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Analytics for Wine Futures: 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 fine wine is sold in the form of wine futures, even before the wine is bottled, determining realistic prices for these wine futures 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.

Key words: wine futures; price; weather; barrel score; Liv-ex 100
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1. Introduction

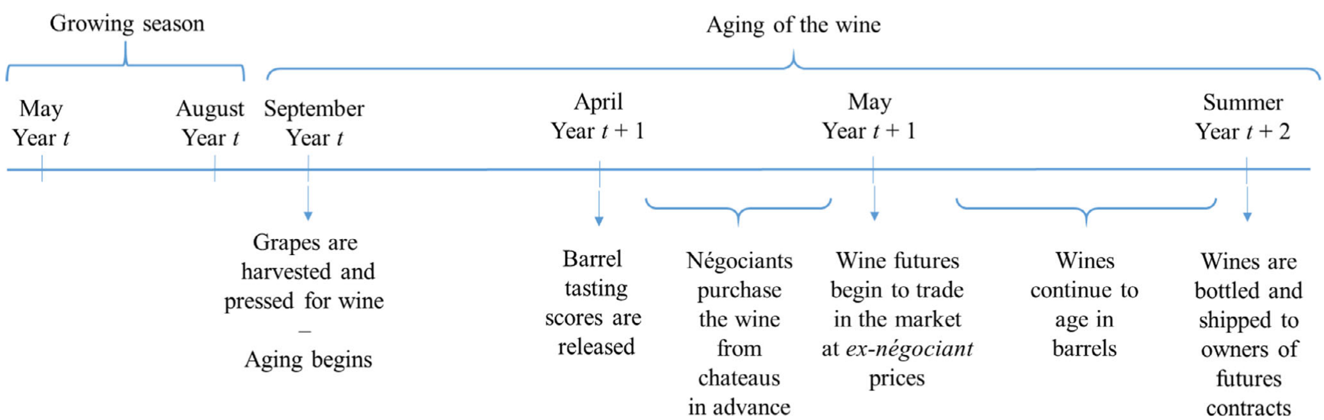
Economists have long tried to estimate wine prices through weather. In two most influential publications, Ashenfelter et al. (1995) and Ashenfelter (2008) provided remarkable insights regarding the impact of weather on *aged* Bordeaux wines. However, these scholars, as well as authors of similar publications, 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*, that is, financial contracts loosely translated into English as wine futures, before the wines are bottled. Our study develops pricing models that estimate the appropriate futures 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 October, and the wine (of vintage t) begins aging in barrels. Tasting experts visit chateaus approximately 8 to 9 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 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 $t + 1$.

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

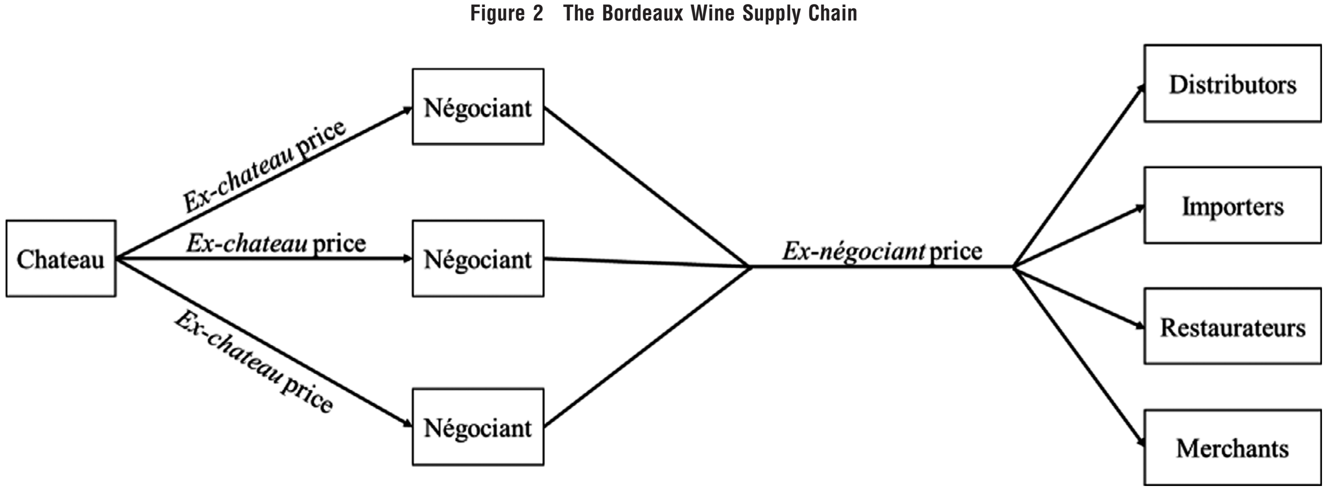
Figure 1 The Sequence of Events Leading to the Revelation of *ex-négociant* Prices for Vintage *t* Wines [Color figure can be viewed at wileyonlinelibrary.com]



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 18–24 months. After bottling, the wine gets delivered to the buyers who purchased the wine in the market from the négociants.

What is the right market price for a wine? Can it be determined accurately before the *en primeur* campaign, that is, 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 €1607.80. After *ex-négociant* prices are established, the basket had an actual value of €2054.40—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

Figure 2 The Bordeaux Wine Supply Chain



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 products where prices are influenced by quality perceptions and weather fluctuations. Examples include olive oil, citrus juice, and wagyu beef where prices are influenced by quality and weather conditions.

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. In this figure, values above zero represent a price increase compared to the price of the previous vintage, whereas the values below zero represent a price decrease. 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. The behavior in Figure 3 resembles the social herding phenomenon commonly observed in agriculture but departs from it with the sequence of events. In Hu et al. (2019), for example, crop prices get revealed in the market first causing farmers to choose the high-priced crop to plant with the assumption that its price will remain the same in the next year. In the fine wine setting, however, the factors are revealed first (i.e., temperature, precipitation, tasting scores, and market conditions) and then prices adjust 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 1-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.

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).

Second, we employ a unique variable definition that compares two consecutive vintages that account for the 1-year planning phenomenon and the use of this "change" variable leads to improved estimation accuracy. Instead of using the level data, for example, the *ex-négociant* price for a specific vintage, our analysis uses a value that corresponds to the change from the *ex-négociant* price of the prior vintage. This definition of variables leads to significant performance improvements over earlier publications that estimate wine prices. Our study is the first to employ this change variable definition and it makes an academic contribution to the existing literature.

