Vienna 2019 Abstract Submission

Title
Predicting the Release Price of Fine Wines

I want to submit an abstract for:
Conference Presentation

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Keywords
en primeur, wine futures, price, weather, temperature, rain, market, barrel score

Research Question
[1] How can we predict the release price of wine futures?
[2] What factors influence the price of young wines?

Methods
Empirical methods combining weather (temperature, rain), market (Liv-ex indices) and tasting expert scores

Results
Higher temperatures, lower precipitation, higher index and barrel scores lead to higher release prices. The mean absolute percentage error of our predictions is substantially smaller than any academic benchmark.

Abstract
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. These scholars, as well as authors of similar publications, admit that their studies fail to predict young wine prices using weather information. For brevity, we limit our definition of young wines to the wines that are still aging in the barrel but traded in the form of en primeur, i.e., financial contracts loosely translated into English as wine futures, before the wines are bottled. Our paper develops empirical models that estimate the initial release price of fine Bordeaux wines, i.e., en primeur prices. 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.
Grapes are grown from May to August each summer. Once harvested and pressed in September, the wine (of vintage t) begins aging in barrels. Tasting experts visit winemakers approximately eight to nine months after the harvest and then release their tasting scores in April of year t + 1. Winemakers begin to reveal their release prices in May. The wine continues to age in barrels (for a total of 18 to 24 months) and does not even get bottled until

year t + 2. However, a vast majority of the wine is sold in the summer of year t + 1 based on the release price. Thus, the release price is a critical decision in the wine supply chain because it sets the pace in the downstream and influences the trade significantly.

How can we predict release prices? As pointed out by the abovementioned academic publications, it turns out that predicting release prices is an incredibly challenging task. 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 predicting the en primeur prices of the 2015 vintage wines (https://www.liv-ex.com/2016/06/merchants-underestimated-bordeaux-2015-release-prices/). The survey constructs a basket where bottles of wine are included from Cheval Blanc, Cos d'Estournel, Leoville Las Cases, Mission Haut Brion, Montrose, Mouton Rothschild, Pavie, Pichon Lalande, Pontet Canet and Talbot – all 2015 vintage wines. The 2016 survey results reveal that these 440 leading wine merchants predicted the above basket of wines to have a value of €1,607.80. After the winemakers released their prices, the basket had an actual value of €2,054.40 – corresponding to a 21% estimation error. The survey also showed that, when these leading wine merchants predicted the release prices, they expected a 17.8% increase in 2015 from the release prices of the 2014 vintage; however, the actual prices increased by a whopping 45.8% from 2014. How can the leading merchants be so inaccurate in their expectations? Is there an empirical way to predict these release prices? Our study provides an accurate price estimation through weather, market and tasting expert scores.

Bordeaux winemakers tend to show similar reactions when they determine release prices in each vintage. One can immediately draw the conclusion that these winemakers exhibit a highly similar behavior in adjusting their prices from the previous vintage. 2003, 2005 and 2009 are identified as phenomenal vintages; en primeur prices soared for these vintages when compared to their respective previous vintages. In those years, the hype leads to greater price adjustments. Our study identifies the factors that influence the price adjustments from the previous vintage.

Our study makes several contributions. First, it identifies four primary factors that are influential in predicting the release prices for fine wines: 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). Our empirical models yield significant accuracy in predicting en primeur prices. Academically, our results provide significant improvements over earlier publications that estimate wine release prices. In practice, Neil Taylor, vice president of data at Liv-ex, describes that "this kind of accuracy is not seen in the wine industry for young wines." To further test our model, we provided Liv-ex with our predictions for the 2017 vintage Bordeaux wines prior to the release of these wine futures. We report that our model performed well and had small prediction error percentages for the 2017 vintage wines. Comprehensive analysis shows that our methodology and results are robust.

Second, our study benefits winemakers in determining the release prices through a comprehensive and rigorous approach. The implication of our contribution is significant in practice. Liv-ex has recently decided to publish our predictions as "realistic prices" prior to each year's en primeur campaigns (as a financial exchange, Liv-ex is legally prohibited to use the phrase "fair prices"). The exchange finds our predicted prices highly accurate and hopes that winemakers anchor their pricing decisions around our prices. Thus, our predictions are expected to be used as the new benchmark prices.

Third, our price predictions enable buyers (e.g. wine distributors) to make effective operational plans influencing the entire downstream in the wine supply chain. A comparison of our predictions with the winemaker's actual release price decisions reveal the buyer whether a wine is under- or over-priced. Moreover, when our price predictions are employed, our study demonstrates the significant financial improvement in the planning of purchasing budgets.

Literature Review

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

Fine wine is also treated as a long-term investment. Storchmann (2012) provides a comprehensive review about wine economics and covers the use of wine as an investment option. Dimson et al. (2015) find that young Bordeaux wines yield greater returns than the mature ones. This finding further amplifies the importance of our study aiming to predict the release prices.

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 original release price to the bottled wine price. While their model assumes a given release price, our study focuses on estimating the initial release price using all factors. In sum, our paper enhances these earlier publications in three ways. First, it identifies the most influential factors in estimating release prices. Second, our study benefits winemakers in determining the release price using these empirical models. Third, it helps buyers in making effective purchasing plans by showing which wines are under- or over-priced. Our study demonstrates the substantial financial impact on the buyer's purchasing plans when they use our predictions.

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Predicting the Release Price of Fine Wines

Problem definition: We develop a prediction model for the release price of fine wines using weather, market and expert reviews.
Academic / Practical Relevance: Earlier publications explained the price of aged wines through weather but failed to estimate the price of young wines. Considering that a majority of wine trade occurs when the wine is young and even before it is bottled, determining the release price accurately is one of the most critical decisions. Surveys of leading wine merchants indicate that their predictions of release prices are highly inaccurate. 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 provides guidance to winemakers in determining the release price, and tells buyers how to plan their purchasing activities.
Methodology: We employ empirical methods to predict the release price of fine wines. Rather than relying on level data, our methodology utilizes a creative approach with changes in variables from one vintage to another.
Results: We show that higher temperatures, lower levels of precipitation, appreciation in the Liv-ex 100 index as a market indicator, and higher barrel scores increase release prices. The mean absolute percentage error of our predictions is substantially smaller than any academic benchmark.
Managerial Implications: Winemakers can use our findings to determine the release prices of their fine wines. The comparison of our price estimations with the winemaker's actual release price tells buyers of these wines (e.g., distributors, restaurateurs, merchants) whether a wine is underpriced or overpriced. With our predictions, we demonstrate that buyers can make effective purchasing arrangements. Recently, the financial exchange for fine wine called Liv-ex has decided to publish our predictions as "realistic prices."

