017 vintage Bordeaux wines prior to the release of these wine futures so as not to influence the wine market. We report that our model performed well and had small deviations from the realized *ex-négociant* prices. Our 9.19% deviation is less than any academic and/or practice benchmark. Comprehensive analysis shows that our methodology and results are robust. These are demonstrated through analyses using robust regression, hierarchical linear modeling, hierarchical Bayes modeling, and dependent variable retransformation.

The implication of our contribution is significant in practice. Liv-ex has recently decided to publish our *ex-négociant* price estimations as “realistic prices” prior to each year’s *en primeur* campaigns. The exchange finds our estimated prices highly accurate and features them as a guidance for buyers. Thus, our realistic prices are expected to be used as the new benchmark prices in the upcoming years.

Second, our realistic prices help create transparency in this otherwise opaque market. Our estimated prices enable buyers (e.g., wine distributors, importers, restaurateurs, merchants) to make effective operational plans influencing the entire downstream in the wine supply chain. Perception of quality in a wine is established by the barrel scores of tasting experts, however, these barrel scores are not easily translated into prices. For buyers, our price estimations convert the barrel scores of tasting experts into prices. This conversion is supplemented by the growing season’s weather conditions and the evolution of market dynamics. A comparison of our estimations with the actual *ex-négociant* prices reveal the buyer whether a wine is under- or over-priced.

Third, our realistic price estimates can help winemakers determine the prices they can charge négociants, i.e., the *ex-chateau* price. Our study develops benchmark *ex-négociant* prices through a comprehensive and rigorous approach. The winemaker can now determine the *ex-chateau* price and its margin given the appropriate *ex-négociant* price that will move the wine in the market.

1.1. Literature Review

The economics literature has examined the pricing of aged wine using weather and expert opinions, however, these studies failed to estimate young wine prices. Leading Bordeaux wines are primarily sold when they are young in the form of advance selling prior to their bottling. Ashenfelter et al. (1995) and Ashenfelter (2008) show that mature Bordeaux wine prices can be explained using weather and age; however, these two publications report significantly high errors for young wines. Jones and Storchmann (2001), Lecocq and Visser (2006), Ali and Nauges (2007), Ali et al. (2008), and Ashenfelter and Jones (2013) also examine Bordeaux wine prices using weather conditions and/or tasting scores. Using a similar approach, Byron and Ashenfelter (1995) and Wood and Anderson (2006) examine Australian wine prices, Haeger and Storchmann (2006) study American wine prices, and Ashenfelter and Storchmann (2010) investigate German wine prices. However, the above publications do not offer a systematic estimation

approach to be used before *ex-négociant* prices are revealed. Our study complements this economics literature by providing an accurate pricing model for young Bordeaux wines.

Our study makes a significant contribution to the operations management literature. Xie and Shugan (2001), Boyacı and Özer (2010), Cho and Tang (2013), Tang and Lim (2013) and Yu et al. (2015a, 2015b) demonstrate the benefits of advance selling in various industries. Noparumpa et al. (2015) develop a mathematical model for a winemaker to determine the proportion of wine to be sold in the form of wine futures with a market-clearing price – the remaining proportion is distributed after the wine is bottled. Their study makes use of barrel scores in establishing the market size and shows that selling wine in the form of futures improves a winemaker’s profit; however, their study ignores weather and market information. Hekimoğlu et al. (2017) develop a stochastic program to examine a wine distributor’s purchasing decision between wine futures and bottled wine. Their study employs the next vintage’s temperature and market information (ignoring rainfall and barrel scores) to understand the evolution of prices from the *ex-négociant* price to the bottled wine price. While their model assumes a given *ex-négociant* price, our study focuses on providing realistic *ex-négociant* prices using all factors. In sum, our paper enhances these earlier publications in three ways. First, it identifies the most influential factors in estimating *ex-négociant* prices using unique variable definitions. Second, our study helps buyers in making effective purchasing plans by showing which wines are underpriced or overpriced. Third, knowing the appropriate *ex-négociant* price, winemakers can benefit from our study in determining the *ex-chateau* price that they charge when they sell their wine to négociants.

2. Data

This section presents our data collection and sample selection. We collect wine price data from Liv-ex (www.liv-ex.com) that operates a global marketplace for fine wine trade and has the world’s largest database for fine wine prices. The Liv-ex Bordeaux 500 Index (shortly, Bordeaux 500) is composed of the leading 50 Bordeaux chateaus that serve as the basis of our sample collection. We exclude the five Sauternes wine producers (Yquem, Climens, Coutet, Suduiraut, and Rieussec) because the production process and timeline of these wines are different than the traditional Bordeaux wines. Latour and Forts Latour wines are not offered in the form of *en primeur* and Petrus, Fleur Petrus, and Pin have missing *ex-négociant* prices in the Liv-ex database. We construct our sample from the remaining 40 chateaus. We collect the *ex-négociant* price (in €/bottle) for the remaining 40 chateaus between 2001 and 2017 as summarized in Table 1.

Chateau	Region	Price (€/bottle)		Chateau	Region	Price (€/bottle)	
		Average	Std. Dev.			Average	Std. Dev.
Angelus	Right Bank	154.12	78.58	Lafleur	Right Bank	400.71	145.57
Ausone	Right Bank	521.29	254.63	Leoville Barton	Left Bank	43.11	14.58
Beychevelle	Left Bank	35.18	14.13	Leoville Las Cases	Left Bank	115.18	52.43
Calon Segur	Left Bank	39.07	14.09	Leoville Poyferre	Left Bank	44.09	18.54
Carruades Lafite	Left Bank	69.40	42.36	Lynch Bages	Left Bank	55.19	24.43
Cheval Blanc	Right Bank	398.35	196.69	Margaux	Left Bank	310.75	165.41
Clarence (Bahans) Haut Brion	Left Bank	56.50	30.81	Mission Haut Brion	Left Bank	216.79	160.99
Clinet	Right Bank	51.35	15.66	Montrose	Left Bank	67.79	31.64
Clos Fourtet	Right Bank	46.11	18.93	Mouton Rothschild	Left Bank	297.82	169.15
Conseillante	Right Bank	78.83	39.76	Palmer	Left Bank	141.88	60.92
Cos d'Estournel	Left Bank	97.85	48.02	Pape Clement	Left Bank	62.14	18.88
Ducru Beaucaillou	Left Bank	86.85	42.75	Pavie	Right Bank	164.76	69.84
Duhart Milon	Left Bank	36.29	16.90	Pavillon Rouge	Left Bank	67.19	35.92
Eglise Clinet	Right Bank	131.35	72.28	Petit Mouton	Left Bank	71.76	34.81
Evangile	Right Bank	112.94	44.44	Pichon Baron	Left Bank	66.69	30.43
Grand Puy Lacoste	Left Bank	36.92	13.10	Pichon Lalande	Left Bank	73.55	31.42
Gruaud Larose	Left Bank	34.45	10.34	Pontet Canet	Left Bank	56.39	26.05
Haut Bailly	Left Bank	47.33	22.39	Smith Haut Lafitte	Left Bank	42.89	18.07
Haut Brion	Left Bank	299.00	184.99	Troplong Mondot	Right Bank	60.19	26.18
Lafite Rothschild	Left Bank	351.31	196.34	Vieux Chateau Certan	Right Bank	99.74	51.50

Table 1. List of chateaus with their region, average *ex-négociant* price and standard deviation.

Weather data comes from Météo-France, the national meteorological service organization providing local weather information, complemented by Wolfram Mathematica. The Bordeaux wine region is divided by the Gironde Estuary into two main regions: Left Bank and Right Bank. We use the weather data recorded at the Merignac weather station (serving as the main weather station for Bordeaux) for the Left Bank and at Saint-Emilion for the Right Bank. We collect daily maximum temperatures (in °C) and daily total rainfall (in cm) during the growing season (May 1 – August 31). Figure 4 illustrates the weather data between 2001 and 2017.

We collect barrel tasting scores from Liv-ex originated from the most influential source RobertParker.com (the late President François Mitterrand recognized Robert Parker with the Chevalier de l'Ordre National du Mérite in 1993, and President Chirac awarded Robert Parker with France's Legion of Honor, an extremely rare distinction, in 2005 for his contributions to the quality and education of French wines). Barrel scores are viewed as early indicators for quality. The tasting expert samples the wine that is still aging in the barrel in the spring of the year following the harvest and establishes the barrel tasting scores approximately one month before the revelation of *ex-négociant* prices.