Third, while earlier publications focus on explaining wine prices, our study tackles a more challenging task of "estimating" fine wine prices. Thus, our study makes a significant contribution to the literature. To our knowledge, the only publication that estimates fine wine prices prior to our study is Ashenfelter (2008) and we show that our approach improves estimation performance drastically.

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 estimations had a mean absolute deviation of 9.19% with a standard deviation of 7.17% where the minimum and the maximum deviations are 0.28% and 27.77%, respectively. The most well-known academic benchmark has

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 [Color figure can be viewed at wileyonlinelibrary.com]

an absolute deviation of 34.38%. The deviations in our estimations are substantially less than any academic and/or practice benchmark. Comprehensive analysis shows that our methodology and results are robust. These are demonstrated through analyses using quantile regression, Lasso analysis, 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.

Fourth, our realistic prices help create transparency in this otherwise opaque market. 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. Our estimated prices enable buyers 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.

Fifth, our realistic price estimates can help winemakers determine the prices they can charge négociants, that is, 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 wine futures 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. Combris et al. (1997), Jones and Storchmann (2001), Cardebat and Figuet (2004), Lecocq and Visser (2006), Ali and Nauges (2007), Ali et al. (2008), Dubois and Nauges (2010), Ashenfelter and Jones (2013), Dimson et al. (2015), Ashton (2016), and Cardebat et al. (2017) also examine Bordeaux fine wine prices using weather conditions and/or tasting scores. Using similar approaches, 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 aim to explain the factors influencing the wine prices rather than predicting the prices. Bazen and Cardebat (2018) focus on predicting the prices of Bordeaux generic wines. However, unlike Bordeaux fine wines and other agricultural commodities, there is no futures market for Bordeaux generic wines. Our study complements this economics literature by providing an accurate pricing model for Bordeaux fine wines that can be used before the *ex-négociant* prices are revealed. Furthermore, our study extends the previous literature in two ways. First, we incorporate the Liv-ex 100 index into the *ex-négociant* pricing; Liv-ex 100 index serves as a proxy for reflecting consumers' willingness to pay for fine wines (Cardebat and Jiao 2018). Second, we develop unique variable definitions that compare two consecutive vintages in order to account for the 1-year planning phenomenon. Table 1 lists previous publications by the main factors examined in this study.

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 study 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

Table 1 List of Publications by the Main Factors Examined in this Study Where + Indicates that the Factor is Investigated in the Corresponding Paper

Publication/Factors examined	Temperature	Rainfall	Tasting score	Liv-ex 100 index	Consecutive vintage comparison
Ashenfelter et al. (1995)	+	+			
Byron and Ashenfelter (1995)	+	+			
Combris et al. (1997)			+		
Jones and Storchmann (2001)	+	+	+		
Cardebat and Figuet (2004)			+		
Haeger and Storchmann (2006)	+	+	+		
Lecocq and Visser (2006)	+	+			
Wood and Anderson (2006)	+	+			
Ali and Nauges (2007)			+		
Ali et al. (2008)			+		
Ashenfelter (2008)	+	+			
Ashenfelter and Storchmann (2010)	+	+			
Dubois and Nauges (2010)			+		
Ashenfelter and Jones (2013)	+	+	+		
Dimson et al. (2015)	+	+			
Ashton (2016)			+		
Cardebat et al. (2017)			+		
This Study	+	+	+	+	+

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 2.

Weather data come 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 1 month before the revelation of *ex-négociant* prices.

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. Even though the index includes only bottled wines of older vintages, the value of the index is an excellent proxy for reflecting consumers' willingness to pay for fine wines. 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.

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 1-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-*

Table 2 List of Chateaus with their Region, Average *ex-négociant* Price and Standard Deviation

		Price (€/bottle)				Price (€/bottle)	
Chateau	Region	Average	SD	Chateau	Region	Average	SD
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

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 [Color figure can be viewed at wileyonlinelibrary.com]**

négociant prices of two consecutive vintages from the same chateau, that is, $\Delta p_{i,t} = \log(p_{i,t}/p_{i,t\text{-}1})$ 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 $i \in \{1, \ldots, 40\}$ and $t \in \{2002, \ldots, 2017\}$.

Warmer temperatures during growing season lead to quicker ripening of grapes with bolder flavors, higher sugar content that converts to alcohol, resulting in consistent grape harvests. Therefore, a warmer growing season implies higher quality of grapes that translates to higher prices of wine.

Change in average temperature. We define the temperature variable as the logarithmic change across the average growing season temperatures of two consecutive vintages, that is, $\Delta m_{i,t} = \log(m_{i,t}/m_{i,t\text{-}1})$ 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.

Higher amounts of rain cause grapes to take on more water diluting flavors and distorting the sugar-acid balance. With too much rain, the grape berries start to swell causing spoilage, mold, and mildew. As a result, higher degrees of precipitation are often associated with lower quality of grapes, and therefore, it is expected to reduce wine prices.

Change in total rainfall. We define the rainfall variable as the logarithmic change across the total growing season rainfall of two consecutive vintages, that is, $\Delta r_{i,t} = \log(r_{i,t}/r_{i,t\text{-}1})$ 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.

Barrel scores of tasting experts provide a proxy for quality of the wine. Higher barrel tasting scores indicate that the wine is going to evolve to a superior quality wine that commands a higher 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, that is, $\Delta s_{i,t} = s_{i,t} - s_{i,t\text{-}1}$ where $s_{i,t}$ is the barrel tasting score of vintage t of chateau i that is revealed approximately 1 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.

Temperature, rainfall and barrel scores are all indicators of quality. Temperature and rainfall directly influence the grape composition. Barrel scores complement temperature and rainfall variables by incorporating the interventions of the winemaker in producing a high-quality wine. Together, these three variables provide a stronger description of the quality

Figure 5 Historical Values of the Liv-ex Fine Wine 100 Index Since its Inception [Color figure can be viewed at wileyonlinelibrary.com]

potential of the wine, and therefore, they influence the *ex-négociant* prices.

The Liv-ex 100 index features the fluctuations in the prices of the world's most-sought after 100 wines. Even though the index includes only bottled wines of older vintages, the value of the index is an excellent proxy for reflecting consumers' willingness to pay for fine wines.

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, that is, $\Delta l_t = \log(l_t^{mar}/l_{t-1}^{may})$ 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 3 presents the correlation coefficients among the dependent variable and the main independent variables. The values are not too strong to indicate any collinearity issue.

