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Master Thesis

Business and Economics – Financial Economics

Price determinants for French fine wine

Examining the effect of aging, drinkability, and subjective quality measures

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Abstract

This paper studies the price determinants of fine French wines using a hedonic regression. The dataset consists of approximately 103,000 price observations between 1997 and 2020 based on worldwide auction data. The sample includes 1,182 unique wines from the French regions Bordeaux, Burgundy, and Rhône of the vintages 1990-2015. It finds significant positive effects between the Parker rating and the price varying. Furthermore, the analysis provides significant evidence for both a linear and quadratic relation between age and prices. Furthermore, the significant interaction effects between age and the quality of the wine, measured by the Parker rating, indicate an increasingly convex relation for high-quality wines. Finally, this study extends the existing literature by examining a new variable regarding the optimal drink date. Significant interaction effects between this variable and the quality of the wine indicate a different three staged price path for wines of different qualities.

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1. Introduction

Nowadays, alternative investments are commonly considered to diversify investment portfolios. Low interest rates and excessive capital on worldwide capital markets increase the attractiveness of alternative investments. Moreover, especially during times of economic downfall, alternative investments provide the possibility to hedge portfolio risk. The worldwide Covid-19 pandemic is a recent example that shows that financial assets become more correlated during a financial crisis. It reminds investors of the increasing importance of alternative investments.

The spectrum of alternative investments is broad. As a portfolio manager seeking to diversify its portfolio, the possibilities are near endless. Nowadays, it is possible to invest in art via several art indices listed on established exchanges. Another option to invest in, which is the focus of this research paper, includes fine wines. These are also tracked by indices. Besides, there also exist fine wine funds, which are a popular investment vehicle to diversify portfolio risk. Besides the perspective of portfolio managers and investors, fine wines are also very popular among wine collectors, connoisseurs, and consumers. This group does not base their decision to buy the wine on potential diversification benefits but on the expected utility they will experience from owning and consuming the wine. Their willingness to pay depends on a variety of price determinants. These include several observable characteristics, such as the chateau that produced the wine, the vintage year, and the implied age of the wine. Other important determinants include the wine's quality and drinkability, which are often determined by established wine critics.

Unlike financial assets, of which the value can be derived from financial statements, a discounted cash flow approach, and risk analysis, the price of fine wine is mainly determined by the underlying characteristics of the wine. Some fine wines and particular vintages exhibit extremely high prices due to their historical meaning. The chateau that produced the wine and the vintage often tell signal the historical importance. Controlling for these fixed effects provides the possibility to examine the effect of the Parker rating as well as the aging effect and drinkability. This study focuses on these last-mentioned price determinants for fine French wines. In addition, it extends the literature by constructing a variable concerning the time between the vintage year and the optimal drink date. The rest of this paper is organized as follows.

Section 1 discusses the literature review. It considers two clusters concerning investment-grade wines and sub-investment-grade wines. The literature review considers various price determinants (i.e., objective variables, subjective variables, and sensory variables). The objective variables include chateau, transactional and temporal factors. Furthermore, the interaction between age and the quality of the wine is discussed. The Parker rating is an example of a subjective variable that is studied in the literature review. At last, section 2 discusses sensory variables which indicate oenological aspects of the wine. Section 3 discusses the hypotheses. These relate to the effect of the Parker rating, the effect of aging, and the interaction effects. It extends the existing literature by hypothesizes that the current year relative to the optimal drink date is also of significant influence on the price of the wine. Section 4 discusses the data. It elaborates on the source of the data, the sample selection, and the construction of our database. Section 5 considers the methodology. It elaborates on the construction of our variables and the hedonic regression technique. Section 6 discusses the contribution to the literature based on the literature review, data section, and methodology. Section 7considers the results and discusses the support or rejection of the hypotheses. Section 7 to 9 includes the robustness check, limitation and discussion, and the conclusion.

2. Literature Review

2.1 Introduction literature review

The central question of this research paper relates to the price determinants of investment-grade wines. Although there is no clear definition of investment-grade wines, this paper follows the reasoning of Cardebat et al. (2017) and Dimson et al. (2015). It assumes they are among the most speculative and most heavily traded wines. Most of the world-famous wines are produced in the Bordeaux region. However, the French regions Burgundy and Rhône also produce investment-grade, although they form a substantially smaller part of the investment-grade wines spectrum.

For this literature review, this paper applies the following approach. Our starting point is the paper of Le Fur and Outreville (2019). They provide an overview of the literature. In general, the literature relating to investment-grade wines consists of studies focusing on, for example, the returns of wine investments (e.g., Masset and Weisskopf, 2018), portfolio construction (e.g., Masset and Henderson, 2010), and macroeconomic factors (e.g., Jiao, 2017). Besides these topics, another large part of the literature consists of papers examining price determinants through a hedonic analysis. The goal of the hedonic analysis in this perspective is to explain variation in price by means of observable attributes, including the name of the chateau, the vintage year, age, and Parker rating. This will also be the focus of this research paper. To study the related literature systemically, this study first examined the most influential papers based on the number of citations. These papers served as a starting point in our literature review. To assure a clear overview of the literature, this paper categorizes the respective studies into two clusters based on their research design.

The rest of this section is organized as follows. First, section 2.2 introduces the clusters and discusses the general aspects of the concerned papers. Thereafter, section 2.3 discusses the results in more detail. The detailed discussion is again categorized in objective, subjective and sensory variables. Section 3 provides several hypotheses.

2.2 Introduction of Cluster A and B

This section discusses the research papers that apply hedonic regressions techniques on wines. As mentioned earlier, this section categorizes the literature into two clusters. The categorization is based on the classification of the wines as being investment-grade or sub-investment-grade and the source of the price data consisting of either auction data, retail data, or experimental studies. In short, cluster A consists of six studies that examine investment-grade wines of Bordeaux based on auction data. Cluster B contains five studies examining wine investment-grade and high-end fine wines from France and Australia based on auction or experimental data.[1]

Each cluster discusses the commonalities and differences between the research design, research goal, and main findings. Regarding the price determinants discussed in the papers, this paper distinguishes three types of determinants, including objective (e.g., chateau, vintage, weather, lot size), subjective (e.g., quality rating), and sensory variables (e.g., quantified tasting experiences). These variables will be further discussed in section 2.3. Appendix A provides an overview of the research papers. The table shows the main aspects concerning the research design, including the considered wine regions, the number of wineries and unique wines, type of wine (investment-grade, high-end fine wine, table), vintage, price granularity, source of price data, and the variables (objective, subjective and sensory) used in the model specification. The next section starts with a discussion of the research design and main findings of the papers in clusters A and B.