Keywords: *en primeur*, *wine futures, price, weather, temperature, rain, market, barrel score*

1. Introduction

Economists have long tried to estimate wine prices through weather. In two most influential publications, Ashenfelter et al. (1995) and Ashenfelter (2008) provided remarkable insights regarding the impact of weather on *aged* Bordeaux wines. These scholars, as well as authors of similar publications, admit that their studies fail to predict *young* wine prices using weather information. For brevity, we limit our definition of *young* wines to the wines that are still aging in the barrel but traded in the form of *en primeur*, i.e., financial contracts loosely translated into English as wine futures, before the wines are bottled. Our paper develops empirical models that estimate the initial release price of fine Bordeaux wines, i.e., *en primeur* prices. 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, and its fine wines generate more than €2 billion during each year's *en primeur* campaign. These Bordeaux wines often influence the trade of the wines produced in other regions of the world, and thus, they are perceived as the pace-setter of worldwide wine supply chains.

Figure 1 presents a timeline of events in the life of a winemaker. Grapes are grown from May to August each summer. Once harvested and pressed in September, the wine (of vintage t) begins aging in barrels. Tasting experts visit winemakers approximately eight to nine months after the harvest and then release their tasting scores in April of year $t + 1$. Winemakers begin to reveal their release prices in May. The wine continues to age in barrels (for a total of 18 to 24 months) and does not even get bottled until year $t + 2$. However, a vast majority of the wine is sold in the summer of year $t + 1$ based on the release price. Thus, the release price is a critical decision in the wine supply chain because it sets the pace in the downstream and influences the trade significantly.

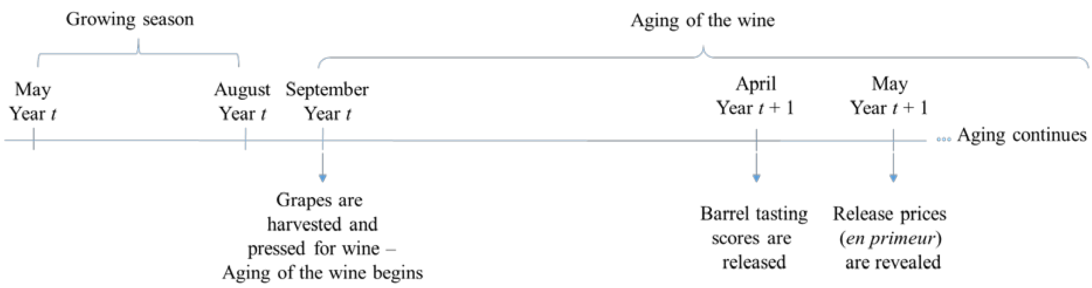

Figure 1. The sequence of events leading to the revelation of release prices for vintage t wines.

How can we predict release prices? As pointed out by the abovementioned academic publications, it turns out that predicting release prices is an incredibly challenging task. 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 predicting the *en primeur* prices of the 2015 vintage wines (https://www.liv-ex.com/2016/06/merchants-underestimated-bordeaux-2015-release-prices/). The survey constructs a basket where bottles of wine are included from Cheval Blanc, Cos d'Estournel, Leoville Las Cases, Mission Haut Brion, Montrose, Mouton Rothschild, Pavie, Pichon Lalande, Pontet Canet and Talbot – all 2015 vintage wines. The 2016 survey results reveal that these 440 leading wine merchants predicted the above basket of wines to have a value of €1,607.80. After the winemakers released their prices, the basket had an actual value of €2,054.40 – corresponding to a 21% estimation error. The survey also showed that, when these leading wine merchants predicted the release prices, they expected a 17.8% increase in 2015 from the release prices of the 2014 vintage; however, the actual prices increased by a whopping 45.8% from 2014. How can the leading merchants be so inaccurate in their expectations? Is there an empirical way to predict these release prices? Our study provides an accurate price estimation through weather, market and tasting expert scores.

Bordeaux winemakers tend to show similar reactions when they determine release prices in each vintage. This is exemplified in Figure 2 which depicts the change in the *en primeur* price of a vintage from the previous vintage for the 40 winemakers included in our study. One can immediately draw the conclusion that these winemakers exhibit a highly similar behavior in adjusting their prices from the previous vintage. Figure 2 identifies 2003, 2005 and 2009 as phenomenal vintages; *en primeur* prices soared for these vintages when compared to their respective previous vintages. In those years, the hype leads to greater price adjustments. Our study identifies the factors that influence the price adjustments from the previous vintage.

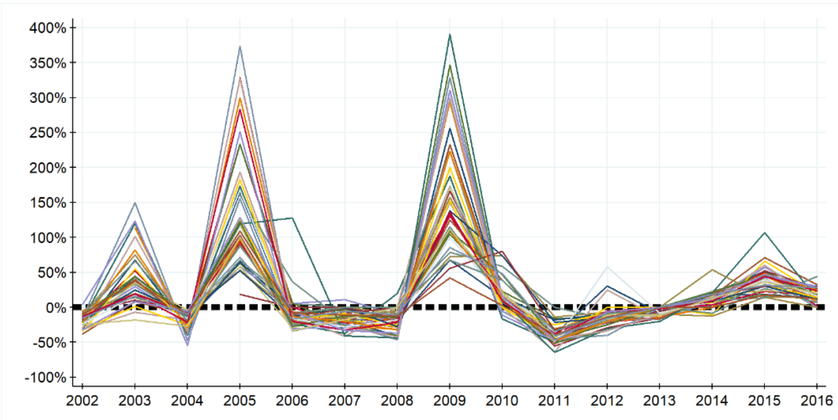

Figure 2: Percentage change in the *en primeur* prices in each vintage (between 2002 and 2016) in comparison to previous vintage for the 40 winemakers included in the study.

Our study makes several contributions. First, it identifies four primary factors that are influential in predicting the release prices for fine wines: 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). Our empirical models yield significant accuracy in predicting *en primeur* prices. Academically, our results provide significant improvements over earlier publications that estimate wine release prices. In practice, Neil Taylor, vice president of data at Liv-ex, describes that "this kind of accuracy is not seen in the wine industry for young wines." To further test our model, we provided Liv-ex with our predictions for the 2017 vintage Bordeaux wines prior to the release of these wine futures. We report that our model performed well and had small prediction error percentages for the 2017 vintage wines. Comprehensive analysis shows that our methodology and results are robust.

Second, our study benefits winemakers in determining the release prices through a comprehensive and rigorous approach. The implication of our contribution is significant in practice. Liv-ex has recently decided to publish our predictions as "realistic prices" prior to each year's *en primeur* campaigns (as a financial exchange, Liv-ex is legally prohibited to use the phrase "fair prices"). The exchange finds our predicted prices highly accurate and hopes that winemakers anchor their pricing decisions around our prices. Thus, our predictions are expected to be used as the new benchmark prices. It is also important to note that while more than 440 wine merchants are surveyed for price predictions, Liv-ex has selected to feature only our predicted prices; their selection demonstrates the continued influence of our study in the upcoming years.