Earlier discussion in this section has identified four variables that potentially influence the *ex-négociant* prices. When the wine industry observes several of these variables moving together in the direction indicating higher prices (e.g., a higher average temperature along with a positive change in Liv-ex 100), an excitement builds up for that vintage. This hype leads to dramatic upswings in prices. 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 positive interaction variables in order to account for such dramatic price increases observed in celebrated vintages.

Positive Interaction variables. 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 have also examined a total of 23 additional explanatory variables including the quadratic terms of main independent variables, the negative interaction variables, the change in exchange rates (e.g., \$/€, £/€), the Left Bank variable, the 1855 Bordeaux Classification variables, the Saint-Emilion Classification variables, the changes in chateau's annual trade volume, annual trade value, and number of unique wines. These variables are used in the Lasso analysis presented in Section 4.1. We omit them here from presentation because none of these variables are selected among the optimal set of variables by the Lasso analysis. Their definitions are provided in Section 4.1.1.

3.2. Analysis and Results

Table 4 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 $i \in \{1, \ldots, 40\}$ and $t \in \{2002, \ldots, 2017\}$. 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 Δl_t, 1.24 for $\Delta s_{i,t}$, 1.41 for $\Delta m_{i,t}$, and 1.62 for $\Delta r_{i,}$.

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 Δl_t, 1.63 for $\Delta m_{i,t}$, 2.01 for $\Delta r_{i,}$, and 2.43 for $(ml_{i,t})^+$. It is worth noting here that a commonly used threshold to identify collinearity is a VIF value greater than 5 (Studenmund 2001). We conclude from these VIF values, combined with the correlation values in Table 3, 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-

Table 3 The Correlation Coefficients among the Dependent Variable and the Main Independent Variables

Correlation Coefficients	Change in *ex-négociant* 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 *ex-négociant* 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 4 Regression Results for the Dependent Variable $\Delta p_{i,t}$

	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	0.077	0.056	–0.007	0.072	0.066	–0.004	–0.056	–0.086	–0.022	–0.049	–0.029	–0.024	–0.061	–0.083	–0.061
	15.64***	*19.59****	*12.35****	*–1.28*	*19.33****	*14.95****	*–0.64*	*–6.65****	*–8.84****	*–2.60***	*–5.80****	*–3.30****	*–2.57***	*–6.85****	*–8.29****	*–6.36****
$\Delta m_{i,t}$	2.931				1.205	1.026	1.594	1.027	0.568	1.189	1.775	1.568	1.538	1.063	0.536	1.465
	13.66***				*6.40****	*5.68****	*8.21****	*5.84****	*3.59****	*5.58****	*8.59****	*8.02****	*7.99****	*6.22****	*3.54****	*6.44****
$\Delta r_{i,t}$		–0.507			–0.427	–0.352	–0.241	–0.114	–0.060	–0.253	–0.054	–0.174	–0.218	–0.117	–0.068	–0.071
		–17.48***			*–16.87****	*–14.57****	*–11.67****	*–5.38****	*–2.99****	*–11.80****	*–2.34***	*–6.79****	*–8.28****	*–5.60****	*–3.17****	*–3.16****
$\Delta s_{i,t}$			0.066			0.035	0.035	0.033	0.032	0.028	0.037	0.029	0.026	0.028	0.034	0.031
			11.76***			*6.88****	*8.14****	*8.35****	*8.76****	*5.66****	*8.95****	*6.65****	*6.91****	*7.72****	*8.39****	*6.72****
Δl_t				1.556			1.405	1.168	0.835	1.391	1.084	1.303	1.196	1.076	0.836	1.087
				18.23***			*16.61****	*14.31****	*12.37****	*16.68****	*14.09****	*16.32****	*14.86****	*14.03****	*12.34****	*14.14****
$(mr_{i,t})^+$								7.626						6.712		
								8.67***						*6.31****		
$(ml_{i,t})^+$									54.318						56.319	
									14.50***						*13.95****	
$(ms_{i,t})^+$										0.393						0.293
										3.15***						*2.81****
$(rl_{i,t})^+$											2.109					2.021
											9.70***					*9.32****
$(rs_{i,t})^+$												0.079			–0.017	
												4.38***			*–0.98*	
$(ls_{i,t})^+$													0.280	0.162		
													3.74***	*2.07***		
R^2	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

Notes: *T*-statistics using cluster-robust standard errors are given in italic below the coefficients. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

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.

The Akaike information criterion (AIC) helps determine the best estimation model. According to this criterion, the preferred model for estimation is the one with the minimum AIC value. Model 9 stands out among other specifications with its minimum AIC value (−133.56), remarkable explanatory power (an R^2 of 74.62%) and statistically significant coefficients. Model 9 has the following equation:

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

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 ($(ml_{i,t})^+ = 0.01 \times 0.01 = 0.0001$). 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 Equation (1), denoted $\hat{\Delta} p_{i,t}$, and the realized *ex-négociant* price of the previous vintage, denoted $p_{i,t\text{-}1}$:

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

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

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 implication of the slope being close to 1 is that our estimations on average are significantly close to the actual prices. 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.

One might intuit that the estimation accuracy might change at different price levels. For example, how does the fit between the actual and estimated *ex-négociant* prices change between less expensive and expensive wines? To provide insight into goodness-of-fit at various price levels, it is useful to regress our data in quantiles. Table 5 shows the regression results for wines at different price quantiles.

Table 5 shows that the fit between the actual and estimated *ex-négociant* prices is consistent at different price levels. In three of the four quantiles, the fitted line features a slope that is close to 1 with remarkably high R^2 values; the only exception appears to be the lower priced wines (i.e., below 25th percentile) where our estimations deviate from the actual prices by 6%.