2.2.1 Cluster A: Investment-grade wines from Bordeaux based on auction data

This subsection introduces cluster A and discusses the research design and main findings. The results will be discussed in more detail in section 2.3. Cluster A contains six studies, including the research of Cardebat et al. (2017), Masset et al. (2016) Dimson et al. (2015), Jones and Storchmann (2001), Di Vittorio and Ginsburgh (1996), and Ashenfelter et al. (1995). Di Vittorio and Ginsburgh (1996) use the most extensive dataset containing 60 chateaux of various regions and include wines that can be considered as high-end fine wines, just below the level of investment-grade wines. The other papers only examine investment-grade wines from the Bordeaux region. The sample size varies from five to 14 chateaux (irrespective of the vintages). The price data originates from worldwide auctions, which consist of price data on a single transaction level. Dimson et al. (2015) and Jones and Strochmann (2001) transform the data to a quarterly or yearly average. Regarding the vintages, the

[1] The term 'high end fine wines' refers to a category of wines which are of high quality and sufficiently liquid to include them in more wider indices. Section 3.1 further discusses the inclusion of wines in indices and the implications.

papers differ both in the range and the specific vintages. Ashenfelter et al. (1995) use the shortest range of nine years (1960-1969) and Dimson et al. the widest range (1900-2012). Most of the papers focus on the vintages before 2000. All papers within this cluster include various objective variables. Some incorporate subjective variables, including a rating (Cardebat et al. (2017) and Masset et al. (2016)). None of these papers make use of sensory variables. The complete overview of papers and the use of various types of variables is shown in appendix A. The next paragraph discusses the main findings.

The most recent paper of cluster A is of Cardebat et al. (2017). They consider whether the strong version of the law of one price ("LOOP") holds for investment-grades wines on the international auction by examining the price data of international auction houses, including Sotheby's and Christie's. Their analysis is based on the studies of Cassel (1918), who first described the LOOP. In addition, their study is inspired by earlier work that examines deviations of the LOOP in art markets (Ashenfelter and Graddy, 2003) and the study of Masset et al. (2017) regarding investment-grade wines. Cardebat et al. (2017) use a hedonic regression formula based on the hedonic framework presented by Triplett (2004). They include both objective (e.g., year of sale, age, lot/case size, chateau and auction house, auction city) and subjective (e.g., Parker rating) variables.[2] They find significant price premia, as large as 26.6%, for the variables indicating the sale at auction houses, primarily in Hong Kong. The price premia outweigh expected transaction costs which give reason to reject the LOOP in that case. They also find significant relations between the price of the wine and all other objective and subjective variables.

Masset et al. (2016) focus on the existence of price premia on the international auction market. They extend the understanding of wine auction prices in emerging wine markets such as China. Previous literature regarding the auction market focuses on the US auction markets (Sanning et al., 2008; Masset and Weisskopf, 2010). Except for some minor differences, they practically examine the auction houses as Cardebat et al. (2017). They apply a hedonic approach, include similar variables as Cardebat et al. (2017), and find comparable significant price premia. However, they observe that the price premia are not uniformly distributed. The price premium is most pronounced for wines with a Parker rating of 100, which is on average twice as high as wines in the rating category 96-98. Furthermore, the premia declining over time. At last, they also report significant results for the subjective quality measures, including the Parker rating itself.

Jones and Storchmann (2001) develop a two-staged econometric model to define the relationship between factors that affect the quality of a wine and those that affect the price. First, they examine the effect of weather conditions (e.g., temperature, precipitation) on grape composition

[2] The Parker rating is a subjective quality measures published by the Robert Parker Wine Advocate. This rating measure is discussed in section 3.2.1

(e.g., sugar and acid levels). Secondly, they examine the effect of grape composition, subjective quality measures (e.g., Parker-points), and the effect of aging on wine prices. They find that aging has a positive effect on wine prices and discover that wines with certain acid levels experience more price sensitivity towards subjective quality measures.

Di Vittorio and Ginsburg's (1996) main goal is examining price determinants. They extend the papers of Ginsburg et al. (1994) and Landon and Smith (1994), who used hedonic pricing techniques to analyze the quality of the wine. They state that in a fully competitive market with informed consumers, the price is a proxy for the quality of the wine. To examine this relation, Di Vittorio and Ginsburg (1996) include objective variables similar to the abovementioned studies, including the bottle size and weather conditions to price out these effects. Furthermore, no subjective or sensory variables are included. They find significant relations between the vintage prices, ranking of the chateau, and grading of wine critics. Also, they find that bottle and lot size have a significant effect on wine prices.

The last paper of cluster A is the study of Ashenfelter et al. (1995). They proposed the 'Bordeaux equation,' including only the age of the wine and weather conditions to show that the quality of red Bordeaux wines, as is determined by the prices of the mature wines, can be predicted by the weather conditions during the respective growing season. Implicitly they assume, similar to Di Vittorio and Ginsburgh (1996), that higher prices indicate higher quality. For both effects (i.e., aging effect and weather conditions), they find significant results. Section 2.3 discusses these results in more detail.

2.2.2 Cluster B: High-end fine wines and investment-grade wines

Similar to the introduction of cluster A, this section discusses the research design in the first paragraph, after which the second paragraph covers the main findings and implications. The results will be discussed in more detail in section 2.3.

Cluster B contains five research papers of Wood and Anderson (2006), Fogarty (2005), Combris et al. (2000), Combris et al. (1997), and Byron and Ashenfelter (1995). In contrast, to cluster A, the commonalities in cluster B are less prominent. In general, these papers do not focus on investment-grade wines from Bordeaux but on high-end fine wines without a focus on a specific region. Besides wines from Bordeaux, these papers also consider wines from Burgundy and Australia.[3] Consistent with cluster A, most of the price data originates from worldwide auctions. The inclusion of price data differs from price per transaction (Wood and Anderson, 2006, and Byron and Ashenfelter, 1995) to quarterly average (Fogarty, 2005). However, the two research papers of Combris et al. (1997, 2000) have a

[3] For the explanation of 'high end fine wines', this paper refers to footnote 1 and section 3.1.

slightly different research design. They also some include investment-grade wines, and their price data originates from an experimental study. Consistent with cluster A, the papers in cluster B consider various ranges of vintages, mainly before 2000. Also, each paper includes objective variables similar to the studies in cluster A. Two papers incorporate subjective variables, including rating (i.e., Combris et al., 1997 and 2000). These papers also add sensory variables to their regression formula. The complete overview is shown in appendix A. Next, this section discusses the main findings of the papers in cluster B. The results will be further discussed in section 2.3.