Third, our price predictions enable buyers (e.g. wine distributors) to make effective operational plans influencing the entire downstream in the wine supply chain. A comparison of our predictions with the winemaker's actual release price decisions reveal the buyer whether a wine is under- or over-priced. Moreover, when our price predictions are employed, our study demonstrates the significant financial improvement in the planning of purchasing budgets.

1.1. Literature Review

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

Fine wine is also treated as a long-term investment. Storchmann (2012) provides a comprehensive review about wine economics and covers the use of wine as an investment option. Dimson et al. (2015) find that young Bordeaux wines yield greater returns than the mature ones. This finding further amplifies the importance of our study aiming to predict the release prices.

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 original release price to the bottled wine price. While their model assumes a given release price, our study focuses on estimating the initial release price using all factors. In sum, our paper enhances these earlier publications in three ways. First, it identifies the most influential factors in estimating release prices. Second, our study benefits winemakers in determining the release price using these empirical models. Third, it helps buyers in making effective purchasing plans by showing which wines are under- or over-priced. Our study demonstrates the substantial financial impact on the buyer's purchasing plans when they use our predictions.

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 winemakers 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 released in the form of *en primeur* and Petrus, Fleur Petrus, and Pin have missing release prices in the Liv-ex database. We construct our sample from the remaining 40 winemakers. We collect the *en primeur* price (in €/bottle) for the remaining 40 winemakers between 2001 and 2016 as presented in Table 1.

Weather data comes from Météo-France, the national meteorological service organization providing local weather information, complemented by Wolfram Mathematica. The Bordeaux wine region is divided by the Gironde Estuary into two main regions: Left Bank and Right Bank. We use the weather data recorded at the Merignac weather station (serving as the main weather station for Bordeaux) for the Left Bank and at Saint-Emilion for the Right Bank. We collect daily maximum temperatures (in °C) and daily total rainfall (in cm) during the growing season (May 1 – August 31). Figure 3 illustrates the weather data between 2001 and 2016.

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

Winemaker	**Region**	**Price (€/bottle)**		**Winemaker**	**Region**	**Price (€/bottle)**	
		Average	**Std. Dev.**			**Average**	**Std. Dev.**
Angelus	Right Bank	146.50	74.40	Lafleur	Right Bank	396.15	150.47
Ausone	Right Bank	524.46	264.74	Leoville Barton	Left Bank	42.51	14.83
Beychevelle	Left Bank	34.08	13.81	Leoville Las Cases	Left Bank	113.38	53.60
Calon Segur	Left Bank	37.76	13.44	Leoville Poyferre	Left Bank	43.47	18.97
Carruades Lafite	Left Bank	65.30	40.12	Lynch Bages	Left Bank	53.95	24.68
Cheval Blanc	Right Bank	396.25	202.94	Margaux	Left Bank	308.27	170.91
Clarence (Bahans) Haut Brion	Left Bank	53.66	29.43	Mission Haut Brion	Left Bank	215.34	166.16
Clinet	Right Bank	51.06	16.13	Montrose	Left Bank	66.03	31.80
Clos Fourtet	Right Bank	44.49	18.29	Mouton Rothschild	Left Bank	294.69	174.18
Conseillante	Right Bank	76.26	39.58	Palmer	Left Bank	138.75	61.48
Cos d'Estournel	Left Bank	97.22	49.52	Pape Clement	Left Bank	62.20	19.50
Ducru Beaucaillou	Left Bank	84.78	43.27	Pavie	Right Bank	157.81	65.77
Duhart Milon	Left Bank	35.56	17.18	Pavillon Rouge	Left Bank	62.56	32.30
Eglise Clinet	Right Bank	129.06	74.01	Petit Mouton	Left Bank	66.60	29.58
Evangile	Right Bank	108.75	42.29	Pichon Baron	Left Bank	64.86	30.45
Grand Puy Lacoste	Left Bank	35.93	12.86	Pichon Lalande	Left Bank	72.53	32.15
Gruaud Larose	Left Bank	33.37	9.64	Pontet Canet	Left Bank	54.91	26.16
Haut Bailly	Left Bank	45.79	22.17	Smith Haut Lafitte	Left Bank	41.37	17.50
Haut Brion	Left Bank	295.94	190.62	Troplong Mondot	Right Bank	59.46	26.86
Lafite Rothschild	Left Bank	346.73	202.34	Vieux Chateau Certan	Right Bank	95.47	49.98

Table 1. List of winemakers with their region, average price and standard deviation.

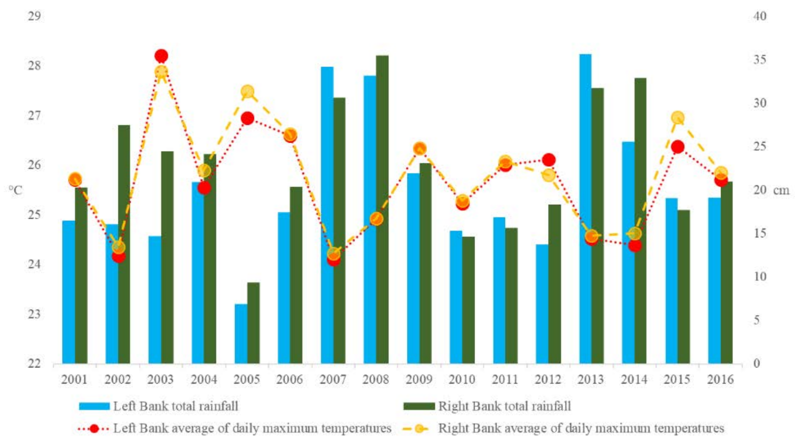

Figure 3. Average of the daily maximum temperatures and the total rainfall observed in the Left Bank and Right Bank of Bordeaux during growing season between years 2001 and 2016.

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 *en primeur* prices of vintages before they are bottled. Liv-ex 100 is quoted by Bloomberg and Reuters as the industry benchmark. Figure 4 illustrates the values of Liv-ex 100 since its inception in July 2001.

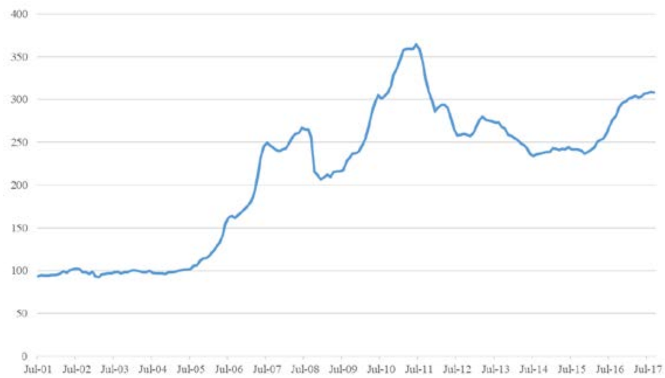

Figure 4. Historical values of the Liv-ex Fine Wine 100 index since its inception.