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 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 Equation (1) is calibrated using the vintages between 2002 and 2016, that is, $t \in \{2002, \ldots, 2016\}$. 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, that is, $\hat{p}_{i,t=2017}$ as described in Equation (2). Once the actual *ex-négociant* prices $p_{i,t=2017}$ are revealed around May 2018, we calculate the percentage error as

$$e_{i,t=2017} = \left(\hat{p}_{i,t=2017} - p_{i,t=2017}\right)/p_{i,t=2017}.$$

Table 6 shows the estimated and actual *ex-négociant* prices for the 2017 vintage and their percentage errors (except for Petit Mouton whose estimation cannot be made using Model 9 due to its missing barrel score observation). The mean absolute percentage error is 9.19% with a standard deviation of 7.17%. Model 9 estimates 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%

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 [Color figure can be viewed at wileyonlinelibrary.com]

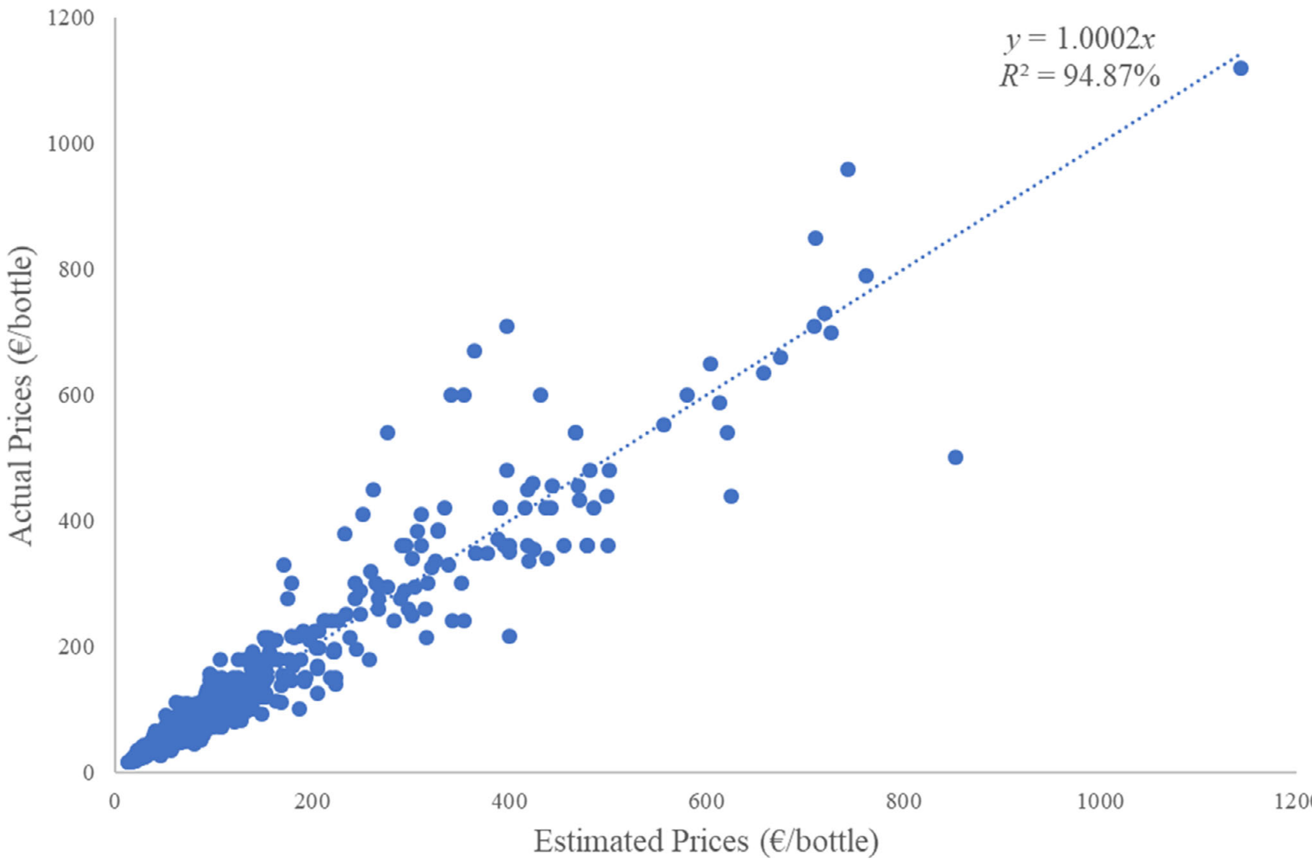


Table 5 Results of Regression in Quantiles using Model 9

Regression percentiles	Price thresholds (€)	Fitted line	R^2
Below 25th percentile	price ≤ 45.86	$y = 1.0600x$	97.36%
Between 25th and 50th percentile	45.86 < price ≤ 72.18	$y = 1.0041x$	95.00%
Between 50th and 75th percentile	72.18 < price ≤ 143.90	$y = 1.0091x$	95.42%
Above 75th percentile	price> 143.90	$y = 0.9989x$	94.81%
All observations		$y = 1.0002x$	94.87%

error in absolute terms. The most accurate prediction belongs to Chateau Grand Puy Lacoste with an absolute percentage error of 0.28%, whereas the least accurate one belongs to Chateau Troplong Mondot with 27.77%.

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 $t \in \{2001, \ldots, 2016\}$ 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.

We next replicate the out-of-sample testing for the 2015 and 2016 vintages in order to demonstrate robustness. We calibrate Model 9 in Equation (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 7 demonstrates that Model 9 achieves significantly smaller mean absolute percentage error values than the benchmark Model B0. Average error

Table 6 The Estimated and Actual *ex-négociant* Prices for the 2017 Vintage and Their Percentage Errors

Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2017}$	Actual price (€) $p_{i,t=2017}$	Error (%) $e_{i,t=2017}$	Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2017}$	Actual price (€) $p_{i,t=2017}$	Error (%) $e_{i,t=2017}$
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% SD of Absolute % Errors = 7.17% Min. of Absolute % Error = 0.28% Max. of Absolute % Error = 27.77%

Table 7 Summary of Out-Of-Sample Testing of Model 9 and the Benchmark Model B0

	Mean absolute % error	
Vintage	**Model 9**	**Model B0**
2015	12.74%	38.20%
2016	11.42%	45.79%
2017	9.19%	34.38%
Average	**11.12%**	**39.46%**

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 Appendix.

Figure 7 shows the distribution of mean absolute percentage errors for the 2015, 2016, and 2017 vintages across chateaus. Estimations for Chateau Duhart Milon yield the highest accuracy with a mean absolute percentage error of 3.12%, whereas the mean absolute percentage error for Chateau Mission Haut Brion is 21.99% leading to the lowest accuracy. The standard deviation of mean absolute percentage errors across chateaus is 4.59%.

Model 9 does not eliminate the estimation errors completely despite its superior accuracy over the academic benchmark. Moreover, one can see from Table 7 and Figure 7 that the estimation accuracy of Model 9 shows variation across both vintages and chateaus. Therefore, it is worth mentioning that there are two factors that make the task of price estimation challenging; these are related with the fine wine market microstructure and the *en primeur* system. The first factor is that négociants have trade allowances (purchase rights) from the chateaus. If négociants do not exercise this right, then they may not be able to buy the same amount of wine futures in the following year. As a result, négociants might buy an overpriced wine at times just to be able to maintain their allowance. The second factor is that chateaus create an impression of scarcity by not revealing the exact production quantity into the market.