The most recent paper of cluster B is the study of Wood and Anderson (2006). They focused on weather variables (e.g., temperature, rainfall, hours of sun), changes in production techniques (e.g., new trellising system, use of refrigeration), and age. To examine to what extent wine prices can be quantitatively determined at the time of their initial sale at the winery. Similar to Combris et al. (1997 and 2000), they do not examine auction data. Wood and Anderson (2006) extend their papers by examining Australian icon wines and explaining the differences in quality using weather conditions during the growing season. They find that the variables regarding the weather and production technique have significant explanatory power in the variation. No other objective, subjective or sensory variables are considered.

Fogarty (2005) examines the return of premium Australian wine using a hedonic regression approach. The application of the hedonic approach is inspired by the studies of Oczkowski (1994) and Schamel and Anderson (2003). He finds that storing these wines provides a higher return than wines from Bordeaux. His results indicate that the risk-return relation of premium Australian wines is comparable to Australian equities. To examine the return, controlled for other characteristics of the wine, they include the vintage and brand as control variables. No other variables are examined.

Combris et al. (1997) and Combris et al. (2000) estimate a hedonic price equation for Bordeaux and Burgundy wines, respectively. They only take young that into account irrespective of their quality. Their research design is, apart from the sample, practically the same. They both include objective characteristics (e.g., chateau ranking in the 1885 Classification), subjective quality measures (i.e., a jury grade not being a Parker rating), and sensory characteristics (e.g., presence of tannings, level of alcohol).[4] However, the aging effect is not considered since they do not use auction data. Instead, they use data from an experimental study and measure the prices at a single point in time, making it less appropriate to examine the aging effect. Both conclude that the objective characteristics mainly determine the price. Additionally, the estimation of a jury grade equation shows that the sensory characteristics mostly determine the perceived quality measured by the jury grade.

[4] The 1885 Classification refers to a ranking system in which almost all chateaus in the Bordeaux region are categorized into 5 categories based on the quality of the wine as well as their establishment. This will be further explained at the discussion of the research paper of Combris et al. (1997,2000) in section 2.3.1.1.

Byron and Ashenfelter (1995) examine fine Australian wine, and their analysis is similar to the study of Ashenfelter et al. (1995), which examines investment-grade wines from Bordeaux. They consider the variables age, temperature, and rainfall to explain the price variation. Byron and Ashenfelter (1995) find a less strong effect of weather on price and quality for Australian wines than for wines from Bordeaux. Though, the results point in the same direction. A warm spring and summer have a positive effect on the quality as price and vice versa.

2.3 Detailed results of clusters A and B

The previous section introduced the research papers of clusters A and B. It covered the research design (e.g., the inclusion of certain vintages, wine regions, price granularity) and the main findings. This section elaborates on these findings and discusses the results in detail per category (i.e., objective, subjective and sensory variables. Each category is again divided into subcategories relating to the type of variables that are discussed. For example, within the subsection of objective variables, this paper separately discusses the temporal variables, including age and the transactional variables. Appendix A shows an overview of the research papers considered in clusters A and B and the variables included in each individual study.

2.3.1 Objective variables

This section discusses the objective variables. These include chateau fixed effects (e.g., producer, production yield, and techniques), transactional factors (e.g., lot size, bottle size, auction house/city), and temporal factors (e.g., year of sale, vintage, and age). Table 1 provides an overview of the variables used in each paper within clusters A and B.

	Cardebat et al. (2017)	Dimson et al. (2015)	Masset et al. (2016)	Jones and Storchmann (2001)	Di Vittorio and Ginsburgh (1996)	Ashenfelter et al. (1995)	wood and anderson (2006)	Fogarty (2005)	byron and ashenfelter (1995)	Combris et al. (1997, 2000)
Objective variables										
Year of sale	X	X	X		X			X	X	
Dealer		X						X		
Age	X	X			X	X	X		X	
Vintage	X		X		X			X		X
Chateau	X	X	X		X					
Lot size	X		X		X					
Bottle size					X					
Case size	X		X		X					
Auction house	X		X							
Production yield		X								
Weather/wine quality		X			X	X	X		X	
Ranking										X
Technology							X			
Interaction[5]		X								
Subjective Variables										
Rating	X		X							X[6]
Sensory variables										
Various										X

Table 1: Overview of the variables uses in the studies within clusters A and B.

[5] It refers in this case to the interaction between wine quality/rating and age. The interaction effect of transactional premia and rating (Masset et al., 2016) are not considered.

[6] Only Combris et al. (2000) examines the effect of jury grades.

2.3.1.1 Chateaux factors

Name of the chateau

Within cluster A, several studies include dummy variables that indicate the chateau to account for chateau fixed effects. This information appears on the label of the wine and can therefore be considered as an observable characteristic that is appropriate to include in the hedonic analysis. After controlling for the quality of the wine and various temporal and transactional factors (e.g., age, auction house, lot size), Cardebat et al. (2017) find significant price premia for all chateaux. They report that especially Château Lafite Rothschild carries a high price premium after controlling for the quality (75.0% relative to Haut-Brion). Other chateaux including Château Margaux (4.2%) and Latour (24.9%) carry a lower price premium. However, the size of the coefficients depends on their other model specifications. Other model specifications result in different price premia.

Dimson et al. (2015) find similar significant chateau fixed effects for the same sample. They report, for example, a price premium of 16.0% for Lafite Rothschild relative to Haut-Brion. The difference with the results of Cardebat et al. (2017) can be explained by the difference in their model specification (see table 1) as well as the research design (i.e., wider price data range, see appendix A).

Masset et al. (2016) examine a larger sample and also find significant chateau fixed effects. Lafite Rothschild is among the wines with the highest price premium (26.3%). Di Vittorio and Ginsburgh (1996) reports similar results. Unfortunately, the coefficients of their regression output are relative to the omitted wine of Chateau du Tertre, which makes it difficult to compare the results with the previously discussed studies. Chateau Lafite Rothschild, Chateau Margaux, Latour, and Mouton Rothschild are among the chateaux with the highest price premium. These vary between approximately 131% to 150% relative to Chateau du Tertre. The large difference relative to the findings of Masset et al. (2015) and Dimson et al. (2015) is due to the difference in quality and establishment between Chateau du Tertre and Haut-Brion.