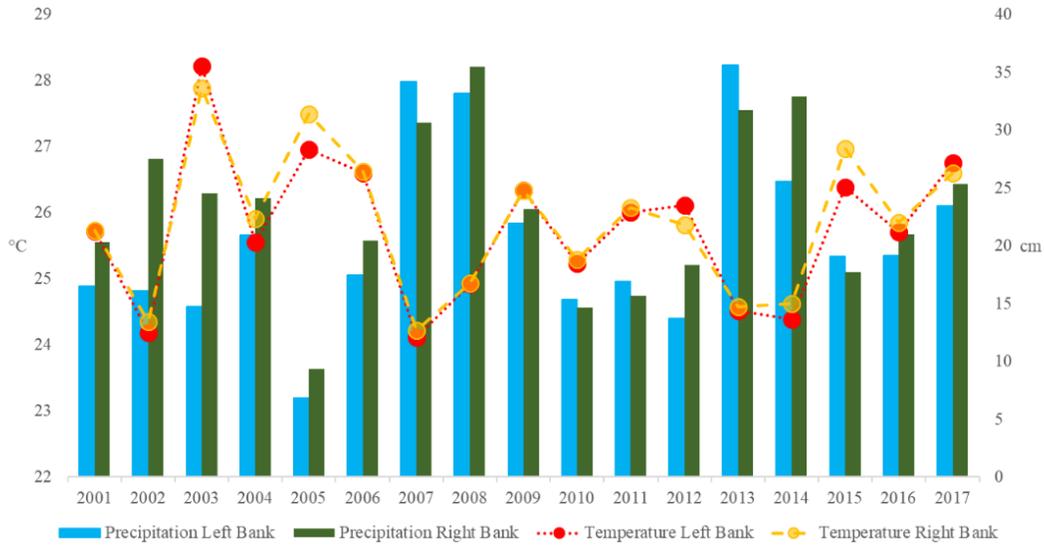


Figure 4. Average of the daily maximum temperatures and the total rainfall observed in the Left Bank and Right Bank of Bordeaux during growing season between years 2001 and 2017.

We use the Liv-ex Fine Wine 100 Index (shortly Liv-ex 100) to capture market-wide fluctuations in the fine wine industry. Liv-ex 100, a monthly index, represents the price movements of the world’s most sought-after 100 wines. The components of Liv-ex 100 include only bottled wine prices of earlier vintages; our study, however, examines the *ex-négociant* prices of vintages that are not bottled. Liv-ex 100 is quoted by Bloomberg and Reuters as the industry benchmark. Figure 5 illustrates the values of Liv-ex 100 since its inception in July 2001.

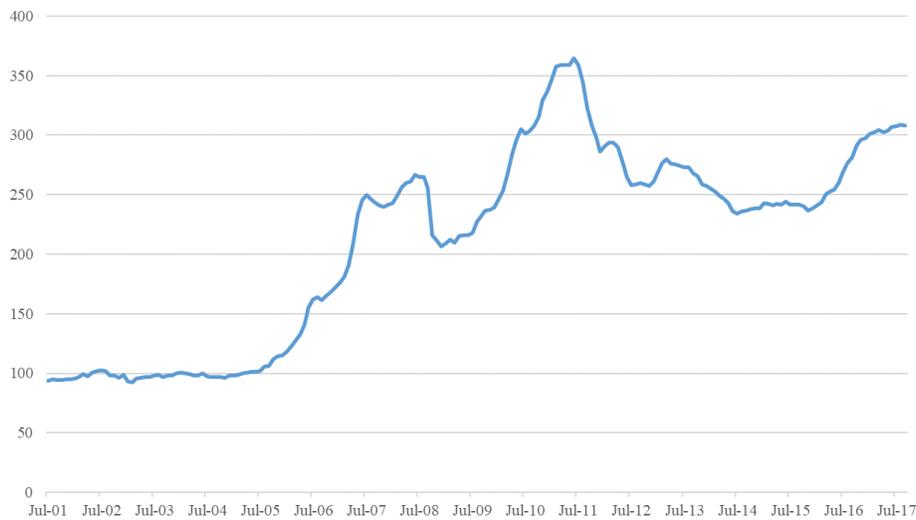


Figure 5. Historical values of the Liv-ex Fine Wine 100 index since its inception.

3. Empirical Analysis

3.1. Variables

This section presents the dependent variable (*ex-négociant* price) and the independent variables (temperature, rainfall, barrel score, Liv-ex 100) used in our models. When *ex-négociant* price of a new vintage is determined, négociants compare it to the previous vintage because of the one-year planning phenomenon explained in Section 1. Therefore, we define the variables based on the change in their values across two consecutive vintages. This type of specification is also consistent with the similar behavior observed in adjusting *ex-négociant* prices in Figure 3.

Change in ex-négociant prices. We define the dependent variable as the logarithmic change across the *ex-négociant* prices of two consecutive vintages from the same chateau, i.e., $\Delta p_{i,t} = \log(p_{i,t}/p_{i,t-1})$ where $p_{i,t}$ is the *ex-négociant* price of vintage t of chateau i that is revealed at the beginning of the *en primeur* campaign (around May of year $t + 1$). Note that $i \in \{1, \dots, 40\}$ and $t \in \{2002, \dots, 2017\}$.

Change in average temperature. We define the temperature variable as the logarithmic change across the average growing season temperatures of two consecutive vintages, i.e., $\Delta m_{i,t} = \log(m_{i,t}/m_{i,t-1})$ where $m_{i,t}$ is the average of daily maximum temperatures during the growing season (May 1 – August 31) of year t in the region where chateau i is located. A warmer growing season is expected to have a positive impact on the *ex-négociant* price.

Change in total rainfall. We define the rainfall variable as the logarithmic change across the total growing season rainfall of two consecutive vintages, i.e., $\Delta r_{i,t} = \log(r_{i,t}/r_{i,t-1})$ where $r_{i,t}$ is the total rainfall during the growing season period of year t in the region where chateau i is located. A rainier growing season is expected to have a negative impact on the *ex-négociant* price.

Change in barrel tasting score. We define the barrel score variable as the difference between the barrel tasting scores of two consecutive vintages of the same chateau, i.e., $\Delta s_{i,t} = s_{i,t} - s_{i,t-1}$ where $s_{i,t}$ is the barrel tasting score of vintage t of chateau i that is revealed approximately one month before the *en primeur* campaign (corresponding to April of year $t + 1$). A higher score is expected to have a positive impact on the *ex-négociant* price.

Change in Liv-ex 100. We define the index variable as the logarithmic change in the value of Liv-ex 100 index between the *en primeur* campaign of the previous vintage and shortly before the *en primeur* campaign of the new vintage, i.e., $\Delta l_t = \log(l_t^{mar}/l_{t-1}^{may})$ where l_{t-1}^{may} is the value of Liv-ex 100 around the *en primeur* campaign of vintage $t - 1$ (corresponding to May of year t), and l_t^{mar} is the value of Liv-ex 100 in March prior to the *en primeur* campaign of vintage t (corresponding to March of year $t + 1$). The reason behind using the value at the end of March is to be able to make timely price estimations before the *en primeur* campaign begins. This variable captures the market-wide changes in the fine wine industry

between the *en primeur* campaigns of two consecutive vintages. Therefore, a positive change in Liv-ex 100 index is expected to have a positive impact on the *ex-négociant* price.

Table 2 presents the correlation coefficients among the dependent variable and the main independent variables. The values are not too strong to indicate any collinearity issue.

Correlation Coefficients	Change in <i>ex-négociant</i> prices ($\Delta p_{i,t}$)	Change in temperature ($\Delta m_{i,t}$)	Change in rainfall ($\Delta r_{i,t}$)	Change in barrel score ($\Delta s_{i,t}$)	Change in Liv-ex 100 (Δl_t)
Change in <i>ex-négociant</i> prices ($\Delta p_{i,t}$)	1				
Change in temperature ($\Delta m_{i,t}$)	0.4358	1			
Change in rainfall ($\Delta r_{i,t}$)	-0.5891	-0.5188	1		
Change in barrel score ($\Delta s_{i,t}$)	0.4627	0.2988	-0.4271	1	
Change in Liv-ex 100 (Δl_t)	0.5343	-0.0381	-0.1742	0.0563	1

Table 2. The correlation coefficients among the dependent variable and the main independent variables.