3. Empirical Analysis

3.1. Variables

This section presents the dependent variable (*en primeur* price) and the independent variables (temperature, rainfall, barrel score, Liv-ex 100) used in our models. When Bordeaux winemakers determine the price of a new vintage, they compare it to the previous vintage. 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 behavior observed earlier in Figure 2 that winemakers make similar adjustments in prices in comparison to the previous vintage.

Change in en primeur prices. We define the dependent variable as the logarithmic change across the *en primeur* prices of two consecutive vintages from the same winemaker, i.e., $\Delta p_{i,t} = \log(p_{i,t}/p_{i,t\text{-}1})$ where $p_{i,t}$ is the *en primeur* price of vintage t of winemaker i at the time of its release (around May of year $t + 1$). Note that $i \in \{1,\ldots, 40\}$ and $t \in \{2002,\ldots, 2016\}$.

Change in average temperature. We define the temperature variable as the logarithmic change across the average growing season temperatures of two consecutive vintages, i.e., $\Delta m_{i,t} = \log(m_{i,t}/m_{i,t\text{-}1})$ 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 winemaker i is located. A warmer growing season is expected to have a positive impact on the release price.

Change in total rainfall. We define the rainfall variable as the logarithmic change across the total growing season rainfall of two consecutive vintages, i.e., $\Delta r_{i,t} = \log(r_{i,t}/r_{i,t-1})$ where $r_{i,t}$ is the total rainfall during the growing season period of year t in the region where winemaker i is located. A rainier growing season is expected to have a negative impact on the release 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 winemaker, i.e., $\Delta s_{i,t} = s_{i,t} - s_{i,t-1}$ where $s_{i,t}$ is the barrel tasting score of vintage t of winemaker i that is revealed approximately one month before the *en primeur* release (corresponding to April of year $t + 1$). A higher score is expected to have a positive impact on the release price.

Change in Liv-ex 100. We define the index variable as the logarithmic change in the value of Liv-ex 100 index between the *en primeur* release of the previous vintage and shortly before the *en primeur* release of the new vintage, i.e., $\Delta l_t = \log(l_t^{mar}/l_{t-1}^{may})$ where l_{t-1}^{may} is the value of Liv-ex 100 around the *en primeur* release 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* release 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 predictions before the new vintage is released. This variable captures the market-wide changes in the fine wine industry between the *en primeur* releases of two consecutive vintages. Therefore, a positive change in Liv-ex 100 index is expected to have a positive impact on the release price.

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

Correlation Coefficients	Change in *en primeur* 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 *en primeur* prices ($\Delta p_{i,t}$)	1				
Change in temperature ($\Delta m_{i,t}$)	0.4630	1			
Change in rainfall ($\Delta r_{i,t}$)	-0.5855	-0.5402	1		
Change in barrel score ($\Delta s_{i,t}$)	0.4239	0.3541	-0.4512	1	
Change in Liv-ex 100 (Δl_t)	0.5346	-0.0310	-0.1725	0.0603	1

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

Positive Interaction variables. We define positive interaction variables in order to account for dramatic price increases observed in celebrated vintages. For example, one may recall from Figure 2 that winemakers showed a strong positive reaction when determining the prices of 2003, 2005, and 2009 vintages. Those vintages were eagerly anticipated by the fine wine industry due to a combination of multiple positive factors such as higher average temperature along with a positive change in Liv-ex 100, etc. Therefore, we define the following six interaction variables to combine the pairwise positive effects of temperature and rainfall ($mr_{i,t}$), temperature and Liv-ex 100 ($ml_{i,t}$), temperature and barrel score ($ms_{i,t}$), rainfall and Liv-ex 100 ($rl_{i,t}$), rainfall and barrel score ($rs_{i,t}$), and Liv-ex 100 and barrel score ($ls_{i,t}$):

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

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

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

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

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

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

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

3.2. Analysis and Results

Table 3 provides the results associated with the 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 $t \in \{2002,\ldots, 2016\}$. Note that the number of observations is less than 600 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 *en primeur* 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%. Model 7, which incorporates all four variables, leads to an impressive explanatory power with an R^2 value of 61.94%. Variance inflation factors (VIF) for Model 7 are 1.05 for Δl_t, 1.28 for $\Delta s_{i,t}$, 1.48 for $\Delta m_{i,t}$, and 1.66 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 *en primeur* prices. It is also worth noting that Model 9 leads to the highest explanatory power among them with an R^2 of 73.76%. VIF for Model 9 are 1.29 for $\Delta s_{i,t}$, 1.41 for Δl_t, 1.73 for $\Delta m_{i,t}$, 2.08 for $\Delta r_{i,}$, and 2.44 for $ml_{i,t}$. We conclude from these VIF values combined with the correlation values (see Table 2) that there is no collinearity issue in our analysis.

	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.	0.081 *20.60****	0.085 *21.61****	0.059 *11.14****	0.006 *1.18*	0.084 *21.50****	0.075 *14.33****	0.006 *1.09*	-0.054 *-6.18****	-0.084 *-8.49****	-0.019 *-2.05***	-0.045 *-5.13****	-0.021 *-2.28***	-0.018 *-1.86**	-0.059 *-6.42****	-0.083 *-7.92****	-0.060 *-5.96****
$\Delta m_{i,t}$	3.114 *14.01****				1.400 *7.00****	1.210 *6.07****	1.782 *8.40****	1.091 *5.93****	0.626 *3.78****	1.236 *5.64****	1.938 *8.75****	1.785 *8.18****	1.700 *8.13****	1.155 *6.46****	0.603 *3.73****	1.519 *6.43****
$\Delta r_{i,t}$		-0.501 *-17.39****			-0.404 *-16.27****	-0.353 *-14.47****	-0.241 *-11.83****	-0.105 *-4.86****	-0.049 *-2.32***	-0.259 *-11.92****	-0.037 *-1.51*	-0.172 *-7.09****	-0.214 *-8.14****	-0.111 *-5.32****	-0.053 *-2.41***	-0.063 *-2.64***
$\Delta s_{i,t}$			0.058 *9.44****			0.024 *4.15****	0.024 *4.75****	0.026 *5.90****	0.026 *6.59****	0.016 *3.13****	0.029 *6.22****	0.017 *3.38****	0.015 *3.54****	0.020 *4.98****	0.027 *6.14****	0.023 *4.66****
Δl_t				1.543 *18.17****			1.399 *16.53****	1.147 *14.54****	0.809 *12.43****	1.382 *16.60****	1.057 *14.21****	1.305 *16.57****	1.151 *15.02****	1.035 *14.22****	0.809 *12.41****	1.065 *14.20****
$mr_{i,t}$								8.101 *9.61****						6.754 *6.53****		
$ml_{i,t}$									56.299 *14.73****						57.372 *14.73****	
$ms_{i,t}$										0.491 *3.76****						0.368 *3.38****
$rl_{i,t}$											2.251 *9.93****					2.111 *9.42****
$rs_{i,t}$												0.079 *4.89****			-0.009 *-0.58*	
$ls_{i,t}$													0.334 *4.65****	0.208 *2.73****		
R^2	21.44%	34.09%	17.97%	28.55%	37.15%	39.73%	61.94%	65.91%	73.76%	63.17%	65.92%	63.65%	64.28%	66.72%	73.78%	66.60%
N	586	586	585	586	586	585	585	585	585	585	585	585	585	585	585	585