Ranking of the chateau

The second factor that is discussed relates to the ranking of the chateau. The ranking is based on the 1885 Classification. This classification ranks the most established chateaux into five rankings based on their heritage, quality, and establishment. This ranking has except one minor change not changed since 1855 and is considered an objective factor. Within cluster B, Combris et al. (1997, 2000) include dummy variables relating to the ranking of the chateau instead of the chateau dummy variables itself. They report that chateaux with a higher raking entail a significant price premium. It is important to note that the ranking of the chateau is only an indication of the quality of the wine. The quality of the wine of the chateau can nevertheless vary from year to year. The estimated effect of the categorial variable is about 40% per ranking variable for Burgundy wines. And 30% for wines from Bordeaux. This more aggregated coefficient points in the same direction as the high premium for Chateau Lafite Rothschild relative to Haut-Brion since these wines can be considered high and low ranked. Within cluster B, no other studies include and discuss the effect of the chateau in their hedonic regression.

Production yield and techniques

Two other factors regarding the chateaux factors include the production yield and production techniques. Dimson et al. (2015) include the production yield of the respective chateaux measured in hectoliters per hectare and is based on Chevet, Lecocq, and Visser (2011). Each equation, which includes the production yield, finds a negative relation between the production yield and the price. This implies that are larger production yield relates to a lower price. The effect on the price varies per model specification from -0.49% to -0.81%. This indicates that chateaux with higher production yields carry a price discount. Wood and Anderson (2006) include dummy variables regarding major changes in production techniques for Australian Chateaux. These production techniques include, among others, the introduction of refrigeration after harvesting and a new trellising system. They find significant breaks in the price data around the implementation of new techniques. The effect of production techniques is discussed in more detail by the study of Gergaud and Ginsburgh (2001, 2007).

2.3.1.2 Transactional factors

The studies shown in table 1 include various transactional factors. They range from lot, bottle, and case size to the specific auction house and city. In comparison to other studies, the papers that examine these effects study the effect on prices on a single transaction level (see appendix A). The other papers aggregate the prices, which makes it impossible to examine transactional factors. Only studies of cluster A examine these effects.

Cardebat et al. (2017) find a significant but small quantity discount of 0.3% per transaction. This small effect is due to the significant and large price premium of 9.5% for full cases of 12 bottles of wine. Masset et al. (2016) also find a small and significant quantity discount of 0.1% per transaction.

Similar to Cardebat et al. (2017), they also include a variable regarding a complete wooden case of 12 bottles of wine, which is shown to be positive and significant. The effect size differs per model specification and varies between approximately 2% to 4% per transaction. Di Vittorio and Ginsburg (1996) find a significant negative relation of 0.25% for any additional bottle of wine in a lot. The effect is of an original case of wine of 3.0% is substantially larger and significant. Consistent with the research of Ashenfelter (1989), they add a variable that captures the ‘order of sale’ if a wine will decrease in auction value if it has appeared earlier in the specific auction. The result is found to be very small (less than 0.1%) but significant. Regarding the bottle size, Di Vittorio and Ginsburgh's (1996) results indicate that there is a price premium for larger bottles of wine. They examine eight sizes and find the largest price premium (37.7%) for imperial bottles corresponding to 8 standard-sized bottles.

Cardebat et al. (2017) find that significant coefficients exist for certain countries, cities, and auction companies despite a few exceptions, including Switzerland, Geneva, and Chicago. In line with their conclusion, they find the largest price premium of 26.6% for Hong Kong. Taking both the auction company and city into account, they find a significant price premium of 37.9% for Christie’s Hong Kong. Although the research design of Masset et al. (2016) differs and results are not one-to-one comparable, they find a significantly positive price premium of 19.7%. Consistent with the research of Cardebat et al. (2017), the Hong Kong premium is significant for all auction houses, especially for the auction house Christie's. At last, Dimson et al. (2015) examine a large dataset containing old transaction data starting at 1900. This early price data is retrieved from price lists of Berry Bros & Rudd and finds significant results for wines that are sold via this dealer.

2.1.1.3 Temporal factors

The temporal factors include the year of sale, vintage, and age. Weather conditions are not a temporal factor. However, the weather conditions are linked to a specific period and contain the same information as the vintage that appears on the label of the wine. Furthermore, this paper extends the literature by introducing a new temporal factor based on the wine's drink date. This variable will be discussed at the end of this section.

Year of sale

Within cluster A, Cardebat et al. (2017), Masset et al. (2016), and Dimson et al. (2015) include the year of sale dummy variables to control for changes over time, independent of aging effects. Besides, the inclusion of year of sale dummies provides the possibility to construct a wine index.

However, they do not discuss the coefficients of the year of sale dummies as it is not the main research goal of their study. Other research papers that are not part of this literature review, including the papers of Masset and Henderson (2010) and Masset and Weisskopf (2018), discuss this topic extensively. In addition, they cover the price developments during the financial crisis and the existence of price bubbles on the international wine market.

Di Vittorio and Ginsburg (1996) also add year of sale dummy variables to capture the time-inflation effect. The coefficients represent the price for a (group of) wines of constant age and quality. They report time effects ranging from 0.05% to 0.60% per year. Ashenfelter et al. (1995) do not include year of sale dummy variables. Within cluster B, only Fogarty (2006) includes quarter of sale dummy variables for a period of 10 years. The 40 coefficients strongly vary per quarter, similar to Di Vittorio and Ginsburgh (1996) and are sometimes negative.

Vintage effects

Besides the year of sale dummies, there are more temporal effects. The vintage year (e.g., Latour '1996') refers to the year the grapes are harvested and indicates the wine's age. Cardebat et al. (2017) find a considerably large and significant vintage effect that shows the preference for recent over past vintages. This observed effect might seem contradictory with the belief that older wines are scarcer and have become a collector's item. The paper, however, does not discuss the potential explanation in detail. Nevertheless, an explanation can be found in the stylized model of aging of Dimson et al. (2015) presented in section 2.1.1.4. In short, this could be since the older wines in the sample (e.g., the vintage '1961') are not drinkable anymore and have already experienced significant price increases at the beginning of their lifetime cycle and are less favored because they provide a relatively low financial return.

Masset et al. (2016) show that average prices for more recent vintages are lower. This relation, however, strongly depends on the quality of the wine. This explains the different outcomes relative to Cardebat et al. (2017) since they only examine the five First Growth wines. These wines are considered to be of the highest possible quality. As a potential explanation, they propose that vintages of outstanding quality are when released sold at higher prices than non-outstanding vintages. Moreover, they refer to a different aging process explained in detail by Dimson et al. (2015).