Positive Interaction variables. We define positive interaction variables in order to account for dramatic price increases observed in celebrated vintages. For example, one may recall from Figure 3 that négociants showed a strong positive reaction when determining the prices of 2003, 2005, and 2009 vintages. Those vintages were eagerly anticipated by the fine wine industry due to a combination of multiple positive factors such as higher average temperature along with a positive change in Liv-ex 100, etc. Therefore, we define the following six interaction variables to combine the pairwise positive effects of temperature and rainfall ($mr_{i,t}$), temperature and Liv-ex 100 ($ml_{i,t}$), temperature and barrel score ($ms_{i,t}$), rainfall and Liv-ex 100 ($rl_{i,t}$), rainfall and barrel score ($rs_{i,t}$), and Liv-ex 100 and barrel score ($ls_{i,t}$):

$$mr_{i,t} = \Delta m_{i,t} \times |\Delta r_{i,t}| \text{ if } m_{i,t} > m_{i,t-1} \text{ and } r_{i,t} < r_{i,t-1}, mr_{i,t} = 0 \text{ if otherwise;}$$

$$ml_{i,t} = \Delta m_{i,t} \times \Delta l_t \text{ if } m_{i,t} > m_{i,t-1} \text{ and } l_t^{mar} > l_{t-1}^{may}, ml_{i,t} = 0 \text{ if otherwise;}$$

$$ms_{i,t} = \Delta m_{i,t} \times \Delta s_{i,t} \text{ if } m_{i,t} > m_{i,t-1} \text{ and } s_{i,t} > s_{i,t-1}, ms_{i,t} = 0 \text{ if otherwise;}$$

$$rl_{i,t} = |\Delta r_{i,t}| \times \Delta l_t \text{ if } r_{i,t} < r_{i,t-1} \text{ and } l_t^{mar} > l_{t-1}^{may}, rl_{i,t} = 0 \text{ if otherwise;}$$

$$rs_{i,t} = |\Delta r_{i,t}| \times \Delta s_{i,t} \text{ if } r_{i,t} < r_{i,t-1} \text{ and } s_{i,t} > s_{i,t-1}, rs_{i,t} = 0 \text{ if otherwise;}$$

$$ls_{i,t} = \Delta l_t \times \Delta s_{i,t} \text{ if } l_t^{mar} > l_{t-1}^{may} \text{ and } s_{i,t} > s_{i,t-1}, ls_{i,t} = 0 \text{ if otherwise.}$$

Other explanatory variables. We examined additional explanatory variables including negative interaction variables, quadratic terms of main independent variables, change in exchange rates (e.g., \$/€, £/€), changes in chateau's annual trade volume, annual trade value, and number of unique wines. We omit them from presentation because we did not encounter any improvement in our results.

3.2. Analysis and Results

Table 3 provides the results associated with the ordinary least squares (OLS) regression of various models using cluster-robust standard errors (using classical standard errors leads to the same statistical inferences). The dependent variable is $\Delta p_{i,t}$ in all models where $i \in \{1, \dots, 40\}$ and $t \in \{2002, \dots, 2017\}$.

Note that the number of observations is less than 640 due to missing data points.

From models 1, 2, 3 and 4, we conclude that temperature, rainfall, barrel score, and Liv-ex 100 have an impact on the *ex-négociant* prices independently. Each of these variables are statistically significant at 1%, and their coefficients fetch signs as expected.

Model 5 can be interpreted as the weather model because it utilizes both temperature and rainfall as explanatory factors. Model 6 adds barrel score to the weather variables, and Model 7 adds Liv-ex 100 to the other three variables. All variables in models 5, 6, and 7 continue to be significant at 1%. Variance inflation factors (VIF) for Model 7 that incorporates all four variables are 1.06 for $\Delta l_{i,t}$, 1.24 for $\Delta s_{i,t}$, 1.41 for $\Delta m_{i,t}$, and 1.62 for $\Delta r_{i,t}$.

Models 8 – 13 build on Model 7 by incorporating the positive interaction variables. Those interaction variables fetch positive coefficients as expected in accordance with their definition and are statistically significant at 1%. These findings support our earlier observation about combined positive factors leading to hype and further increases in *ex-négociant* prices. It is also worth noting that Model 9 leads to an impressive explanatory power with an R^2 value of 74.62%. VIF for Model 9 are 1.24 for $\Delta s_{i,t}$, 1.41 for $\Delta l_{i,t}$, 1.63 for $\Delta m_{i,t}$, 2.01 for $\Delta r_{i,t}$, and 2.43 for $ml_{i,t}$. We conclude from these VIF values combined with the correlation values (see Table 2) that there is no collinearity issue in our analysis.

Models 14 – 16 examine the combined effects of two interaction terms: Model 14 uses temperature and rainfall ($mr_{i,t}$) with Liv-ex 100 and barrel score ($ls_{i,t}$), Model 15 uses temperature and Liv-ex 100 ($ml_{i,t}$) with rainfall and barrel score ($rs_{i,t}$), and Model 16 uses temperature and barrel score ($ms_{i,t}$) with rainfall and Liv-ex 100 ($rl_{i,t}$). In Model 14, the temperature and rainfall interaction ($mr_{i,t}$) is significant at 1% and the Liv-ex 100 and barrel score interaction ($ls_{i,t}$) is significant at 5%. In Model 15, the temperature and Liv-ex 100 interaction ($ml_{i,t}$) is significant at 1% but the rainfall and barrel score interaction ($rs_{i,t}$) is not statistically significant. In Model 16, both interaction terms are statistically significant at 1%. We exclude the remaining combinations of interaction terms from presentation where two interaction terms share a common factor (e.g., temperature and rainfall ($mr_{i,t}$) with temperature and Liv-ex 100 ($ml_{i,t}$) where temperature is a common factor) due to strong correlation among them.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Int.	0.060 <i>15.64***</i>	0.077 <i>19.59***</i>	0.056 <i>12.35***</i>	-0.007 <i>-1.28</i>	0.072 <i>19.33***</i>	0.066 <i>14.95***</i>	-0.004 <i>-0.64</i>	-0.056 <i>-6.65***</i>	-0.086 <i>-8.84***</i>	-0.022 <i>-2.60**</i>	-0.049 <i>-5.80***</i>	-0.029 <i>-3.30***</i>	-0.024 <i>-2.57**</i>	-0.061 <i>-6.85***</i>	-0.083 <i>-8.29***</i>	-0.061 <i>-6.36***</i>
$\Delta m_{i,t}$	2.931 <i>13.66***</i>				1.205 <i>6.40***</i>	1.026 <i>5.68***</i>	1.594 <i>8.21***</i>	1.027 <i>5.84***</i>	0.568 <i>3.59***</i>	1.189 <i>5.58***</i>	1.775 <i>8.59***</i>	1.568 <i>8.02***</i>	1.538 <i>7.99***</i>	1.063 <i>6.22***</i>	0.536 <i>3.54***</i>	1.465 <i>6.44***</i>
$\Delta r_{i,t}$		-0.507 <i>-17.48***</i>			-0.427 <i>-16.87***</i>	-0.352 <i>-14.57***</i>	-0.241 <i>-11.67***</i>	-0.114 <i>-5.38***</i>	-0.060 <i>-2.99***</i>	-0.253 <i>-11.80***</i>	-0.054 <i>-2.34**</i>	-0.174 <i>-6.79***</i>	-0.218 <i>-8.28***</i>	-0.117 <i>-5.60***</i>	-0.068 <i>-3.17***</i>	-0.071 <i>-3.16***</i>
$\Delta s_{i,t}$			0.066 <i>11.76***</i>			0.035 <i>6.88***</i>	0.035 <i>8.14***</i>	0.033 <i>8.35***</i>	0.032 <i>8.76***</i>	0.028 <i>5.66***</i>	0.037 <i>8.95***</i>	0.029 <i>6.65***</i>	0.026 <i>6.91***</i>	0.028 <i>7.72***</i>	0.034 <i>8.39***</i>	0.031 <i>6.72***</i>
Δl_t				1.556 <i>18.23***</i>			1.405 <i>16.61***</i>	1.168 <i>14.31***</i>	0.835 <i>12.37***</i>	1.391 <i>16.68***</i>	1.084 <i>14.09***</i>	1.303 <i>16.32***</i>	1.196 <i>14.86***</i>	1.076 <i>14.03***</i>	0.836 <i>12.34***</i>	1.087 <i>14.14***</i>
$mr_{i,t}$								7.626 <i>8.67***</i>						6.712 <i>6.31***</i>		
$ml_{i,t}$									54.318 <i>14.50***</i>						56.319 <i>13.95***</i>	
$ms_{i,t}$										0.393 <i>3.15***</i>						0.293 <i>2.81***</i>
$rl_{i,t}$											2.109 <i>9.70***</i>					2.021 <i>9.32***</i>
$rs_{i,t}$												0.079 <i>4.38***</i>			-0.017 <i>-0.98</i>	
$ls_{i,t}$													0.280 <i>3.74***</i>	0.162 <i>2.07**</i>		
R²	19.00%	34.48%	21.41%	28.52%	36.82%	41.83%	63.76%	67.32%	74.62%	64.50%	67.26%	65.29%	65.30%	67.78%	74.68%	67.66%
N	626	626	623	626	626	623	623	623	623	623	623	623	623	623	623	623
AIC	581.41	448.63	562.69	503.15	427.81	379.20	86.40	24.05	-133.56	75.52	25.23	61.57	61.40	17.24	-133.05	19.44

Table 3. Regression results for the dependent variable $\Delta p_{i,t}$. *T*-statistics using cluster-robust standard errors are given in italic below the coefficients. *, **, *** denote statistical significance at 10%, 5%, 1%, respectively.