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 1 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) Liv-ex 100 as market index, (2) barrel scores, (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:

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

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

where μ_i represents the time-invariant chateau characteristics and the coefficients are estimated using the within regression. Benchmark Model B1 adds the Liv-ex 100 index to Model B0 in order to demonstrate the value of the market index, and the benchmark Model B2 adds the barrel scores to Model B1 in order to show the value of the tasting experts. 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 4), 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 8 compares the out-of-sample testing of models B0, B1, B2, 7, and 9.

We find that the addition of the Liv-ex 100 index to the weather variables improves the out-of-sample performance by 20.97%. Inclusion of barrel scores further accounts for another 3.17% 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%.

4. Robustness

4.1. Lasso (Least Absolute Shrinkage and Selection Operator) for Variable Selection

We begin our robustness analysis by conducting a variable selection analysis. Lasso is a popular machine learning methodology for variable selection relying on the sparsity principle. Conceptually, Lasso methods select the most-relevant variables among a broad set of potentially relevant variables with the aim to balance the in-sample fit and the out-of-sample prediction accuracy. On the other hand, traditional approaches like OLS regression can yield good in-sample performance (e.g., high R^2 values) with a relatively poorer prediction performance in an out-of-sample. We find that the optimal variable selection according to the Lasso analysis features the exact same variables as Model 9. This confirms the model selection presented in 3.2.

Ahrens et al. (2020) provide a comprehensive discussion of various Lasso applications along with the use of *lassopack* module of Stata featured in Ahrens et al. (2018). The square-root Lasso with theory-driven rigorous penalization, as described in Belloni et al. (2011, 2012, 2014, 2016), is known to control overfitting and to guarantee consistent out-of-sample prediction performance (Ahrens et al. 2020). The square-root Lasso estimates the coefficients that minimize the following expression:

$$\hat{\beta}_{\sqrt{lasso}} = \arg\min \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i^T\beta\right)^2} + \frac{\lambda}{n}\sum_{j=1}^{p}\psi_j\left|\beta_j\right|,$$

where the first term is the square root of mean squared error and the second term is a penalty term with the overall penalty level λ and individual penalty loading ψ_j for each regressor under n observations and p regressors. The square-root Lasso with theory-driven rigorous penalization approach yields the optimal overall penalty level $\lambda = (1.1)(n)^{1/2}\Phi^{-1}(1 - 0.05/(\log(n)p))$, where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal cumulative distribution, and computes the individual penalty loading ψ_j using an iterative algorithm (see Ahrens et al. 2020).

Figure 7 Mean Absolute Percentage Errors for the 2015, 2016, and 2017 Vintages Across Chateaus [Color figure can be viewed at wileyonlinelibrary.com]

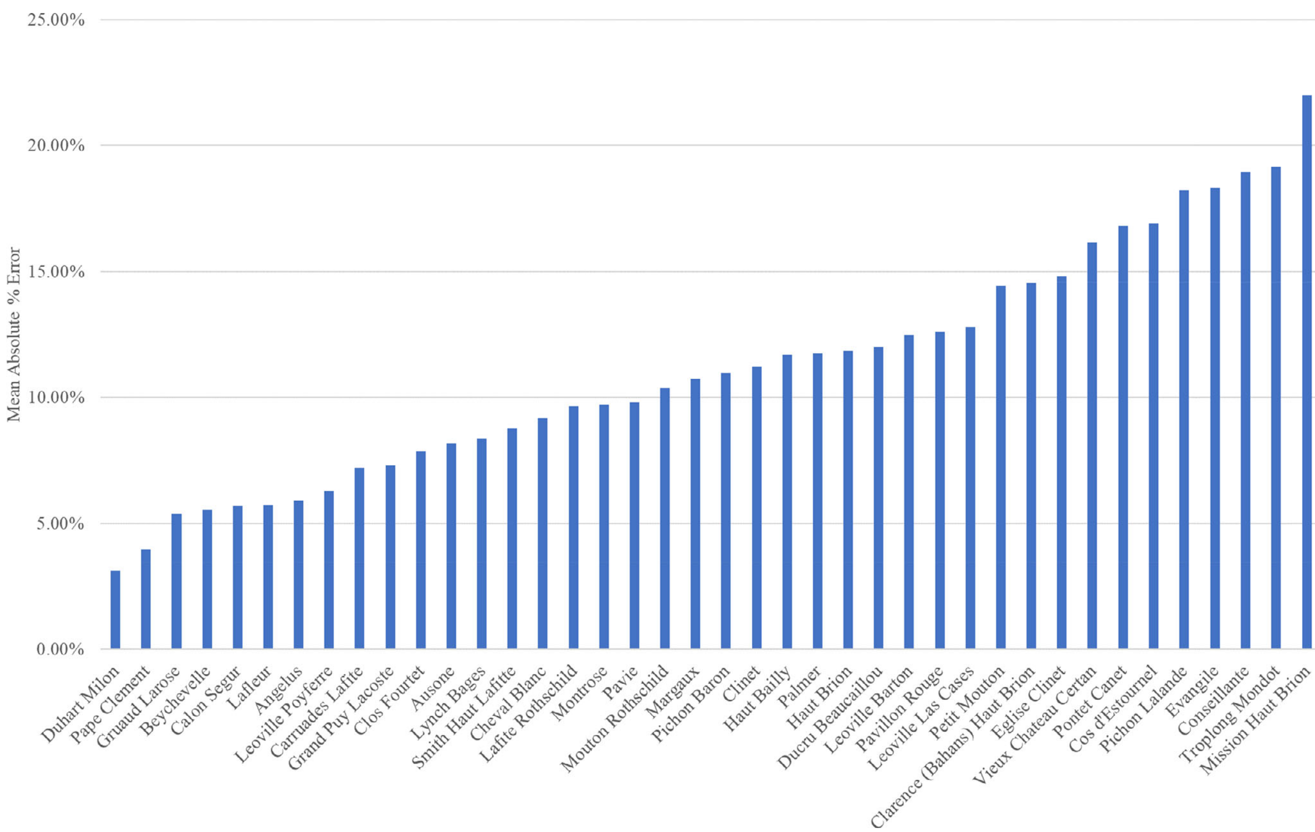


Table 8 Summary of Out-Of-Sample Testing of Models B0, B1, B2, 7, and 9

	Mean absolute % error				
Vintage	**Model B0**	**Model B1**	**Model B2**	**Model 7**	**Model 9**
2015	38.20%	18.57%	16.10%	10.12%	12.74%
2016	45.79%	21.24%	16.20%	12.29%	11.42%
2017	34.38%	15.66%	13.66%	12.61%	9.19%
Average	**39.46%**	**18.49%**	**15.32%**	**11.67%**	**11.12%**
Δ Liv-ex 100 (B0–B1)		**20.97%**			
Δ barrel score (B1–B2)			**3.17%**		
Δ variable definition (B2–7)				**3.65%**	
Δ positive interaction (7–9)					**0.55%**