Di Vittorio and Ginsburgh (1996) point out that the vintage itself does not explain the price variation. However, in that particular year corresponding to the vintage, the weather conditions explain the price variation. The average effect of vintage differs substantially, indicating that poor vintages entail a price discount and vice versa. They state that taking the average vintage effect reduces the potential to obtain clear conclusions since there is a particular vintage variation in quality due to weather conditions. Ashenfelter et al. (1995) state that the variability in prices between vintages has two reasons. First, wines with a higher age have been held longer, so they must grant a higher price. Second, the price depends on the grapes' quality, depending on the weather conditions during a specific year. Jones and Storchmann (2001) acknowledge that according to the general belief, older wines are more valuable. In addition, they state that this only holds for wines of outstanding quality. The aging effect is caused by the long transition towards maturity and the absolute scarcity of the wine. This effect is later discussed in more detail in the next section.

Within cluster B, Combris et al. (1997, 2000) and Fogarty (2006) include vintage dummy variables. Combris et al. (1997, 2000) find that the older vintages carry a price premium. However, they examine only three vintages and use price data measured at a single point in time. Therefore, their results are not appropriate to compare to the papers in cluster A. Fogarty (2006) does not discuss the coefficients of the vintage dummy variables since it only focuses on the year of sale dummy variable to construct an index.

Weather conditions

Weather and the implied wine quality are assumed to behave similarly to the vintage factors. The weather conditions vary per year, and each vintage comprises information about the weather conditions of the harvesting year and the quality of the grapes. Since each study in this section includes a mix of weather variables or constructs its own weather quality measure (e.g., Dimson et al., 2015), it is impossible to compare the size of the effect between the research papers. Nevertheless, this section discusses the significance and signs of the variables.

Within cluster A, Dimson et al. (2015) indicate that favorable weather conditions, measured on their self-constructed measurement scale, positively affect wine the quality of the wine and price. The weather quality is also included as a linear and third-degree polynomial interaction effect of age and weather quality. The linear coefficients indicate a significant effect of on average 4% to 8% per weather quality category depending on the exact model specification. This implies that favorable conditions have a positive effect on the quality of the wine and the price.

Di Vittorio and Ginsburg (1996) include various weather variables, including frost, hail, and temperature, that significantly affect the price. The results indicate that favorable (not favorable) weather conditions have a positive (negative) effect on the price. Ashenfelter et al. (1995) include various weather variables regarding the average temperature and rainfall and conclude that these variables have significant explanatory power in the so-called Bordeaux equation. Jones and

Storchmann (2001) find that wines consisting of Merlot grapes are more climate-sensitive. Overall, they find that weather conditions influence the quality of the wine. Dimson et al. (2015) add to the knowledge that weather has become less of an influence on the quality of the wine due to technological advances. This implies that the weather effect changes over time which can be considered a drawback of the variable. Dimson et al. (2015) have deliberately chosen not to include expert ratings as a quality measure. First, they argue that the expert ratings are not exogeneous since the current ratings are usually based on the previous tasting notes, and wine reviewers are reserved for updating their opinions. Second, Dimson et al. (2015) do not include expert ratings since they examine a very long period and they note that no rating system covers all wines in their sample. Nevertheless, they state that the weather data and implied quality correlate with the perceived quality based on ratings. The correlation is statistically significant at a 0.01 level. Overall, the significant correlation between subjective quality ratings and implied quality based on weather conditions is confirmed by Ashenfelter et al. (1995), Byron and Ashenfelter (1995), and Jones and Storchmann (2001).

Aging effects

The next factor that is examined in this paper is the aging effect. Within cluster A, Cardebat et al. (2017) find a significant linear effect for aging, ranging from 8.3% to 8.7% per year, depending on the model specification. This effect indicates the average nominal rate of return for the five First Growth wines from Bordeaux. As an explanation for the relatively high return to age, Cardebat et al. (2017) link their results to the peak in wine pricing during their sample period (2001-2012). Di Vittorio and Ginsburgh (1996) also find a significant result for the linear factor relating to age. Their results indicate that one year of aging entails a price increase of 3.7%. However, they find that the size of the effect differs strongly among the included wines. Their findings suggest that there might be interaction effects between the quality of the wine and the aging effect. For example, the effect of aging on a Cos-d'Estournel wine is even negative (-0.2%). They argue that vintages of bad years do not sell after a certain time. Ashenfelter et al. (1995) find significant effects of aging ranging from 2.4% to 3.5%, depending on the exact model specification. In the famous Bordeaux equation of Ashenfelter et al. (1995), the effect of aging is on average 2.4% per year. Jones and Storchmann (2001) find a significant effect of aging on Bordeaux wine pricing due to the increased maturity and absolute scarcity. In their analysis, they report that Merlot-dominated wines have more aging potential than Cabernet Sauvignon-dominated wines.

Dimson et al. (2015) also examine the effect of aging. They include third-degree polynomial aging effects and report significant coefficients. They extend the findings of Wood and Anderson (2005), who first examined the polynomial function of age. The results of Dimson et al. (2005) confirm that there is a curvature in the relationship between age and price based on their stylized model of aging. This stylized model of aging will be discussed in the next section. The first and third coefficients of the polynomial function suggest that the wines in their sample first increase in price, then stabilize for a certain period, after which they rise again.

Di Vittorio and Ginsburgh (1996) find that the aging potential strongly differs among the wines is also further examined by Dimson et al. (2015). Their stylized model assumes that the quality of the wine affects the aging effect. They examine this effect by including interaction effects between the weather quality (and implied wine quality) and age in a polynomial function. They find that wines of a high quality strongly increase in price until 30 to 40 years old. Around that time, prices stabilize for about 20 years, after which they start rising again. This does not hold for low-quality wines. These experience little price increases during the first 30 years, after which they show near-linear price appreciations.

Within cluster B, Wood and Anderson (2006) examine the non-linear relation between age and price by including a third-degree polynomial function of age. Wood and Anderson (2006) report that the aging effect of wines is related to the scarcity that is assumed to increase with age. The level of scarcity affects the supply resulting in a higher supply and demand equilibrium. For most of the auction years, they find significant coefficients that prove that prices increase with age, stabilize for a certain number of years, and increase in price again thereafter. They run a regression per auction year and find the same curvature as Dimson et al. (2015) in nearly each auction year. Wood and Anderson (2006) find overall higher coefficients which imply that their curvature is less flat than the implied relation found by Dimson et al. (2015). Ashenfelter et al. (1995) and Byron and Ashenfelter (1995) examine the linear effect between age and price. They find on average effects varying from 2.4%-3.6% and 3.8%-4.7%, respectively, depending on their model specification.

2.1.1.4 Interaction effects: a stylized model of aging

To better understand the effect of aging, this paper presents the stylized model of Dimson et al. (2015). They state that the fundamental value of a wine is the maximum of three possible measures:

1. The value of instant consumption;
2. The discounted value of the consumption at maturity plus the non-pecuniary dividend received from owning the wine until consumption;
3. The discounted value of lifelong storage perceiving the wine as collectible.