The Akaike information criterion (AIC)¹ helps determine the best estimation model. Model 9 stands out among other specifications with its minimum AIC value (-133.56), remarkable explanatory power (an R² of 74.62%) and statistically significant coefficients. Model 9 has the following equation:

$$\Delta p_{i,t} = \alpha_0 + \alpha_1 \Delta m_{i,t} + \alpha_2 \Delta r_{i,t} + \alpha_3 \Delta s_{i,t} + \alpha_4 \Delta l_t + \alpha_5 m l_{i,t} + \varepsilon_{i,t}. \quad (1)$$

The coefficient estimates of this model suggest that 1% increase in temperature ($\Delta m_{i,t} = 0.01$) and Liv-ex 100 index ($\Delta l_t = 0.01$) lead to a price increase of 0.57% and 0.84%, respectively. Furthermore, when both factors show improvement, the positive interaction between these two variables yields an additional increase of 0.54% for each percent increase in both variables ($m l_{i,t} = 0.01 \times 0.01 = 0.0001$). One point increase in barrel score ($\Delta s_{i,t} = 1$) has a positive impact of 3.2% whereas 1% increase in rain ($\Delta r_{i,t} = 0.01$) shows a negative effect by 0.06%.

We next calculate the estimated *ex-négociant* prices, denoted $\hat{p}_{i,t}$, using the fitted values from Model 9 in (1), denoted $\hat{\Delta p}_{i,t}$, and the realized *ex-négociant* price of the previous vintage, denoted $p_{i,t-1}$:

$$\hat{p}_{i,t} = \exp(\hat{\Delta p}_{i,t}) p_{i,t-1}. \quad (2)$$

Figure 6 illustrates actual *ex-négociant* prices $p_{i,t}$ plotted against the estimated *ex-négociant* prices $\hat{p}_{i,t}$.

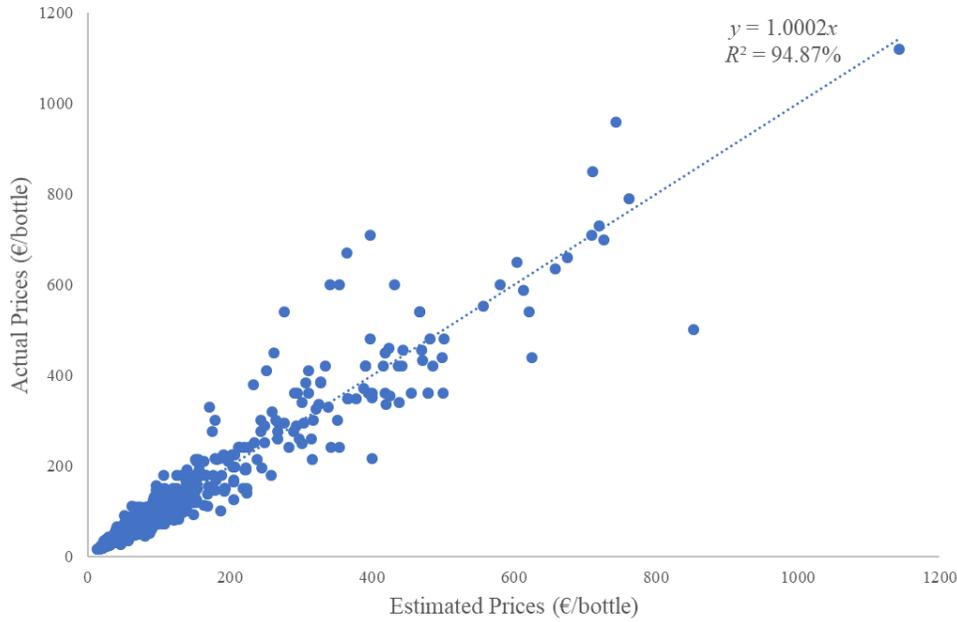


Figure 6. The fit between the actual and estimated *ex-négociant* prices for the vintages between 2002 and 2017 using Model 9 where $N = 623$.

¹ Describing the number of estimated parameters in a model with k and the maximum value of the likelihood function with L , the AIC value of each model is calculated as $AIC = 2k - 2\log(L)$. According to this criterion, the preferred model for estimation is the one with the minimum AIC value.

We would like to underline the strikingly accurate fit that Model 9 generates where the $y = 1.0002x$ line has a slope extremely close to 1 with an R^2 value of 94.87%. The high value of R^2 is not caused by omitting the intercept; when the intercept is included in the fitted line, we obtain $y = 3.53 + 0.988x$ with an R^2 of 90.97% and the intercept is not statistically significant.

3.3. Out-of-Sample Testing

This section demonstrates the impressive out-of-sample performance of Model 9 by benchmarking against the Ashenfelter (2008) approach that utilizes temperature and rain variables in the form of level data. According to the estimated and actual prices reported in Ashenfelter (2008), their weather-based approach leads to a mean absolute percentage error of 36.14% for vintages between 1967 and 1972 (details are provided in the Appendix).

Prior to the *en primeur* campaign of the 2017 vintage in the summer of 2018, we provided our estimated *ex-négociant* prices to Liv-ex in order to test the out-of-sample performance of Model 9 and asked Liv-ex executives not to share it with chateaus/négociants in order not to influence their price decisions. We present the results of this test in this section. In order to compute the *ex-négociant* prices of the 2017 vintage wines (i.e., $t = 2017$), the model in (1) is calibrated using the vintages between 2002 and 2016, i.e., $t \in \{2002, \dots, 2016\}$. The temperature ($m_{i,t=2017}$) and rainfall ($r_{i,t=2017}$) observations become available by the end of August 2017. The Liv-ex 100 value ($l_{t=2017}^{mar}$) was recorded on March 31, 2018. Barrel tasting scores ($s_{i,t=2017}$) were published in April 2018. Using these new observations with the calibrated Model 9 coefficients, we compute the *ex-négociant* prices of the 2017 vintage wines, i.e., $\hat{p}_{i,t=2017}$ as described in (2). Once the actual *ex-négociant* prices $p_{i,t=2017}$ are revealed around May 2018, we calculate the absolute percentage error as

$$e_{i,t=2017} = \left| \frac{\hat{p}_{i,t=2017} - p_{i,t=2017}}{p_{i,t=2017}} \right| \cdot$$

Table 4 shows the estimated and actual *ex-négociant* prices for the 2017 vintage and their absolute percentage errors (except for Petit Mouton whose estimation cannot be made using Model 9 due to its missing barrel score observation). Model 9 estimated the prices of three wines with less than 1% error, 12 wines with less than 5% error, and 26 wines (corresponding to two-thirds of our estimations) with less than 10% error.

We compare our Model 9 estimations against the most well-known publication in the area. The benchmark model relies on the approach of Ashenfelter (2008) that makes use of weather information alone. The benchmark model (denoted Model B0) which is calibrated for $t \in \{2001, \dots, 2016\}$ using the within regression is:

$$\text{Model B0: } \log(p_{i,t}) = \alpha_0 + \alpha_1 \log(m_{i,t}) + \alpha_2 \log(r_{i,t}) + \mu_i + \varepsilon_{i,t}$$

where μ_i represents the time-invariant chateau characteristics. This benchmark model yields a mean absolute percentage error of 34.38% for the 2017 vintage. Therefore, we conclude that Model 9 with a mean absolute percentage error of 9.19% significantly outperforms the most well-known academic benchmark.