The square-root Lasso with theory-driven rigorous penalization is employed in order to find the optimal selection among 33 explanatory variables investigated in this study. Section 3.1 describes the four main explanatory variables, that is, $\Delta m_{i,t}$, $\Delta r_{i,t}$, $\Delta s_{i,t}$, Δl_t, and the six positive interaction terms, that is, $(mr_{i,t})^+$, $(ml_{i,t})^+$, $(ms_{i,t})^+$, $(rl_{i,t})^+$, $(rs_{i,t})^+$, $(ls_{i,t})^+$. The remaining variables are described in the following subsection.

4.1.1. Definitions of Other Explanatory Variables.

The remaining 23 explanatory variables examined in this study are as follows:

Quadratic variables. We define quadratic terms of the changes in temperature, rainfall, barrel score, and Liv-ex 100 variables in order to account for potential nonlinearity in the form of convexity/concavity, denoted by $(\Delta m_{i,t})^2$, $(\Delta r_{i,t})^2$, $(\Delta s_{i,t})^2$, and $(\Delta l_t)^2$, respectively.

Negative interaction variables. We define negative interaction variables in order to account for possible negative synergies stemming from multiple negative news. These serve the opposite purpose of positive interaction variables. The following six interaction variables combine the pairwise negative 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 $(ls_{i,t})^-$:

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

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

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

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

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

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

Change in exchange rates. We define $\Delta fx\_\$_t$ as the logarithmic change in the USD ($) to Euro (€) exchange rate between the *en primeur* campaign of the previous vintage and shortly before the *en primeur* campaign of the new vintage, that is, $\Delta fx\_\$_t = \log(fx\_\$_t^{mar}/fx\_\$_{t-1}^{may})$ where $fx\_\$_{t-1}^{may}$ is the value of $/€ rate around the *en primeur* campaign of vintage $t-1$ (corresponding to May of year t), and $fx\_\$_t^{mar}$ is the value of $/€ rate in March prior to the *en primeur* campaign of vintage t (corresponding to March of year $t+1$). Similarly, we define $\Delta fx\_£_t = \log(fx\_£_t^{mar}/fx\_£_{t-1}^{may})$ as the logarithmic change in the Pound Sterling (£) to Euro (€) exchange rate. These exchange rate variables aim to capture any effect that currency fluctuations may have on prices.

Left Bank dummy. We define a binary variable lb_i that takes a value of 1 if chateau i is located in the Left Bank region and a value of 0 if it is in the Right Bank region. This variable aims to account for the effect that grape varieties may have on the prices as the wines made by the Left Bank chateaus are primarily dominated by Cabernet Sauvignon, whereas the Right Bank chateaus focus more on Merlot.

The 1855 Bordeaux Classification (for Left Bank) variables. The 1855 Bordeaux Classification is an official ranking system that was put in place by Napoleon III in 1855 that has been in effect since then. This ranking system categorizes the chateaus according to their reputation into five groups from first to fifth growths where the first growths represent the most reputable chateaus. We define five binary variables ($first_i$, $second_i$, $third_i$, $fouth_i$, $fifth_i$) that take a value of 1 if chateau i belongs to the corresponding category and a value of 0 if it does not. These five binary variables aim to capture the reputation effects on prices. Note that the 1855 Bordeaux Classification spans Left Bank chateaus only. Table 9 lists the chateaus included in our sample according to this ranking system.

The Saint-Emilion Classification (for Right Bank) variables. We use the Saint-Emilion Classification for the Right Bank chateaus. Like the 1855 Bordeaux Classification, the Saint-Emilion Classification categorizes the notable Right Bank chateaus based on their reputation. We define a binary variable for each category, that is, Premier Grand Cru Classe A (pga_i) and Premier Grand Cru Classe B (pgb_i) that take a value of 1 if chateau i belongs to the corresponding category and a value of 0 if it does not. Table 9 lists the chateaus included in our sample according to this ranking system.

Other chateau variables. In addition to the time-invariant classification variables above, we define three additional chateau-related variables that are time-variant. The first variable is the change in chateau's annual trade volume $\Delta vol_{i,t} = vol_{i,t} - vol_{i,t-1}$ where $vol_{i,t}$ describes the percentage of the total trade volume that belongs to chateau i in year t. The second variable is the change in chateau's annual trade value $\Delta val_{i,t} = val_{i,t} - val_{i,t-1}$ where $val_{i,t}$ describes the percentage of the total trade value that belongs to chateau i in year t. These two variables capture the impact of chateau popularity in terms of trade volume and value. The third variable is the change in the number of unique wines produced by chateau i between two consecutive vintages, that is, $\Delta unq_{i,t} = unq_{i,t} - unq_{i,t-1}$ where $unq_{i,t}$ is the number of unique wines produced by chateau i in year t. This information is collected through Liv-ex.

4.1.2. Results from the Lasso Analysis.

Table 10 presents the results of the square-root Lasso with theory-driven rigorous penalization using the 33

Table 9 Chateaus According to the 1855 Bordeaux Classification and the Saint-Emilion Classification

The 1855 Bordeaux classification (for left bank)		The Saint-Emilion classification (for right bank)
First growth	**Fourth growth**	**Premier Grand Cru Classe A**
Haut Brion	Beychevelle	Angelus
Lafite Rothschild	Duhart Milon	Ausone
Margaux	**Fifth Growth**	Cheval Blanc
Mouton Rothschild	Grand Puy Lacoste	Pavie
Second Growth	Lynch Bages	**Premier Grand Cru Classe B**
Cos d'Estournel	Pontet Canet	Clos Fourtet
Ducru Beaucaillou	**Unclassified**	Troplong Mondot
Gruaud Larose	Carruades Lafite	**Unclassified**
Leoville Barton	Clarence (Bahans) Haut Brion	Clinet
Leoville Las Cases	Haut Bailly	Conseillante
Leoville Poyferre	Mission Haut Brion	Eglise Clinet
Montrose	Pape Clement	Evangile
Pichon Baron	Pavillon Rouge	Lafleur
Pichon Lalande	Petit Mouton	Vieux Chateau Certain
Third Growth	Smith Haut Lafitte	
Calon Segur		
Palmer		