They state that the consumption value of low-quality wines, which influences the first two measures of fundamental value, quickly decreases after bottling and results in a lower price. The reduction of gastronomic appeal continues until the fundamental value based on the third measure, the non-pecuniary dividend received from lifelong storage, takes over, and the fundamental value of the wine starts to increase. Regarding high-quality wines, they argue a different price pattern. In contrast to low-quality wines, high-quality wines increase in value immediately after bottling because of the increasing gastronomical appeal while maturing. At some point time, after the wine has matured, the consumption value decreases, and the value based on the wine being a collectible increase resulting in an overall upward price trend. Their results confirm their hypothesized model. The price of high-quality wines steeply rises during the first decades the wine is maturing until, around maturity, the price stabilizes. The price increases when the wine becomes antique, and the third measure of the fundamental value takes over. They find that the price for low-quality vintages is stable the first part of the life cycle and tends to rise near-linear afterward.

The interaction between quality and aging is first studied by Dimson et al. (2015). They use weather data as an indicator for quality and finds significant coefficients for the polynomial set of weather variables interacting with age. They show that the predicted life-cycle price patterns for the lowest implied quality wine in their sample differ from the wine with the highest implied quality. They do this by plotting the relative price level against the age, keeping other factors constant. Based on this graph, they conclude that the highest quality wines increase significantly more than the lowest quality wines during the first 40 years. After that, the aging tends to converge. However, in their sample, including wines of 100 years old, the aging effect of high-quality wines remains higher than for low-quality wines.

2.3.2 Subjective variables

The previous section discussed the objective variables. This section discusses the subjective quality measures indicated by a (Parker-)rating. Within cluster A, Cardebat et al. (2017) and Masset et al. (2016) use the Parker rating. Combris et al. (2000) include a jury rating unrelated to the Robert

Parker Wine Advocate. Section 3.1 will further discuss the Robert Parker Wine Advocate and the Parker ratings.

Within cluster A, Cardebat et al. (2017) find a significant positive linear price effect of 3.3% per Parker-point on average.[7] However, they acknowledge the possible endogeneity of Parker points, also discussed by Dimson et al. (2015). Therefore, the Parker rating is only assumed to proxy the quality of the wine. Masset et al. (2016) also use a Parker rating in their regression formula. Contrary to Cardebat et al. (2017), who include the rating as a continuous variable, Masset et al. (2016) use the rating categories. They include both a linear and squared Parker rating variable. Both are positive and significant, suggesting a non-linear relation between the rating and the price. The linear coefficient implies an average price increase of 49% per rating category. This relatively high effect is due to the determination of the rating categories.

The studies of Combris et al. (1997, 2000) do not include the Parker rating in their regression. Combris et al. (1997) criticize the inclusion of jury grades in the hedonic pricing model. They state that the inclusion of a jury grade is incorrect for two reasons. First, a jury grade is not an observable attribute of the wine but a quality measure that depends on the attributes of the wine. According to Rosen (1974), a hedonic price equation must be a function of intrinsic characteristics only. A rating is not an intrinsic characteristic but a result of it. Second, they state that bottles are purchased before they are tasted and that in practice, a jury grade cannot affect the price level. In theory, the rating can therefore not be used in a hedonic regression. It is, however, a widely accepted and used measure for the perceived quality and serves as a significant proxy for the observable quality of the wine. Besides, Combris et al. (1997) examine the jury grade in more detail. They set the logarithm of the jury grade as the dependent variable and regressed it on sensory and objective variables. They find a R^2 0.66 and variables significant at a 5% level. The sign of the variables is as expected, that is, a positive relation between positive sensory characteristics and the quality measure. Positive sensory characteristics increase the price. However, Combris et al. (2000) experiment with the inclusion of jury grades into their hedonic regression model. They argue that there is a strong relation between the price and quality in a competitive market with the presence of expert opinions. The effects of jury grade comprise 2.4% and 8.8% per jury grade. The two effects differ in their estimation procedure and the type of wine that is tested.

[7] The rating scale of Parker-points are discussed in more detail in section 3.2.1.

2.3.3 Sensory variables

The previous sections discussed the objective and subjective variables. This section paragraph briefly discusses the sensory variables used in the studies of Combris et al. (1997, 2000). No other research papers within the scope of this literature review discuss sensory variables. Sensory characteristics are not commonly used in studies related to investment-grade wines.

Combris et al. (1997) examine various dummy and categorical variables regarding sensory characteristics, including the aromatic intensity, harmony between components, and finishing. In their final regression, they included only two variables related to the concentration and maturity of the wine since they have the most explanatory power. The price is, on average, 17.7% higher if the wine is considered as well concentrated. If the wine is young and considered to improve when stored, the effect is 22.9%. These variables are also explanatory for the jury grade, which signals the quality of the wine. However, they conclude that the price of the wine is nonetheless mainly determined by the objective characteristics that appear on the label.

Combris et al. (2000) apply the same research design on Burgundy wines (instead of wines of Bordeaux). They also conclude that the objective characteristics have the most explanatory power in their hedonic analysis. Besides the concentration and maturity, they also include dummy and categorial variables relating to acids and fat. These variables have an effect size of -1.1% and 8.4%, respectively.

3. Hypotheses

This section discusses three hypotheses based on the abovementioned literature. The first hypothesis regards to the quality of the wine measured by Parker points. The second hypothesis takes the aging effect into account. Finally, the third hypothesis also takes the aging effect into accounts but considers a different measure that incorporates the optimal drink date. For a detailed explanation of this variable, this paper refers to section 5.1. This section is organized as follows. Each subsection first briefly mentions the relevant research papers discussed in the literature review and after which the (sub)hypotheses are formulated.

3.1 Hypotheses related to the rating

The studies of Cardebat et al. (2018) and Masset and Henderson (2015) examine the effect of the quality of the wine, measured by the Parker rating, on the price. Cardebat et al. (2018) find a linear positive effect on the price. However, these papers only take wines into account of the highest quality (see appendix A). That is wines of chateaux with the highest ranking in the 1855 Classification. We extend the perspective of Cardebat et al. (2018) and Masset and Henderson (2015) by examining only wines of lower quality. Other studies in the literature review do not examine Parker ratings but related variables such as a jury grade or the implied quality of the wine based on weather conditions. These findings support our hypotheses. Combris et al. (1997, 2000) report significant positive effects between the jury grade and price. Various other papers, including Dimson et al. (2015), Wood and Anderson (2005), Di Vittorio and Ginsburgh (1996), and Combris (1997, 2000), report positive effects of favorable weather conditions during the growing season on the price. It is found that favorable weather conditions are positively correlated with the Parker rating (Dimson et al., 2015) and positively impact the quality of the wine. These findings support our hypothesis. Hypothesis 1 reads:

Hypothesis 1. The quality of the wine, measured by the Parker rating, has a positive effect on the price.