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

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 ($rl_{i,t}$). The interaction term combinations in models 14 and 16 are statistically significant at 1% but neither model reaches to the explanatory power achieved with Model 9. In Model 15, the temperature and Liv-ex 100 interaction ($ml_{i,t}$) is significant at 1% but the rainfall and barrel score interaction ($rs_{i,t}$) is not statistically significant. Moreover, Model 15 does not bring additional explanatory power compared to Model 9. We exclude the remaining combinations of interaction terms from presentation where two interaction terms share a common factor (e.g., temperature and rainfall ($mr_{i,t}$) with temperature and Liv-ex 100 ($ml_{i,t}$) where temperature is a common factor) due to strong correlation among them.

Model 9, which is represented by the equation below, stands out among other specifications with its remarkable explanatory power (an R^2 of 73.76%) and statistically significant coefficients:

$$\Delta p_{i,t} = \alpha_0 + \alpha_1 \Delta m_{i,t} + \alpha_2 \Delta r_{i,t} + \alpha_3 \Delta s_{i,t} + \alpha_4 \Delta l_t + \alpha_4 ml_{i,t} + \varepsilon_{i,t}.$$

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

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

For robustness, we also replicate this step using the smearing estimation method in Duan (1983) which accounts for potential retransformation bias. We find highly similar results (see the appendix for details). Figure 5 illustrates the actual *en primeur* prices, $p_{i,t}$ plotted against the estimated *en primeur* prices $\hat{p}_{i,t}$.

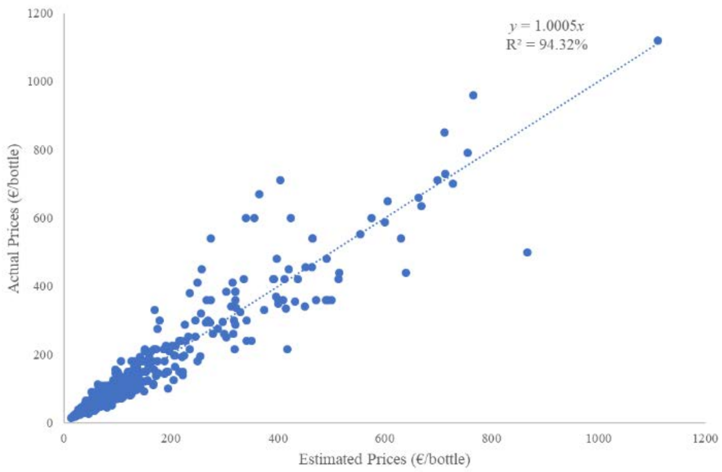

Figure 5. The fit between the actual and estimated *en primeur* prices for the vintages between 2002 and 2016 using Model 9 where $N = 585$.

We would like to underline the strikingly accurate fit that Model 9 generates where the $y = 1.0005x$ line has a slope extremely close to 1 with an R^2 value of 94.32%. The high value of R^2 is not caused by omitting the intercept; when the intercept is included in the fitted line, we obtain $y = 3.81 + 0.9874x$ with an R^2 of 90.22% and the intercept is not statistically significant.

3.3. Predictive Power

This section demonstrates the impressive predictive power of Model 9 by benchmarking against the Ashenfelter (2008) approach that utilizes temperature and rain variables as level panel data. According to the predicted and actual release prices reported in Ashenfelter (2008), their weather-based approach leads to an average prediction error of 36.14% for vintages between 1967 and 1972 (details are provided in the appendix).

Prior to the *en primeur* campaign of the 2017 vintage in the summer of 2018, we provided our estimated release prices to Liv-ex in order to test the predictive power of Model 9 and asked Liv-ex executives not to share it with winemakers in order not to influence the winemakers' price decisions. We present the results of this predictive test in this section. In order to estimate the release prices of the 2017 vintage wines (i.e., $t = 2017$), the model is calibrated using the vintages between 2002 and 2016, i.e., $t \in \{2002,\ldots, 2016\}$. 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 predict the release prices of the 2017 vintage wines, i.e., $\hat{p}_{i,t=2017}$. Once the actual release prices $p_{i,t=2017}$ are revealed around May 2018, we calculate the absolute percentage error as

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

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

We compare our Model 9 predictions 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 which is calibrated for $t \in \{2002,\ldots, 2016\}$ using the least squares dummy variable approach is:

$$\log(p_{i,t}) = \alpha_0 + \alpha_1\log(m_{i,t}) + \alpha_2\log(r_{i,t}) + \sum_{i=2}^{40}\beta_i d_i + \varepsilon_{i,t}$$

where d_i is a dummy variable such that $d_i = 1$ for $i = i$ and $d_i = 0$ for $i \neq i$. This benchmark model yields a mean absolute percentage error of 32.88% for the 2017 vintage. Therefore, we conclude that Model 9 with a mean absolute percentage error of 10.04% significantly outperforms the most well-known academic benchmark.

Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2017}$	Actual Price (€) $p_{i,t=2017}$	Absolute % Error $e_{i,t=2017}$	Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2017}$	Actual Price (€) $p_{i,t=2017}$	Absolute % Error $e_{i,t=2017}$
Angelus	272.70	276.00	1.20%	Lafleur	428.52	460.00	6.84%
Ausone	517.43	480.00	7.80%	Leoville Barton	63.49	52.80	20.24%
Beychevelle	48.25	52.80	8.63%	Leoville Las Cases	157.52	144.00	9.39%
Calon Segur	57.56	60.00	4.07%	Leoville Poyferre	59.30	54.00	9.81%
Carruades Lafite	134.76	135.00	0.18%	Lynch Bages	81.83	75.00	9.11%
Cheval Blanc	485.75	432.00	12.44%	Margaux	377.36	348.00	8.44%
Clarence (Bahans) Haut Brion	101.82	102.00	0.18%	Mission Haut Brion	294.05	240.00	22.52%
Clinet	65.05	56.00	16.16%	Montrose	94.09	96.00	1.99%
Clos Fourtet	74.81	72.00	3.90%	Mouton Rothschild	377.36	348.00	8.44%
Conseillante	135.52	120.00	12.93%	Palmer	227.29	192.00	18.38%
Cos d'Estournel	107.82	108.00	0.17%	Pape Clement	60.88	61.20	0.52%
Ducru Beaucaillou	128.40	120.00	7.00%	Pavie	251.99	276.00	8.70%
Duhart Milon	50.73	48.00	5.70%	Pavillon Rouge	105.16	132.00	20.34%
Eglise Clinet	208.70	168.00	24.22%	Pichon Baron	105.16	96.00	9.54%
Evangile	158.40	180.00	12.00%	Pichon Lalande	110.69	90.00	22.99%
Grand Puy Lacoste	53.91	52.80	2.10%	Pontet Canet	99.62	80.00	24.53%
Gruaud Larose	48.70	51.75	5.89%	Smith Haut Lafitte	70.84	67.20	5.42%
Haut Bailly	75.47	72.00	4.82%	Troplong Mondot	93.37	72.00	29.68%
Haut Brion	387.42	348.00	11.33%	Vieux Chateau Certan	182.84	168.00	8.83%
Lafite Rothschild	442.39	420.00	5.33%				
Mean Absolute % Error							
10.04%							

Table 4. The estimated and actual *en primeur* prices for the 2017 vintage and their absolute percentage errors.