	Estimated Price (€)	Actual Price (€)	Absolute % Error		Estimated Price (€)	Actual Price (€)	Absolute % Error
Chateau (<i>i</i>)	$\hat{P}_{i,t=2017}$	$P_{i,t=2017}$	$e_{i,t=2017}$	Chateau (<i>i</i>)	$\hat{P}_{i,t=2017}$	$P_{i,t=2017}$	$e_{i,t=2017}$
Angelus	269.38	276.00	2.40%	Lafleur	425.56	460.00	7.49%
Ausone	505.77	480.00	5.37%	Leoville Barton	63.33	52.80	19.94%
Beychevelle	46.62	52.80	11.70%	Leoville Las Cases	153.04	144.00	6.27%
Calon Segur	56.51	60.00	5.81%	Leoville Poyferre	57.91	54.00	7.25%
Carruades Lafite	134.42	135.00	0.43%	Lynch Bages	79.08	75.00	5.44%
Cheval Blanc	474.80	432.00	9.91%	Margaux	368.55	348.00	5.90%
Clarence (Bahans) Haut Brion	101.56	102.00	0.43%	Mission Haut Brion	285.67	240.00	19.03%
Clinet	63.92	56.00	14.14%	Montrose	92.38	96.00	3.77%
Clos Fourtet	73.51	72.00	2.09%	Mouton Rothschild	368.55	348.00	5.90%
Conseillante	133.17	120.00	10.97%	Palmer	224.34	192.00	16.84%
Cos d'Estournel	105.30	108.00	2.50%	Pape Clement	59.77	61.20	2.33%
Ducru Beaucaillou	126.07	120.00	5.06%	Pavie	245.02	276.00	11.23%
Duhart Milon	49.81	48.00	3.77%	Pavillon Rouge	103.25	132.00	21.78%
Eglise Clinet	206.16	168.00	22.72%	Pichon Baron	103.25	96.00	7.55%
Evangile	154.83	180.00	13.98%	Pichon Lalande	108.68	90.00	20.76%
Grand Puy Lacoste	52.65	52.80	0.28%	Pontet Canet	97.81	80.00	22.27%
Gruaud Larose	47.82	51.75	7.60%	Smith Haut Lafitte	69.56	67.20	3.51%
Haut Bailly	73.71	72.00	2.37%	Troplong Mondot	91.99	72.00	27.77%
Haut Brion	380.38	348.00	9.30%	Vieux Chateau Certan	181.57	168.00	8.08%
Lafite Rothschild	438.97	420.00	4.52%				
Mean Absolute % Error							
9.19%							

Table 4. The estimated and actual *ex-négociant* prices for the 2017 vintage and their absolute percentage errors.

We next replicate the out-of-sample testing for the 2015 and 2016 vintages in order to demonstrate robustness. We calibrate Model 9 in (1) and the benchmark model using data up until vintage $t - 1$ in order to generate the prices of vintage $t \in \{2015, 2016\}$. Table 5 demonstrates that Model 9 achieves significantly smaller mean absolute percentage error values than the benchmark Model B0. Average error during 2015 – 2017 is 11.12% in our Model 9 and 39.46% in the benchmark model B0. Details of the out-of-sample testing of Model 9 for vintages 2015 – 2016 are provided in the Appendix.

Vintage	Mean Absolute % Error	
	Model 9	Model B0
2015	12.74%	38.20%
2016	11.42%	45.79%
2017	9.19%	34.38%
Average	11.12%	39.46%

Table 5. Summary of out-of-sample testing of Model 9 and the benchmark Model B0.

Going forward, Liv-ex has determined to publish our prices as “realistic prices” prior to each *en primeur* campaign. It is important to note that our model allows for estimations to be made approximately one month before the actual *ex-négociant* prices are revealed since all explanatory observations can be collected by April of each calendar year and wine futures trade starts around May. Given the accuracy and strength of our model, Liv-ex executives expect buyers to rely on our realistic prices in determining which wines to purchase during the *en primeur* campaign. They also hope that the market prices are anchored to our realistic prices. The adoption of our Model 9 by the financial exchange shows the impact of our study’s contribution to the practice in the wine industry.

3.4. Value of Barrel Scores, Market Index, Variable Definitions, and Positive Interaction Term

Section 3.3 establishes that Model 9 significantly outperforms the benchmark Model B0 by incorporating (1) barrel scores, (2) Liv-ex 100 as market index, (3) variable definitions based on comparison of two consecutive vintages, and (4) positive interaction between temperature and Liv-ex 100 index. This section provides a breakdown of these contributions in the out-of-sample performance. We first define the following benchmark models:

$$\text{Model B1: } \log(p_{i,t}) = \alpha_0 + \alpha_1 \log(m_{i,t}) + \alpha_2 \log(r_{i,t}) + \alpha_3 s_{i,t} + \mu_i + \varepsilon_{i,t};$$

$$\text{Model B2: } \log(p_{i,t}) = \alpha_0 + \alpha_1 \log(m_{i,t}) + \alpha_2 \log(r_{i,t}) + \alpha_3 s_{i,t} + \alpha_4 \log(I_t^{mar}) + \mu_i + \varepsilon_{i,t}$$

where μ_i represents the time-invariant chateau characteristics and the coefficients are estimated using the within regression. Benchmark Model B1 adds barrel scores to Model B0 in order to demonstrate the value of barrel scores, and the benchmark Model B2 adds Liv-ex 100 to Model B1 in order to show the value of the market index. It is important to note that Model B2 uses all four explanatory factors investigated in this study in the form of level data. Recall that Model 7 (presented in Table 3), on the other hand, uses the same four factors where the variables are defined based on the comparison of two consecutive vintages instead of level data. Therefore, comparing the out-of-sample performance of Model 7 with that of Model B2 represents the value of our variable definitions as explained in Section 3.1. Finally, we compare the performance of Model 9 to Model 7 in order to demonstrate the value of positive interaction term between temperature and market index variables. We compute our estimated prices for vintage t by calibrating models B1, B2, and 7 using data up until vintage $t - 1$ where $t \in \{2015, 2016, 2017\}$. Table 6 compares the out-of-sample testing of models B0, B1, B2, 7, and 9.

Vintage	Mean Absolute % Error				
	Model B0	Model B1	Model B2	Model 7	Model 9
2015	38.20%	24.04%	16.10%	10.12%	12.74%
2016	45.79%	26.90%	16.20%	12.29%	11.42%
2017	34.38%	19.34%	13.66%	12.61%	9.19%
Average	39.46%	23.43%	15.32%	11.67%	11.12%
Δ barrel score (B0 – B1)	16.03%				
Δ Liv-ex 100 (B1 – B2)		8.11%			
Δ variable definition (B2 – 7)			3.65%		
Δ positive interaction (7 – 9)				0.55%	

Table 6. Summary of out-of-sample testing of models B0, B1, B2, 7, and 9.

We find that the addition of barrel scores to the weather variables improves the out-of-sample performance by 16.03%. Inclusion of Liv-ex 100 as market indicator further accounts for another 8.11% improvement. Moreover, our unique variable definitions enhance the accuracy by 3.65% – this result is consistent with the pricing practice we explained earlier that the *ex-négociant* price of a new vintage is determined by comparing the values of its explanatory factors with the values of the previous vintage. Therefore, Model 7 using variables defined based on the change in their values across two consecutive vintages shows a better out-of-sample performance than Model B2 using level data. As explained before, the positive impact of the variable definition in Model 7 stems from the operational decisions of négociants (who have to turn around its cash investments) and chateaus (who have to replace its wine in the cellar with the upcoming vintage’s wine). Finally, the positive interaction term between temperature and Liv-ex 100 brushes up the performance by 0.55%.