3.2 Hypotheses related to the age

Various studies consider the effect of aging. For example, the studies of Cardebat et al. (2017), Jones and Storchmann (2001), Di Vittorio and Ginsburgh (1996), Ashenfelter et al. (1995), and Byron and Ashenfelter (1995) find a significant positive and linear effect of aging on the price. Based on the findings of these studies, this paper formulates sub-hypothesis 2A.

Hypothesis 2. The effect of aging has a positive effect on the price of wine.

This hypothesis is divided into five sub-hypotheses:

- **Hypothesis 2A:** The return to age is linear and positive.

Moreover, Dimson et al. (2015) and Wood and Anderson (2006) examine the aging effect using a third-degree polynomial function. Both papers find significant positive effects. Irrespective of the quality, their results indicate that the price developments of wines can be divided into three periods. First, wines increase in value until they approximately reach maturity. Second, around maturity, the price of wine in general stabilizes. Thereafter, the price of the wine increases again. The second and especially the third period are predominantly applicable to old wines. Dimson et al. (2015) and Wood and Anderson (2005) include old wines of the vintages as old as 1900 and 1960, respectively. This paper only focuses on the price behavior of wines of the vintages as early as 1990. Therefore, the oldest wine in our dataset (i.e., 30 years old) differs substantially from the above-mentioned studies. This paper assumes that the wines in our sample are within the first and second period of the life cycle. Accordingly, this paper expects that the aging effect of the wines in our sample is best captured by a squared relation between age and price. We hypothesize that the return to age is positive and that the rate of return decreases with age. In other words, the return to age is concave. This effect is similar to the effect observed for wines between the ages of 0 and 30, as observed in the abovementioned papers.

- **Hypothesis 2B:** The positive rate of return to age diminishes when wines become older.

In addition, Dimson et al. (2015) include interaction variables regarding the quality of the wine and the age. Instead of using the Parker rating, they use the weather quality as a proxy for the quality of the wine and find significant results for each of the three coefficients. This paper does not incorporate the weather quality. As an alternative measure for the quality of the wine, the Parker rating is used. Referring to the linear aging effect proposed in sub-hypothesis 2A, this paper hypothesizes that the quality of the wine, measured by the Parker rating, positively affects the linear effect of age on the price. In other words, wines of a high-quality experience have a more positive rate of return to age than low-quality wines. Sub-hypothesis 2C therefore reads

- **Hypothesis 2C:** The quality of the wine, measured by the Parker rating, positively influences the linear aging effect.

Dimson et al. (2015) examine this interaction effect concerning a third-degree polynomial function. They present a stylized model of aging, which is discussed in section 2.1.1.4. In short, according to this model, high-quality wines experience large increases in price during the first 30 years. Around maturity, the prices stabilize, after which they increase again when they are considered as collectibles. The price path for low-quality wines is different. Over the first decades, the prices increase little, after which they experience linear price appreciations over time. Sub-hypotheses 2D and 2E read:

- **Hypothesis 2D:** High-quality wines experience a concave return to age the first 30 years after which the price stabilizes.
- **Hypothesis 2E:** Low-quality wines experience little return to age little price the first 30 years after which they linearly increase in price.

3.3 Hypotheses related to the CTTMDDR

Hypothesis 3 is also based on the stylized model of Dimson et al. (2015). For a better understanding of these hypotheses, it is recommended first to read section 5.2. In short, this variable (i.e., CurrentTimeToMDDR, hereafter: "CTTMDDR") is based on the difference between the current year and the the midpoint of the drink date ("MDDR") expressed in years. This midpoint is considered as the optimal drink date. The MDDR is unique for each wine. If a wine becomes one year older, the CTTMDDR decreases. A negative value indicates that the wine is not yet in the MDDR. A positive value indicates that the wine is past the MDDR.

Our dataset consists of wines of the age between 5 and 30 years old. This limits the possibility of examining the aging effect over the long run. However, the values of CTTMDDR for the wines in our dataset vary between 60 and -20. In other words, our dataset contains price observations for wines that are 60 years before the MDDR and 20 years thereafter. This provides the possibility to examine the aging effect, measured in CTTMDDR, in the long run in this dimension. The hypothesized price paths are based on the findings of Dimson et al. (2015), as discussed in the previous section. The hypotheses read:

Hypothesis 3. The quality of the wine, measured by the Parker rating, has a significant effect on the return to age, measured by the CTTMDDR.

This hypothesis is divided into two sub-hypotheses:

- **Hypothesis 3A:** High-quality wines experience a concave return to CTTMDDR until the price stabilizes around the MDDR, after which the price increases again.
- **Hypothesis 3B:** Low-quality wines experience little price appreciation until the MDDR, after which the prices increase linearly.

4. Data

This chapter covers the data used in this study. Section 3.1 introduces the databases, including the Robert Parker Wine Advocate database, Liv-Ex, and Wine Market Journal. The database of Robert Parker Wine Advocate is used to collect both qualitative and quantitative data. The data consists of information regarding the origin of the wine and a subjective quality measure, including a Parker Rating and an ideal drink date range. The Wine Market Journal database contains auction price data. Both the Wine Market Journal and Liv-Ex compose fine wine indices based on auction price data consisting of the most liquid wines on the international wine auction market. These indices are used to track the monthly price movements of fine wines and are among other criteria used to determine our sample. Section 4.2 further discusses the sample selection criteria. Section 4.3 and 4.4 discuss the dataset construction and descriptive statistics.

4.1 Introduction to the databases

4.2.1 Robert Parker Wine Advocate

In essence, the main purpose of the Robert Parker Wine Advocate is to inform both consumers and investors about the latest trends regarding wines by publishing the magazine *The Wine Advocate*. More importantly, related to this study, they publish tasting notes of fine wines. The origins of the Robert Parker Wine Advocate can be traced back to 1967. Every review is monitored to ensure *The Wine Advocate's* high standard and consistency of tasting notes across the reviewers and various wine regions worldwide. Since the establishment of the magazine and the first wine review, the same rating system is used, known as *The Wine Advocate Rating System* ("TWA Rating System"). This rating system and rating categories will be discussed in further detail in Appendix B. This will be of use again in section 7. For a long period, Robert Parker was the only reviewer of *The Wine Advocate*. Nowadays, he employs nine full-time reviewers to cover every major wine region in the world. Today, the Robert Parker Wine Advocate has the most significant influence on market trends and consumer buying behavior on fine wine in the world's major wine markets, including Europe, Asia, and North and South America. Masset et al. (2016) favor the wine scores of Robert Parker since it is the most followed wine critic by wine investors “due to his preciseness in wine tasting and the impact his scores and notes have on wine prices.” This is also acknowledged by Jones and Storchmann (2001) and Masset et al. (2015).