We next provide a robustness check with a holdout sample including vintages 2014 – 2016. We calibrate Model 9 and the benchmark model using data up until vintage $t - 1$ for price predictions of vintage $t \in \{2014, 2015, 2016\}$. Table 5 demonstrates that Model 9 achieves a significant improvement in predicting release prices over the benchmark model. Average errors during 2014 – 2017 is 12.95% in our Model 9 and 34.03% in the benchmark model. Details of prediction errors of Model 9 are provided in the appendix for each winemaker for vintages 2014 – 2016.

Going forward, Liv-ex has determined to publish our price predictions as “realistic prices” prior to each *en primeur* campaign. It is important to note that our model allows for predictions to be made approximately one month before the actual release prices are revealed since all explanatory observations can be collected by April of each calendar year and wine futures are released around May. Given the accuracy and strength of our model, Liv-ex executives expect winemakers’ *en primeur* prices to converge to our realistic prices.

Vintage	Mean Absolute % Error	
	Model 9	**Benchmark**
2014	16.41%	22.86%
2015	13.42%	36.46%
2016	11.91%	43.95%
2017	10.04%	32.88%
Average	**12.95%**	**34.03%**

Table 5. Summary of predictive power of Model 9 and the benchmark model.

3.3.1. Financial Impact

While our work is highly beneficial for winemakers in determining the release prices, it also provides insights to the buyers (e.g., wine merchants, distributors, restaurateurs and collectors). The higher the winemakers deviate from our price predictions, the more likely that buyers will interpret such wines as under- or over-priced. Hence, buyers of these wines also benefit from these predictions while making financial and operational plans for the upcoming *en primeur* campaign.

In this section, we illustrate how a buyer makes more effective purchasing plans using our price predictions. The executives at the largest wine distributor in the US expressed anecdotally that they do not want to purchase *en primeur* due to the concerns regarding the uncertainty surrounding the release prices. Moreover, the 2016 Liv-ex survey discussed in Section 1 shows that wine merchants’ expectations could be drastically lower than the actual release prices. The budget plans made with such low price expectations can lead to serious inefficiencies in financial plans. When the predicted release prices are lower than the actual release prices, the buyer experiences an immediate need for additional budget in order to comply with the original operational/purchasing plans.

Prior to the *en primeur* campaign for vintage t wines, a buyer plans its purchasing budget in April of year $t + 1$. Recall that the release prices are announced beginning from May of year $t + 1$. To illustrate the financial impact on the purchasing budget, let us construct a portfolio of wines that includes the purchase of exactly one *en primeur* contract for each of the 40 winemakers listed in our sample. If the sum of the actual release prices exceeds a buyer’s reserved budget (equal to the sum of predicted prices), then the buyer has to supplement its original financial plans with additional money in order to ensure the purchase of each wine in the portfolio. The percentage of additional budget necessary for this operational plan can be expressed as follows:

$$\text{\% of Additional Budget Necessary}_t = \left[\sum_{i=1}^{40}\left(p_{i,t}-\hat{p}_{i,t}\right)\right]^{+} / \sum_{i=1}^{40}\hat{p}_{i,t} \quad \text{for } t \in \{2014, 2015, 2016, 2017\}.$$

Table 6 presents the percentage of excess budget needed when the price predictions are drawn from Model 9 and the benchmark model. It shows that a buyer who relies on the benchmark model is estimated to increase its budget by an average of 46.67% after the release prices are announced. The percentage of additional budget necessary can be as high as 70.74%. This is a substantial deviation from the original budgetary commitment and it is no surprise that some wine distributors lose confidence and do not engage in the purchase of *en primeur* contracts. On the other hand, a buyer who relies on Model 9 predictions is estimated to increase its budget only by an average of 11.03%. This is a substantial improvement from the benchmark model: A 35.64% reduction in additional budget. More importantly, Model 9 increases confidence in purchasing activities because the buyer does not have to deviate significantly from its original budgetary commitments. For the vintage 2017 wines, for example, our Model 9 leads to no additional budgetary needs and it establishes buyer confidence.

Vintage	**Percentage of Additional Budget Necessary**	
	Model 9	**Benchmark**
2014	15.21%	19.79%
2015	19.45%	52.94%
2016	9.46%	70.74%
2017	0%	43.20%
Average	**11.03%**	**46.67%**
Improvement	**35.64%**	

Table 6. Financial impact of release price predictions on the additional budget necessary for purchase of the 40 wines in our sample.

The findings presented in Table 6 provide two conclusions. First, predictions made through Model 9 enables buyers to make effective purchasing plans. Second, the performance of Model 9 provides further justification for Liv-ex to feature our predictions as “realistic prices.” The results create evidence that the use of our Model 9 predictions can increase buyer confidence leading to a higher purchase volume of *en primeur* contracts.

3.4. Robustness Check for Fixed Effects

Sections 3.1 – 3.3 present our approach that utilizes variables defined based on the change in their values across two consecutive vintages; this approach accounts for time-invariant characteristics of winemakers similar to the first-differences method.

To demonstrate the robustness of our results, we employ the fixed-effects method on the following two models:

Model R1: $\log(p_{i,t}) = \alpha_0 + \alpha_1\log(m_{i,t}) + \alpha_2\log(r_{i,t}) + \alpha_3 s_{i,t} + \alpha_4\log(l_t^{mar}) + \mu_i + \varepsilon_{i,t}$

Model R2: $\log(p_{i,t}) = \alpha_0 + \alpha_1\log(m_{i,t}) + \alpha_2\log(r_{i,t}) + \alpha_3 s_{i,t} + \alpha_4\log(l_t^{mar}) + \alpha_5\log(p_{i,t\text{-}1}) + \mu_i + \varepsilon_{i,t}$

where μ_i represents the time-invariant winemaker characteristics. Model R1 uses all four explanatory factors we define in Section 3.1. Model R2 further includes a lagged price term. Table 7 shows the fixed-effects regression results for $i \in \{1,\ldots, 40\}$ and $t \in \{2002,\ldots, 2016\}$.