Table 10 The results of the square-root Lasso with theory-driven rigorous penalization using heteroscedasticity-robust errors. The optimal overall penalty level λ is 96.007

Variable	Selected (Y/N)	Square-root Lasso Coefficient, $\hat{\beta}_{\sqrt{lasso}}$	Post-estimation OLS Coefficient, $\hat{\beta}_{OLS}$
Int.	Included	–0.071	–0.086
$\Delta m_{i,t}$	Y	0.267	0.568
$\Delta r_{i,t}$	Y	–0.029	–0.060
$\Delta s_{i,t}$	Y	0.026	0.032
Δl_t	Y	0.598	0.835
$(mr_{i,t})^+$	N	–	–
$(ml_{i,t})^+$	Y	52.819	54.318
$(ms_{i,t})^+$	N	–	–
$(rl_{i,t})^+$	N	–	–
$(rs_{i,t})^+$	N	–	–
$(ls_{i,t})^+$	N	–	–
$(\Delta m_{i,t})^2$	N	–	–
$(\Delta r_{i,t})^2$	N	–	–
$(\Delta s_{i,t})^2$	N	–	–
$(\Delta l_t)^2$	N	–	–
$(mr_{i,t})^-$	N	–	–
$(ml_{i,t})^-$	N	–	–
$(ms_{i,t})^-$	N	–	–
$(rl_{i,t})^-$	N	–	–
$(rs_{i,t})^-$	N	–	–
$(ls_{i,t})^-$	N	–	–
$\Delta fx\_\$_t$	N	–	–
$\Delta fx\_£_t$	N	–	–
lb_i	N	–	–
$first_i$	N	–	–
$second_i$	N	–	–
$third_i$	N	–	–
$fouth_i$	N	–	–
$fifth_i$	N	–	–
pga_i	N	–	–
pgb_i	N	–	–
$\Delta vol_{i,t}$	N	–	–
$\Delta val_{i,t}$	N	–	–
$\Delta unq_{i,t}$	N	–	–

explanatory variables. For selected variables, $\hat{\beta}_{\sqrt{lasso}}$ represents the coefficient estimates using the square-root Lasso regression which induces biased estimates (due to the penalty term). Therefore, Lasso methods are ideal for variable selection but not for coefficient estimation. Once the optimal set of variables is determined, the OLS regression provides the unbiased coefficient estimates for the selected variables.

It is important to highlight that the variables selected by the Lasso method are identical to the variables of Model 9: $\Delta m_{i,t}$, $\Delta r_{i,t}$, $\Delta s_{i,t}$, Δl_t, and $(ml_{i,t})^+$. This is a strong support for Model 9 because the Lasso analysis identifies this optimal selection among a broad set of 33 explanatory variables corresponding to 2^{33} selection combinations (equivalent to 8,589,934,592 unique models). Moreover, the post-estimation OLS coefficients $\hat{\beta}_{OLS}$ following the Lasso analysis are equal to the coefficient estimates of Model 9 as presented in Table 4; this is an expected result because the optimal Lasso selection and Model 9 both feature the same variables. As a result, the Lasso analysis confirms that Model 9 features the optimal set of variables.

The Lasso analysis does not select the negative interaction terms. This implies that negative news does not lead to dramatic price reductions because of the reputation of Bordeaux chateaus. Lasso analysis also does not select the quadratic terms. This suggests that a linear specification is sufficient in estimating the *ex-négociant* prices.

4.2. 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 11 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.

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 12 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.

4.3. Hierarchical Linear Modeling

Our data are 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 $k \in \{0,\ldots, 5\}$. 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 13 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 4. 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.

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 14 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 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.

4.4. Hierarchical Bayes Modeling

This section presents a Bayesian alternative to hierarchical modeling of the group-level effects. In Section 4.3, 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 follows:

$$\Delta p_{i,t} \sim N\left(\alpha_0 + \beta_{0,i} + (\alpha_1 + \beta_{1,i})\Delta m_{i,t} + (\alpha_2 + \beta_{2,i})\Delta r_{i,t} + (\alpha_3 + \beta_{3,i})\Delta s_{i,t} + (\alpha_4 + \beta_{4,i})\Delta l_t + (\alpha_5 + \beta_{5,i})(ml_{i,t})^+, \sigma_{\varepsilon^2}\right)$$

where the prior and hyperprior distributions are $\alpha_k \sim N(0,\ 10{,}000)$, $\beta_{k,i} \sim N(0,\ \sigma_k^2)$, $\sigma_k^2 \sim$ Inv-Gamma (0.01, 0.01) for $k \in \{0, \ldots, 5\}$, and $\sigma_\varepsilon^2 \sim$ Inv-Gamma (0.01, 0.01). We use Metropolis-Hastings and Gibbs sampling to simulate the posterior distributions. Table 15 shows 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 4. This further reassures that our variable definitions resembling a first-difference approach account

Table 11 Robust regression results for the dependent variable $\Delta p_{i,t}$.

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

Notes: *T*-statistics using standard errors based on the pseudovalues approach (Street et al., 1988) are given in italic below the coefficients.*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Table 12 Summary of Out-Of-Sample Testing of Model 9 using OLS and Robust Regression

	Mean absolute % error	
Vintage	OLS	Robust regression
2015	12.74%	13.39%
2016	11.42%	11.69%
2017	9.19%	9.29%
Average	**11.12%**	**11.46%**

Table 13 Mixed-Effects Regression Results for the Dependent Variable $\Delta p_{i,t}$

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

The values under the α_k column denote the fixed-effect estimates and their *z*-statistics (italic) where *, **, and *** denote statistical significance at 10%, 5%, and 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.

Table 14 Summary of Out-Of-Sample Testing of Model 9 Using OLS and Mixed-Effects Regression

	Mean absolute % error	
Vintage	OLS	Mixed-effects
2015	12.74%	12.88%
2016	11.42%	11.39%
2017	9.19%	9.15%
Average	**11.12%**	**11.14%**

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 16 presents the results. We find that hierarchical Bayes modeling does not bring any improvement over OLS regression in our study.

Table 15 Hierarchical Bayes Estimation Results for the Dependent Variable $\Delta p_{i,t}$

	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 2500		

The values represent the estimated mean values of the posterior distribution parameters α_k, σ_k^2, and σ_ε^2.