3.5. Robustness

3.5.1. Robust Regression

As can be seen in Figure 3, *ex-négociant* prices of the highly anticipated vintages like 2003, 2005, and 2009 feature greater variation. We replicate our analysis presented in sections 3.2 – 3.3 using robust regression in order to ensure that our statistical results are robust to outlying observations in the sample. Our approach first determines if any outlying observation needs to be dropped from the analysis based on Cook’s *D* – no observations are eventually dropped in our sample. It then performs iterative regressions using Huber weights followed by biweights until the weights of observations converge (Li 1985); this approach assigns smaller weights to outliers to mute their effect in the results. Table 7 shows the robust regression results for Models 1 – 16 and we find that all statistical inferences remain intact. This suggests that our findings are robust to outliers.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Int.	0.023 <i>1.76*</i>	0.052 <i>4.09***</i>	0.011 <i>0.79</i>	-0.032 <i>-2.24**</i>	0.054 <i>4.35***</i>	0.045 <i>3.71***</i>	-0.027 <i>-2.61***</i>	-0.067 <i>-5.83***</i>	-0.082 <i>-7.79***</i>	-0.043 <i>-3.81***</i>	-0.054 <i>-4.70***</i>	-0.046 <i>-4.09***</i>	-0.038 <i>-3.47***</i>	-0.069 <i>-5.91***</i>	-0.080 <i>-7.47***</i>	-0.066 <i>-5.43***</i>
$\Delta m_{i,t}$	2.306 <i>11.12***</i>				1.153 <i>5.08***</i>	0.990 <i>4.46***</i>	1.418 <i>7.89***</i>	0.803 <i>4.37***</i>	0.504 <i>2.89***</i>	1.031 <i>4.99***</i>	1.609 <i>8.99***</i>	1.356 <i>7.57***</i>	1.425 <i>7.83***</i>	0.837 <i>4.51***</i>	0.491 <i>2.79***</i>	1.289 <i>6.20***</i>
$\Delta r_{i,t}$		-0.435 <i>-16.91***</i>			-0.356 <i>-12.23***</i>	-0.292 <i>-9.66***</i>	-0.237 <i>-9.58***</i>	-0.108 <i>-3.90***</i>	-0.076 <i>-3.05***</i>	-0.250 <i>-10.12***</i>	-0.054 <i>-1.65*</i>	-0.162 <i>-5.89***</i>	-0.188 <i>-7.41***</i>	-0.105 <i>-3.75***</i>	-0.081 <i>-3.13***</i>	-0.075 <i>-2.25**</i>
$\Delta s_{i,t}$			0.054 <i>12.00***</i>			0.029 <i>6.40***</i>	0.032 <i>9.02***</i>	0.030 <i>8.85***</i>	0.031 <i>9.65***</i>	0.025 <i>6.21***</i>	0.035 <i>9.90***</i>	0.027 <i>7.25***</i>	0.028 <i>7.05***</i>	0.029 <i>7.65***</i>	0.032 <i>9.41***</i>	0.029 <i>7.25***</i>
Δl_t				1.293 <i>14.06***</i>			1.264 <i>18.78***</i>	1.028 <i>14.69***</i>	0.802 <i>11.44***</i>	1.243 <i>18.58***</i>	0.998 <i>13.02***</i>	1.161 <i>16.69***</i>	1.122 <i>14.38***</i>	0.997 <i>13.08***</i>	0.805 <i>11.45***</i>	0.991 <i>12.99***</i>
$mr_{i,t}$								7.496 <i>8.62***</i>							7.089 <i>7.69***</i>	
$ml_{i,t}$									52.167 <i>15.62***</i>						53.398 <i>14.33***</i>	
$ms_{i,t}$										0.379 <i>3.73***</i>						0.295 <i>2.91***</i>
$rl_{i,t}$											2.001 <i>8.00***</i>					1.916 <i>7.64***</i>
$rs_{i,t}$												0.081 <i>5.73***</i>			-0.012 <i>-0.82</i>	
$ls_{i,t}$													0.300 <i>5.84***</i>	0.087 <i>1.69*</i>		
<i>N</i>	626	626	623	626	626	623	623	623	623	623	623	623	623	623	623	623

Table 7. Robust regression results for the dependent variable $\Delta p_{i,t}$. *T*-statistics using standard errors based on the pseudovalues approach (Street et. al 1988) are given in italic below the coefficients. *, **, *** denote statistical significance at 10%, 5%, 1%, respectively.

Using robust regression, we next replicate the out-of-sample testing of Model 9. We follow the same approach as described in Section 3.3 with one difference: we use the robust regression coefficients instead of the OLS regression coefficients. Table 8 compares the accuracy of these two methodologies. By looking at these highly similar results, we can conclude that our approach continues to yield accurate estimations using a robust regression methodology.

Vintage	Mean Absolute % Error	
	OLS	Robust Regression
2015	12.74%	13.39%
2016	11.42%	11.69%
2017	9.19%	9.29%
Average	11.12%	11.46%

Table 8. Summary of out-of-sample testing of Model 9 using OLS and robust regression.

3.5.2. Hierarchical Linear Modeling

Our data is grouped in chateaus that may be featuring some group-level effects that OLS regression does not capture. To account for this issue, we replicate our analysis pertaining to Model 9 using linear mixed-effects regression where each chateau represents a group. For generality, we allow for varying intercept and varying coefficients at group-level for all variables used in Model 9. This revised version of Model 9 can be represented as follows:

$$\Delta p_{i,t} = \alpha_0 + \beta_{0,i} + (\alpha_1 + \beta_{1,i})\Delta m_{i,t} + (\alpha_2 + \beta_{2,i})\Delta r_{i,t} + (\alpha_3 + \beta_{3,i})\Delta s_{i,t} + (\alpha_4 + \beta_{4,i})\Delta l_t + (\alpha_5 + \beta_{5,i})ml_{i,t} + \varepsilon_{i,t}$$

where α_k represents the fixed (average) effect and $\beta_{k,i}$ represents the random effect for chateau i such that $\beta_{k,i} \sim N(0, \sigma_k^2)$ for $k \in \{0, \dots, 5\}$. We use maximum likelihood in order to estimate the parameters α_k and σ_k^2 for each k , along with σ_ε^2 denoting the variance for $\varepsilon_{i,t}$. Table 9 shows the mixed-effects regression results.

The fixed (average) effect estimates, denoted α_k , are very close to the OLS estimates of Model 9 presented in Table 3. However, the likelihood ratio test favors the mixed-effects regression over the standard linear regression at 1% significance level meaning that there exist group-level random effects. From the σ_k^2 estimates for variance, we can conclude that the effects of temperature, Liv-ex 100 index and their positive interaction vary across chateaus. This means that *ex-négociant* prices across chateaus respond differently to these factors. Before we explain our interpretation of this finding, first recall from Figure 3 that the prices of hyped vintages like 2003, 2005, 2009 show great variation across chateaus. In those years, both temperature and Liv-ex 100 variables show improvement ($\Delta m_{i,t}, \Delta l_t > 0$) which triggers the positive interaction term $ml_{i,t} > 0$. Therefore, when varying coefficients for variables are allowed via mixed-effects modeling, temperature and Liv-ex 100, along with their positive interaction, account for the price variations across chateaus, especially for the highly anticipated vintages.

	α_k	σ_k^2	σ_ε^2
Int.	-0.085 <i>-9.12***</i>	≈ 0	
$\Delta m_{i,t}$	0.564 <i>3.18***</i>	0.2686	
$\Delta r_{i,t}$	-0.060 <i>-2.69***</i>	≈ 0	
$\Delta s_{i,t}$	0.032 <i>9.13***</i>	0.0001	
Δl_t	0.832 <i>12.19***</i>	0.0298	
$m l_{i,t}$	53.781 <i>13.41***</i>	287.5531	
$\varepsilon_{i,t}$			0.0366
LR test ($H_0: \sigma_k^2 = 0$)	59.35***		
N	623		

Table 9. Mixed-effects regression results for the dependent variable $\Delta p_{i,t}$. The values under the α_k column denote the fixed-effect estimates and their z-statistics (italic) where *, **, *** denote statistical significance at 10%, 5%, 1%, respectively. The values under the σ_k^2 column denote the variance estimates of random effects. The value under the σ_ε^2 column denotes the variance estimate of residuals.

We next investigate whether the mixed-effects modeling leads to any improvement over OLS in terms of the out-of-sample performance. We calibrate the mixed-effects version of Model 9 (presented above) using data up until vintage $t - 1$ to generate the prices of vintage $t \in \{2015, 2016, 2017\}$. Table 10 compares the out-of-sample performance of OLS with that of the mixed-effects regression. One can see that no improvement is achieved on average by using mixed-effects modeling. This is an expected result given that our variable definitions, resembling a first-difference approach, already eliminate most of the group-level effects by comparing two consecutive vintages. Therefore, we can conclude that out-of-sample performance of our OLS approach is robust to group-level mixed effects.

Vintage	Mean Absolute % Error	
	OLS	Mixed-Effects
2015	12.74%	12.88%
2016	11.42%	11.39%
2017	9.19%	9.15%
Average	11.12%	11.14%

Table 10. Summary of out-of-sample testing of Model 9 using OLS and mixed-effects regression.