	Model R1	**Model R2**
Int.	-8.835 *-9.87****	-3.334 *-5.81****
log($m_{i,t}$)	1.823 *7.14****	0.780 *5.50****
log($r_{i,t}$)	-0.247 *-12.67****	-0.219 *-14.15****
$s_{i,t}$	0.038 *5.56****	0.013 *2.26***
log(l_t^{mar})	0.843 *16.13****	0.859 *17.84****
log($p_{i,t\text{-}1}$)		0.384 *33.21****
within R^2	72.21%	80.27%
***F*-statistic (H_0: $\mu_i = 0$)**	90.66***	136.49***
N	591	586

Table 7. Fixed-effects regression results for the dependent variable $\log(p_{i,t})$. *T*-statistics using cluster-robust standard errors are given in italic below the coefficients. *, **, *** denote statistical significance at 10%, 5%, 1%, respectively. Using classical standard errors does not alter our statistical inferences.

The *F*-statistics indicate that both models feature significant fixed effects at 1%. Moreover, we rule out random effects by conducting the Hausman test and a cluster-robust version of the Hausman test (Wooldridge 2010) where the null hypothesis suggesting random effects is rejected at 1% significance level. Models R1 and R2 results show that our main explanatory factors (temperature, rainfall, barrel score, Liv-ex 100) continue to be significant.

We next compare the predictive power of models R1 and R2 to the predictive power of Model 9. We compute our estimated prices for vintage t by calibrating models R1 and R2 using data up until vintage t – 1 where $t \in \{2014, 2015, 2016, 2017\}$. Table 8 demonstrates that models R1 and R2 achieve a considerably high predictive power. However, it is worth noting that both models come short of the performance of Model 9. This result is consistent with the pricing practice we explained earlier that when

Bordeaux winemakers determine the price of a new vintage, they compare it to the previous vintage. Therefore, Model 9 using variables defined based on the change in their values across two consecutive vintages achieves the highest predictive power.

Vintage	Mean Absolute % Error		
	Model 9	**Model R1**	**Model R2**
2014	16.41%	16.95%	15.89%
2015	13.42%	15.61%	14.94%
2016	11.91%	16.23%	18.83%
2017	10.04%	13.92%	16.75%
Average	**12.95%**	**15.68%**	**16.60%**

Table 8. Summary of predictive power of Model 9, Model R1 and Model R2.

4. Conclusions and Managerial Insights

Our study makes three contributions that have significant practical implications for the wine industry. Our first contribution involves developing an empirical model that predicts the release prices of the infamous Bordeaux wines. The model leads to an accuracy that the industry has not seen before. This is evident from the statement of Neil Taylor, vice president of data at Liv-ex where he claims that our study is "the most accurate work they have seen internally and externally." Our study identifies four primary determinants of the price fluctuations from one vintage to another at the highest statistical significance. Two of these four determinants are weather related: The average of daily maximum temperatures and the total precipitation during the growing season of the wine. The third factor is the appreciation in the Liv-ex 100 index as an indicator of the fine wine market. The fourth determinant is the barrel scores established by the tasting experts. In addition to these four factors, our statistical method employs an interaction term that captures the combined benefits from an increase in the temperatures and the improvement in the market conditions from the previous vintage. The fit between our estimated release prices and the realized prices features an R^2 of 94.32% with a slope of 1.0005. Through a comprehensive analysis, we demonstrate that our methodology and results are robust.

Our second contribution has significant practical implications. Liv-ex classifies our price predictions as "realistic prices." They guide winemakers in determining their release prices using a precise approach, one based on a rigorous methodology that incorporates weather, market and tasting expert reviews.

Our third contribution shows the buyers of fine wines (e.g., wine merchants, distributors, restaurateurs and collectors) that they can compare our realistic prices with the winemaker's price and determine whether a wine is underpriced or overpriced. It helps these buyers make an informed decision about how to utilize their limited budgets. We demonstrate that using our model leads to an average financial improvement of 35.64% in budgeting for purchasing activities.

In addition to the above three contributions, our study shows that tasting experts and their barrel reviews are essential to the pricing decision in the wine industry. Tasting experts sample the wine in the barrel and establish a score (approximately a year before the wine is bottled) creating a perception of quality. Our study shows that barrel scores play a significant role in determining release prices.

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 in the critical decision regarding the release prices of fine wines. We expect other scholars to examine the same problem with the goal of improving our methodology. Moreover, our study can be expanded to predict wine prices in other geographic regions. Liv-ex has determined to feature our predicted prices as "realistic prices" in the upcoming vintages, establishing a benchmark for winemakers. In the future, it is important to study how the presence of this benchmark will influence these winemakers' pricing decisions. Another future research question is whether winemakers will anchor their prices to these realistic prices. In the event that some winemakers intentionally deviate from these benchmark prices, new studies should identify the reasons behind such reactions.

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

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Appendix

Robustness check for retransformation bias:

We calculate $\hat{p}_{i,t}$ using Model 9 as explained in Section 3.2. In order to account for potential retransformation bias, we replicate these calculations using the smearing estimation method in Duan (1983), denoted $\hat{p}^D_{i,t}$. We find that both methods lead to highly similar and accurate results in predicting $p_{i,t}$ as shown in Table A1:

	$p_{i,t}$	$\hat{p}_{i,t}$	$\hat{p}^D_{i,t}$
Mean	127.85	125.62	128.82
Standard Deviation	149.79	144.10	147.77

Table A1. Comparison of $\hat{p}_{i,t}$ and $\hat{p}^D_{i,t}$.

Predictive Power of Ashenfelter (2008):

Table A2 shows the predicted prices and the actual release prices for Bordeaux wines of vintages 1967 through 1972 as reported in Ashenfelter (2008). It should be noted that Ashenfelter (2008) reports these prices relative to the value of a benchmark portfolio, whose value is normalized to 1, to account for the differences in price levels among winemakers.

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

Table A2. Prediction performance reported in Table 3 of Ashenfelter (2008). * The predicted 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.

Predictive Power of Model 9 for Vintage 2014 – 2016:

Tables A3, A4, and A5 present the estimated and actual *en primeur* prices and their absolute percentage errors using Model 9 for the 2016, 2015, and 2014 vintages, respectively.

Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2016}$	Actual Price (€) $p_{i,t=2016}$	Absolute % Error $e_{i,t=2016}$	Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2016}$	Actual Price (€) $p_{i,t=2016}$	Absolute % Error $e_{i,t=2016}$
Angelus	260.03	294.00	11.55%	Lafleur	410.99	450.00	8.67%
Ausone	587.57	588.00	0.07%	Leoville Barton	53.73	63.60	15.52%
Beychevelle	57.26	56.60	1.16%	Leoville Las Cases	152.68	180.00	15.18%
Calon Segur	60.21	62.40	3.51%	Leoville Poyferre	61.07	66.00	7.47%
Carruades Lafite	122.61	135.00	9.18%	Lynch Bages	95.43	96.00	0.59%
Cheval Blanc	542.62	552.00	1.70%	Margaux	382.07	420.00	9.03%
Clarence (Bahans) Haut Brion	82.36	102.00	19.26%	Mission Haut Brion	314.75	336.00	6.32%
Clinet	60.29	72.00	16.26%	Montrose	115.88	102.00	13.61%
Clos Fourtet	67.33	82.80	18.69%	Mouton Rothschild	402.89	420.00	4.07%
Conseillante	116.60	150.00	22.27%	Palmer	214.56	240.00	10.60%
Cos d'Estournel	143.76	120.00	19.80%	Pape Clement	60.08	66.00	8.97%
Ducru Beaucaillou	129.29	139.20	7.12%	Pavie	267.02	294.00	9.18%
Duhart Milon	51.71	55.00	5.97%	Pavillon Rouge	101.49	114.00	10.98%
Eglise Clinet	185.74	225.00	17.45%	Petit Mouton	107.02	132.00	18.93%
Evangile	142.94	180.00	20.59%	Pichon Baron	98.08	114.00	13.96%
Grand Puy Lacoste	50.36	60.00	16.07%	Pichon Lalande	100.72	120.00	16.07%
Gruaud Larose	51.72	52.80	2.04%	Pontet Canet	78.69	108.00	27.14%
Haut Bailly	69.25	84.00	17.56%	Smith Haut Lafitte	62.95	76.80	18.03%
Haut Brion	383.06	420.00	8.79%	Troplong Mondot	86.58	102.00	15.12%
Lafite Rothschild	452.50	455.00	0.55%	Vieux Chateau Certan	139.20	192.00	27.50%
Mean Absolute % Error **11.91%**							

Table A3. The estimated and actual *en primeur* prices for the 2016 vintage and their absolute percentage errors.

Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2015}$	Actual Price (€) $p_{i,t=2015}$	Absolute % Error $e_{i,t=2015}$	Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2015}$	Actual Price (€) $p_{i,t=2015}$	Absolute % Error $e_{i,t=2015}$
Angelus	233.27	252.00	7.43%	Lafleur	416.49	420.00	0.83%
Ausone	442.50	540.00	18.06%	Leoville Barton	52.04	54.00	3.62%
Beychevelle	49.77	50.40	1.26%	Leoville Las Cases	110.59	138.00	19.86%
Calon Segur	47.12	53.00	11.09%	Leoville Poyferre	51.15	55.20	7.34%
Carruades Lafite	103.68	120.00	13.60%	Lynch Bages	69.12	84.00	17.72%
Cheval Blanc	442.50	540.00	18.06%	Margaux	307.32	384.00	19.97%
Clarence (Bahans) Haut Brion	63.87	85.00	24.85%	Mission Haut Brion	171.51	300.00	42.83%
Clinet	60.12	60.00	0.20%	Montrose	94.49	102.00	7.36%
Clos Fourtet	67.20	67.00	0.29%	Mouton Rothschild	291.49	384.00	24.09%
Conseillante	83.30	113.00	26.28%	Palmer	189.25	210.00	9.88%
Cos d'Estournel	92.33	120.00	23.06%	Pape Clement	58.91	58.80	0.18%
Ducru Beaucaillou	88.86	120.00	25.95%	Pavie	221.25	252.00	12.20%
Duhart Milon	48.38	48.00	0.80%	Pavillon Rouge	94.73	102.00	7.12%
Eglise Clinet	166.60	180.00	7.45%	Petit Mouton	89.85	102.00	11.91%
Evangile	116.63	150.00	22.24%	Pichon Baron	82.31	96.00	14.26%
Grand Puy Lacoste	44.35	48.00	7.60%	Pichon Lalande	76.65	96.00	20.16%
Gruaud Larose	43.16	46.75	7.68%	Pontet Canet	76.03	75.00	1.37%
Haut Bailly	53.87	66.00	18.37%	Smith Haut Lafitte	55.38	60.00	7.70%
Haut Brion	307.32	385.00	20.18%	Troplong Mondot	68.83	82.80	16.87%
Lafite Rothschild	323.11	420.00	23.07%	Vieux Chateau Certan	128.73	150.00	14.18%
Mean Absolute % Error							
13.42%							

Table A4. The estimated and actual *en primeur* prices for the 2015 vintage and their absolute percentage errors.

Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2014}$	Actual Price (€) $p_{i,t=2014}$	Absolute % Error $e_{i,t=2014}$	Winemaker (i)	Estimated Price (€) $\hat{p}_{i,t=2014}$	Actual Price (€) $p_{i,t=2014}$	Absolute % Error $e_{i,t=2014}$
Angelus	145.38	180.00	19.24%	Lafleur	353.22	330.00	7.04%
Ausone	261.18	360.00	27.45%	Leoville Barton	38.68	44.00	12.10%
Beychevelle	35.79	43.20	17.15%	Leoville Las Cases	76.32	96.00	20.50%
Calon Segur	31.51	42.00	24.98%	Leoville Poyferre	34.12	44.40	23.15%
Carruades Lafite	101.57	90.00	12.86%	Lynch Bages	50.07	60.00	16.55%
Cheval Blanc	301.47	360.00	16.26%	Margaux	210.21	240.00	12.41%
Clarence (Bahans) Haut Brion	46.05	54.00	14.72%	Mission Haut Brion	124.56	145.00	14.10%
Clinet	32.37	44.00	26.44%	Montrose	60.51	88.80	31.86%
Clos Fourtet	40.18	50.50	20.43%	Mouton Rothschild	201.33	240.00	16.11%
Conseillante	53.31	66.00	19.22%	Palmer	152.02	160.00	4.99%
Cos d'Estournel	83.59	84.50	1.08%	Pape Clement	46.98	49.80	5.67%
Ducru Beaucaillou	64.53	79.20	18.52%	Pavie	150.68	180.00	16.29%
Duhart Milon	45.82	42.00	9.10%	Pavillon Rouge	66.31	78.00	14.98%
Eglise Clinet	94.52	132.00	28.40%	Petit Mouton	62.26	78.00	20.18%
Evangile	96.95	90.00	7.72%	Pichon Baron	47.98	66.00	27.30%
Grand Puy Lacoste	29.08	38.50	24.47%	Pichon Lalande	57.68	64.80	10.99%
Gruaud Larose	33.25	39.50	15.83%	Pontet Canet	55.92	66.00	15.27%
Haut Bailly	34.36	43.20	20.47%	Smith Haut Lafitte	38.45	45.60	15.67%
Haut Brion	200.40	240.00	16.50%	Troplong Mondot	44.88	57.50	21.95%
Lafite Rothschild	295.38	288.00	2.56%	Vieux Chateau Certan	96.01	102.00	5.87%
Mean Absolute % Error							
16.41%							

Table A5. The estimated and actual *en primeur* prices for the 2014 vintage and their absolute percentage errors.