Table 16 Summary of Out-Of-Sample Testing of Model 9 using OLS and Hierarchical Bayes Modeling

	Mean absolute % error	
Vintage	OLS	Hierarchical Bayes
2015	12.74%	12.55%
2016	11.42%	12.22%
2017	9.19%	9.58%
Average	**11.12%**	**11.45%**

4.5. Dependent Variable Retransformation

When computing the prices of vintage t in Section 3.3, we first calibrate Model 9 (see Equation (1)) using data up until vintage $t-1$, then compute the estimations using Equation (2). This procedure involves retransformation of a logarithmic dependent variable back to its untransformed scale. In this section, we revise Equation (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 Equation (1) are normally distributed. In light of this assumption, we revise Equation (2) as

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

where $\hat{\sigma}^2$ denotes the mean squared error in Equation (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 Equation (2) as follows:

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

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

Table 17 compares the out-of-sample performance of our original estimates $\hat{p}_{i,t}$ utilizing Equation (2)

Table 17 Summary of Out-Of-Sample Testing of Model 9 using $\hat{p}_{i,t}$, $p^N_{i,t}$, and $p^D_{i,t}$

	Mean absolute % error		
Vintage	$\hat{p}_{i,t}$	$\hat{p}^N_{i,t}$	$\hat{p}^D_{i,t}$
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%**

with that of the normal theory estimates $\hat{p}^N_{i,t}$ utilizing Equation (3) and the smearing estimates $\hat{p}^D_{i,t}$ utilizing Equation (4) for vintages 2015–2017. We find that $\hat{p}_{i,t}$ yields the highest accuracy for the 2017 estimates, whereas $\hat{p}^N_{i,t}$ and $\hat{p}^D_{i,t}$ achieve better accuracy for vintages 2015 and 2016. This suggests that our original estimates $\hat{p}_{i,t}$ do not feature a systematic bias.

5. Conclusions and Impact of the Study

Our study makes several contributions that have significant practical implications for the wine industry. We develop an empirical model that determines the appropriate market prices of the infamous Bordeaux wines. Our first contribution involves identifying 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.

Our second contribution stems from the unique variable definition in our statistical analyses. Rather than using level data, our analysis relies on vintage-to-vintage comparison. We show that our variable definitions enhance the accuracy of estimated prices by 3.65%. This technical contribution comes from practice and stems from 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 1-year planning horizon. This operational phenomenon influences the adjustments in market prices. However, there are exceptions to this 1-year planning phenomenon. Selling wine in advance is a form raising capital to finance wine production operations. Some chateaus that have good financial standing do not need to sell their wines in advance. For example, Chateau Latour is a financially well-off winemaker that has stopped selling its wine in the *en primeur* market beginning from 2012 in order to benefit from the increase in its wines' value.

Third, while earlier publications aim to explain wine prices, our study accomplishes the more challenging task of estimating wine prices. To our knowledge, there is only one publication that estimates fine wine prices, and our proposed method improves estimation performance dramatically. Thus, our study makes a significant contribution to the literature.

The estimation performance of our proposed approach is extraordinary. This can be seen from the fit between our estimated market prices and the realized prices that features an R^2 of 94.87% and a slope of 1.0002. Through a comprehensive analysis, we demonstrate that our methodology and results are robust. Our robustness analyses include quantile regression, Lasso analysis, 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.

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.

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 fourth 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.

Fifth, 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. For example, our study relies on a single tasting expert who might be influential for most chateaus and perhaps not for all chateaus. Creating a composite tasting score based on the tasting scores of various critics can be one avenue for improvement in the future. Our wine futures price estimations can also shed light into the estimations for the bottled wine prices. 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.

5.1. Generalization to Other Products

While our study focuses on wine prices, our approach can be generalized to other settings where pricing decisions are influenced by weather conditions, market fluctuations, and quality perceptions. It is known that weather influences other products, and the changing market conditions can alter consumers' willingness to pay for various products. Moreover, while barrel scores of tasting experts establish the initial quality perception in fine wines, similar but different quality measures are established for other agricultural products.

For olive oil, oleic acidity tests reveal information about the quality of the oil. Specifically, a lower degree of oleic acidity implies a higher value for the olive oil. Such tests are applied immediately after harvest and pressing of olives. The results of these oleic acidity tests can be used as a measure of quality replacing the barrel tasting scores of our model. Using similar weather and market variables, our approach can be replicated to estimate the futures prices for premium olive oil. Such estimations can be particularly beneficial in determining both retail prices and payments made to the olive growers from processors. The application of our approach is not limited to olive oil and it extends to other agricultural products such as orange juice futures where weather conditions, market fluctuations and quality perceptions (as in the brix levels of frozen concentrated orange juice) are influential in the evolution of prices.

Wagyu beef, a crossbreed between Aberdeen Angus and Japanese Kobe beef, is often considered to be the finest beef in the US. Its status resembles that of fine wine because of its rich flavors. Wagyu beef prices are also impacted by weather fluctuations but the relationship is reversed when compared with agricultural products. Higher temperatures imply lower quality product because the wagyu cattle reduce their nutritional intake while increasing water consumption. In the United States, upscale restaurateurs often pay premium prices for the finest wagyu beef, creating a need for establishing a similar financial exchange to Liv-ex. Such a platform would benefit from adopting our approach in order to develop futures price estimations for wagyu beef.

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Appendix A
Predictive Power of Ashenfelter (2008)

Table A1 shows the estimated prices and the actual market prices for Bordeaux wines of vintages 1967–1972 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.

Table A1 Prediction performance reported in Table 3 of Ashenfelter (2008).

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%

*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 percentage errors using Model 9 for the 2016 and 2015 vintages, respectively.

Table A2 The Estimated and Actual *ex-négociant* Prices for the 2016 Vintage and Their Percentage Errors

Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2016}$	Actual price (€) $p_{i,t=2016}$	Error (%) $e_{i,t=2016}$	Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2016}$	Actual price (€) $p_{i,t=2016}$	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%				Min. of Absolute % Error = 0.39%			
SD of Absolute % Errors = 7.34%				Max. of Absolute % Error = 28.08%			

Table A3 The Estimated and Actual *ex-négociant* Prices for the 2015 Vintage and Their Percentage Errors

Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2015}$	Actual price (€) $p_{i,t=2015}$	Error (%) $e_{i,t=2015}$	Chateau (i)	Estimated price (€) $\hat{p}_{i,t=2015}$	Actual price (€) $p_{i,t=2015}$	Error (%) $e_{i,t=2015}$
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%				Min. of Absolute % Error = 0.48%			
SD of Absolute % Errors = 8.86%				Max. of Absolute % Error = 42.08%			

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