3.5.3. Hierarchical Bayes Modeling

This section presents a Bayesian alternative to hierarchical modeling of the group-level effects. In Section 3.5.2, α_k , σ_k^2 , and σ_ε^2 are treated as fixed unknown parameters which are estimated using maximum

likelihood. We next adopt a Bayesian alternative which treats those parameters as random variables. We define a normal likelihood model as

$\Delta p_{i,t} \sim N(\alpha_0 + \beta_{0,i} + (\alpha_1 + \beta_{1,i})\Delta m_{i,t} + (\alpha_2 + \beta_{2,i})\Delta r_{i,t} + (\alpha_3 + \beta_{3,i})\Delta s_{i,t} + (\alpha_4 + \beta_{4,i})\Delta l_t + (\alpha_5 + \beta_{5,i})ml_{i,t}, \sigma_\varepsilon^2)$ where the prior and hyperprior distributions are $\alpha_k \sim N(0, 10000)$, $\beta_{k,i} \sim N(0, \sigma_k^2)$, $\sigma_k^2 \sim \text{Inv-Gamma}(0.01, 0.01)$ for $k \in \{0, \dots, 5\}$, and $\sigma_\varepsilon^2 \sim \text{Inv-Gamma}(0.01, 0.01)$. We use Metropolis-Hastings and Gibbs sampling to simulate the posterior distributions. Table 11 shows the estimated mean values of the posterior distribution parameters α_k , σ_k^2 , and σ_ε^2 .

	α_k	σ_k^2	σ_ε^2
Int.	-0.084	0.0021	
$\Delta m_{i,t}$	0.559	0.1834	
$\Delta r_{i,t}$	-0.064	0.0054	
$\Delta s_{i,t}$	0.032	0.0011	
Δl_t	0.826	0.0416	
$ml_{i,t}$	53.295	358.3151	
$\varepsilon_{i,t}$			0.0367
MCMC iterations	10,000 after a burn-in of 2,500		

Table 11. Hierarchical Bayes estimation results for the dependent variable $\Delta p_{i,t}$. The values represent the estimated mean values of the posterior distribution parameters α_k , σ_k^2 , and σ_ε^2 .

One can notice that the mean values of α_k are once again close to Model 9’s OLS estimates given in Table 3. This further reassures that our variable definitions resembling a first-difference approach account for the group-level effects, therefore, using OLS methodology is suitable in our study.

We demonstrate the out-of-sample performance using hierarchical Bayes and compare with that using OLS. Like the previous section, calibration of the model uses data up until vintage $t - 1$ to generate the prices of vintage $t \in \{2015, 2016, 2017\}$. Table 12 presents the results. We find that hierarchical Bayes modeling does not bring any improvement over OLS regression in our study.

Vintage	Mean Absolute % Error	
	OLS	Hierarchical Bayes
2015	12.74%	12.55%
2016	11.42%	12.22%
2017	9.19%	9.58%
Average	11.12%	11.45%

Table 12. Summary of out-of-sample testing of Model 9 using OLS and hierarchical Bayes modeling.

3.5.4. Dependent Variable Retransformation

When computing the prices of vintage t in Section 3.3, we first calibrate Model 9 (see (1)) using data up until vintage $t - 1$, then compute the estimations using (2). This procedure involves retransformation of a logarithmic dependent variable back to its untransformed scale. In this section, we revise (2) using the following two alternative methods that can account for potential bias due to this retransformation: The normal theory estimation and the smearing estimation in Duan (1983).

Normal theory estimation assumes that errors in (1) are normally distributed. In light of this assumption, we revise (2) as

$$\hat{p}_{i,t}^N = \exp\left(\hat{\Delta}p_{i,t} + \hat{\sigma}^2/2\right)p_{i,t-1} \quad (3)$$

where $\hat{\sigma}^2$ denotes the mean squared error in (1). Duan's smearing estimation, on the other hand, is a nonparametric method which does not require any knowledge on the error distribution. For the smearing estimates, we revise (2) as follows:

$$\hat{p}_{i,t}^D = \left[N^{-1} \sum_i \sum_t \exp(\hat{\varepsilon}_{i,t}) \right] \exp\left(\hat{\Delta}p_{i,t}\right) p_{i,t-1} \quad (4)$$

where $\hat{\varepsilon}_{i,t}$ denotes the residual for vintage t of chateau i in (1).

Table 13 compares the out-of-sample performance of our original estimates $\hat{p}_{i,t}$ utilizing (2) with that of the normal theory estimates $\hat{p}_{i,t}^N$ utilizing (3) and the smearing estimates $\hat{p}_{i,t}^D$ utilizing (4) for vintages 2015 – 2017. We find that $\hat{p}_{i,t}$ yields the highest accuracy for the 2017 estimates whereas $\hat{p}_{i,t}^N$ and $\hat{p}_{i,t}^D$ achieve better accuracy for vintages 2015 and 2016. This suggests that our original estimates $\hat{p}_{i,t}$ do not feature a systematic bias.

Vintage	Mean Absolute % Error		
	$\hat{p}_{i,t}$	$\hat{p}_{i,t}^N$	$\hat{p}_{i,t}^D$
2015	12.74%	11.31%	11.31%
2016	11.42%	10.22%	10.23%
2017	9.19%	10.45%	10.44%
Average	11.12%	10.66%	10.66%

Table 13. Summary of out-of-sample testing of Model 9 using $\hat{p}_{i,t}$, $\hat{p}_{i,t}^N$, and $\hat{p}_{i,t}^D$.

4. Conclusions and Impact of the Study

Our study makes several contributions that have significant practical implications for the wine industry. Our first contribution involves developing an empirical model that determines the appropriate market prices of the infamous Bordeaux wines. The model leads to an accuracy that the industry has not seen

before. This is evident from the statement of Neil Taylor, vice president of data at Liv-ex where he claims that our study is “the most accurate work they have seen internally and externally.” As a result, Liv-ex determined to release our *ex-négociant* price estimations as “realistic prices” to all wine industry participants and individual collectors.

Our study identifies four primary determinants of the price fluctuations from one vintage to another at the highest statistical significance. Two of these four determinants are weather related: The average of daily maximum temperatures and the total precipitation during the growing season of the wine. The third factor is the appreciation in the Liv-ex 100 index as an indicator of the fine wine market. The fourth determinant is the barrel scores established by the tasting experts. In addition to these four factors, our statistical method employs an interaction term that captures the combined benefits from an increase in the temperatures and the improvement in the market conditions from the previous vintage. This interaction enables the estimates to capture the hype effect in phenomenal vintages. The fit between our estimated market prices and the realized prices features an R^2 of 94.87% with a slope of 1.0002. Through a comprehensive analysis, we demonstrate that our methodology and results are robust. Our robustness analyses include robust regression, hierarchical linear modeling, hierarchical Bayes modeling, and dependent variable retransformation. These various approaches show that our initial approach continue to yield the most accurate price estimates.

It is important to highlight that the variable definition in our statistical analysis that relies on vintage-to-vintage comparison is a technical contribution that stems from practice. We show that our variable definitions enhance the accuracy of estimated prices by 3.65%. The reason for this improvement is due to the operational planning decisions of négociants and chateaus. Négociants buy the wine from chateaus and make a financial investment in futures. They need to circulate this cash by selling all of their futures contracts in order to collect their investment back and reinvest in the next vintage. Similarly, chateaus have to clear the space in their winemaking facilities in order to store the next vintage’s barrels. As a result, the industry operates with the mindset of a one-year planning horizon. This operational phenomenon influences the adjustments in market prices.

The implication of identifying barrel tasting scores as a factor in determining realistic prices is significant in practice. Buyers often see a barrel tasting score from influential tasting experts, however, these barrel scores are not easily translated into prices. Our approach provides a bridge in converting these barrel scores into prices while incorporating the information associated with the growing weather conditions and the evolution of market dynamics.

Our second contribution is that our realistic prices lead to a transparent market for fine wines. Buyers (e.g., wine merchants, distributors, restaurateurs and collectors) can now compare our realistic price estimates with the realized market prices in order to determine whether a wine is underpriced or

overpriced. As a result of our realistic prices, the fine wine market can invest in futures in confidence, leading to a more efficient marketplace.

Third, our study provides insights into the winemaker's *ex-chateau* price decision which reflects the selling price of the wine to négociants. Our realistic price is an estimate of the market price that the wine will move to the downstream in the supply chain. Using our realistic price estimate, the winemaker can then estimate the potential margin and determine the terms of the advance selling agreement with the négociant. Thus, our realistic price estimates are helpful in determining *ex-chateau* price decisions.

Our findings provide valuable insights for future academic research. Our variable definitions with the change in value from the previous vintage (and not from earlier vintages) resembles the behavior in the modeling approaches observed in Markov decision processes. One might intuit that the memoryless property of the Markov decision process is in place and wine prices jump from their values in the earlier vintage release epoch to new values in the next vintage release epoch. Thus, our study provides justifications for future research that might model wine prices using a Markov process.

Our study opens new avenues for continued research involving market prices for fine wines. We expect other scholars to examine the same problem with the goal of improving our methodology. Moreover, our study can be expanded in order to estimate benchmark wine prices in other geographic regions. Another future research question is whether négociants will anchor their prices to these realistic prices. In the event that some négociants intentionally deviate from these benchmark prices, new studies should identify the reasons behind such reactions. Finally, we anticipate that our realistic prices will trigger future research featuring new bargaining models between the chateaus and négociants.

While our study focuses on wine prices, our approach can be generalized to other settings where pricing decisions are influenced by quality perceptions. For fine wines, barrel scores of tasting experts establish the initial quality perception. In other agricultural products, similar quality measures are established. For olive oil, oleic acidity tests reveal information about the quality of the oil and influence both retail prices and payments made to the olive growers. Our approach can be extended to studies that examine how weather, market and oleic acidity test can be combined to estimate the price of premium quality olive oil. Similar to olive oil, wagyu beef prices are influenced by weather fluctuations and our approach can be adopted to develop similar benchmark prices. Fine wine prices resemble the price of technology products revisions. However, for technology products, the price of the new version is often greater than the previous version. For agricultural products, on the other hand, prices can go up or down depending on the influence of weather, market and expert reviews. Thus, the pricing decisions for agricultural products at the time of harvest/release require a careful and in-depth examination of influential factors.

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Appendix

Predictive Power of Ashenfelter (2008):

Table A1 shows the estimated prices and the actual market prices for Bordeaux wines of vintages 1967 through 1972 as reported in Ashenfelter (2008). It should be noted that Ashenfelter (2008) reports these prices relative to the value of a benchmark portfolio, whose value is normalized to 1, to account for the differences in price levels among chateaus.

Vintage	Estimated Price	Actual Price	Absolute % Error
1967	0.49	0.77	36.36%
1968	0.21	0.28	25.00%
1969	0.29	0.75	61.33%
1970	0.60	0.83	27.71%
1971	0.53	0.61	13.11%
1972	0.14*	0.30	53.33%
Average			36.14%

Table A1. Prediction performance reported in Table 3 of Ashenfelter (2008). * The estimated price for the 1972 vintage is reported as 0.014 in Ashenfelter (2008). We believe that it was a typo and we use 0.14 in order not to exacerbate the average percentage error.

Out-of-Sample Testing of Model 9 for Vintages 2015 – 2016:

Tables A2 and A3 present the estimated and actual *ex-négociant* prices and their absolute percentage errors using Model 9 for the 2016 and 2015 vintages, respectively.

Chateau (<i>i</i>)	Estimated Price (€) $\hat{P}_{i,t=2016}$	Actual Price (€) $P_{i,t=2016}$	Absolute % Error $e_{i,t=2016}$	Chateau (<i>i</i>)	Estimated Price (€) $\hat{P}_{i,t=2016}$	Actual Price (€) $P_{i,t=2016}$	Absolute % Error $e_{i,t=2016}$
Angelus	263.64	294.00	10.33%	Lafleur	412.19	450.00	8.40%
Ausone	602.24	588.00	2.42%	Leoville Barton	53.97	63.60	15.14%
Beychevelle	59.11	56.60	4.43%	Leoville Las Cases	156.74	180.00	12.92%
Calon Segur	62.15	62.40	0.39%	Leoville Poyferre	62.70	66.00	5.00%
Carruades Lafite	123.84	135.00	8.27%	Lynch Bages	98.51	96.00	2.61%
Cheval Blanc	547.17	552.00	0.87%	Margaux	383.81	420.00	8.62%
Clarence (Bahans) Haut Brion	82.29	102.00	19.33%	Mission Haut Brion	319.65	336.00	4.87%
Clinet	60.80	72.00	15.56%	Montrose	119.62	102.00	17.27%
Clos Fourtet	67.89	82.80	18.01%	Mouton Rothschild	409.15	420.00	2.58%
Conseillante	118.22	150.00	21.19%	Palmer	216.72	240.00	9.70%
Cos d'Estournel	150.02	120.00	25.01%	Pape Clement	60.68	66.00	8.06%
Ducru Beaucaillou	132.01	139.20	5.16%	Pavie	272.20	294.00	7.41%
Duhart Milon	52.80	55.00	3.99%	Pavillon Rouge	101.95	114.00	10.57%
Eglise Clinet	188.31	225.00	16.30%	Petit Mouton	108.68	132.00	17.67%
Evangile	142.58	180.00	20.79%	Pichon Baron	99.07	114.00	13.10%
Grand Puy Lacoste	51.14	60.00	14.76%	Pichon Lalande	102.29	120.00	14.76%
Gruaud Larose	53.10	52.80	0.57%	Pontet Canet	79.91	108.00	26.01%
Haut Bailly	70.32	84.00	16.28%	Smith Haut Lafitte	63.93	76.80	16.76%
Haut Brion	384.81	420.00	8.38%	Troplong Mondot	86.58	102.00	13.71%
Lafite Rothschild	462.04	455.00	1.55%	Vieux Chateau Certan	139.20	192.00	28.08%
Mean Absolute % Error							
11.42%							

Table A2. The estimated and actual *ex-négociant* prices for the 2016 vintage and their absolute percentage errors.

Chateau (<i>i</i>)	Estimated Price (€)	Actual Price (€)	Absolute % Error	Chateau (<i>i</i>)	Estimated Price (€)	Actual Price (€)	Absolute % Error
	$\hat{P}_{i,t=2015}$	$P_{i,t=2015}$	$e_{i,t=2015}$		$\hat{P}_{i,t=2015}$	$P_{i,t=2015}$	$e_{i,t=2015}$
Angelus	239.52	252.00	4.95%	Lafleur	425.46	420.00	1.30%
Ausone	449.70	540.00	16.72%	Leoville Barton	52.72	54.00	2.36%
Beychevelle	50.16	50.40	0.48%	Leoville Las Cases	111.46	138.00	19.23%
Calon Segur	47.25	53.00	10.86%	Leoville Poyferre	51.55	55.20	6.61%
Carruades Lafite	104.49	120.00	12.92%	Lynch Bages	69.66	84.00	17.07%
Cheval Blanc	449.70	540.00	16.72%	Margaux	316.18	384.00	17.66%
Clarence (Bahans) Haut Brion	64.71	85.00	23.87%	Mission Haut Brion	173.75	300.00	42.08%
Clinet	62.37	60.00	3.95%	Montrose	93.77	102.00	8.07%
Clos Fourtet	69.36	67.00	3.52%	Mouton Rothschild	296.82	384.00	22.70%
Conseillante	85.09	113.00	24.70%	Palmer	191.73	210.00	8.70%
Cos d'Estournel	92.10	120.00	23.25%	Pape Clement	59.67	58.80	1.49%
Ducru Beaucaillou	89.09	120.00	25.76%	Pavie	224.85	252.00	10.77%
Duhart Milon	48.76	48.00	1.59%	Pavillon Rouge	96.47	102.00	5.42%
Eglise Clinet	170.18	180.00	5.45%	Petit Mouton	90.56	102.00	11.22%
Evangile	119.76	150.00	20.16%	Pichon Baron	84.25	96.00	12.24%
Grand Puy Lacoste	44.70	48.00	6.88%	Pichon Lalande	77.65	96.00	19.12%
Gruaud Larose	43.05	46.75	7.91%	Pontet Canet	76.63	75.00	2.17%
Haut Bailly	55.14	66.00	16.45%	Smith Haut Lafitte	56.40	60.00	6.01%
Haut Brion	316.18	385.00	17.87%	Troplong Mondot	69.59	82.80	15.95%
Lafite Rothschild	323.97	420.00	22.86%	Vieux Chateau Certan	131.50	150.00	12.33%
Mean Absolute % Error							
12.74%							

Table A3. The estimated and actual *ex-négociant* prices for the 2015 vintage and their absolute percentage errors.