The database comprises over 236,000 unique wines and 450,000 tasting notes ranging from the vintages 1760-2020. Approximately 96% of the wines in the database are of vintages 1990-2020 with an emphasis on the vintages 2007-2017, which entails about 65% of the total number of wines. The database contains wines from all regions worldwide, ranging from Australia and Europe to North and South America. Famous wine countries including France, Italy and several countries in South America form a relatively larger part of the database. The tasting note consists of a quantitative rating, ideal drinking date range, release price, information about the publication, including the data and reviewer, and a qualitative description of the wine. Besides the tasting note, the dataset contains information about the color, maturity, type of wine, sweetness, variety, and origin, indicated by a country, region and subregion.

4.2.2 Wine Market Journal and Liv-Ex

The Wine Market Journal is one of the most established and comprehensive resources for fine wine auction price data. Established in 1997, the Wine Market Journal has since then included every sold lot wine auction by all the major houses in Europe, Asia and the United States. The major auction houses include, for example, Christie's, Acker, Hart Davis Hart and Winefield Auctioneers. The Wine Market Journal maintains a strong relationship with these auction houses and ensures the reliability of the data. Apart from this, the WMJ also tracks increasingly important internet trades. The database counts in total 1.9 million unique values. This data contributes to the composition of the fine wine market indices set up by the Wine Market Journal. Like the Wine Market Journal, Liv-Ex is a global marketplace for fine wine trades. Established in 2000, Liv-Ex provides access to real-time transaction prices and investor-oriented exclusive market data and insights. However, without a wine merchant certification, the part of the database containing transactions is not accessible.

Both Wine Market Journal and Liv-Ex use the price data to set up fine wine market indices. These are both publicly available. The indices vary from broad to niche, recognizable by their names, including ‘Liv-Ex Fine Wine 50’ and ‘Liv-Ex Fine Wine 1000’. Like stock indices, wine indices consist of a certain group of wines of which the combined value is tracked based on the prices of its constituents.

The Wine Market Journal has created two databases based on the auction prices in the database, including the ‘WMJ-150’ and the ‘TOP-500’. The WMJ-150 is claimed to be akin to the Dow Jones Industrial Index and represents five modern vintages of thirsty, frequently traded blue-chip wines from various regions around the world. The second, broader market index represents the top five hundred wines measured by the worldwide dollar and trade volume and is claimed to be comparable to the S&P 500 index.

4.2 Sample selection criteria

This section covers the sample selection of three main aspects, including the selection of wines, vintages, and the range of price data. Overall, the sample selection is based on the literature, existing wine indices, and professional insights based on an interview with Wine Market Journal. The main criteria include the availability and quality of the data, a certain level of liquidity and scientific relevance.

First, our selection of wines is based on the studies of Cardebat (2017), Dimson et al. (2015), who both examine five First Growth wines from Bordeaux. Moreover, it is based on the research of Masset et al. (2016) and Di Vittorio and Ginsburgh (1996), who examine the same five First Growth plus nine and 55 additional wines, respectively. Liquidity played an important role in their selection process. Their selection of Bordeaux wines is consistent with the composition of wine indices by the Wine Market Journal and Liv-ex. These indices consist of the most liquid wines in the market. Our sample selection procedure is therefore based on the above-mentioned research and confirmed by the composition of indices of Wine Market Journal. Our definite sample of wines is based on an analysis of a preview of data provided by the Wine Market Journal. They provided an overview of the number of observations per wine, of which this paper has chosen the 50 most liquid wines irrespective of the vintages. Our sample includes the wines of Cardebat (2017) and Dimson et al. (2015). The exact list of wines in the research of Masset et al. (2016) and Di Vittorio and Ginsburg (1996) is not available, but it is assumed to correspond to a high extent.

Second, our selection of vintages is based on an interview with a professional of the Wine Market Journal, wine indices, and the abovementioned studies. The Wine Market Journal does provide the customized data drop services on request. The Wine Market Journal sends the price information monthly or quarterly granularity based on a requested list of wines. They have set a maximum of approximately 100,000 observations for noncommercial purposes. This has influenced the decision to include certain wines and vintages. Peter Gibson, responsible for the database and indices at the Wine

Market Journal, shared the knowledge that wines before 1990 are subject to bottle variations that radically impact their trade price and desirability. The conditions include but are not limited to label scuffs, scrapes and staining by water, wine, and ambient cellar matter, fill levels, capsule damages, and raised or depressed corks. Based on this information, only vintages of 1990 and later.

Third, besides the vintages, it is important to choose the range of price data. It implicitly determines the age of the wine in our research. The range of price data available in the database of the Wine Market Journal comprises the years 1997-2020. This study incorporates all the years available in the database.

4.3 Dataset construction

The website of the Robert Parker Wine Advocate does not offer any possibilities to download any data. With the permission of the company representative, the data is scraped on a large scale of the website with the help of the online tool Parsehub. In contrast to the Robert Parker Wine Advocate, the Wine Market Journal did not allow any form of web scraping. The price data is provided on request. Next, both datasets needed to be merged to be suitable for our analysis. Two aspects are worth mentioning. First, the datasets needed to be merged based on their name and vintage. However, both datasets often used a slightly different spelling. Referring to stocks, there exists no similar type of ISIN code for wines. Therefore, both datasets are merged based on a self-constructed unique identifier. Secondly, a single wine can have multiple tastings notes over time, which sometimes has different ratings. Therefore, each tasting note of time (t) must be linked to the corresponding wine price at (t) price. Since there might exist no price data at time (t) for that wine, we created new observations without price data. Then, the tasting notes are linked to the corresponding wine at time (t). Thereafter, the information of the tasting notes is copied to the observations of time ($t + n$) until a new tasting note was published. Wines of which no tasting note existed are deleted. At last, the observations without price data are also deleted.

4.4 Descriptive statistics

Our tasting note dataset consists of 1,182 unique wines originating from 3 regions and 12 subregions. Most of the wines come from the region Bordeaux. These wines are of vintages ranging between 1990-2015. The wines are approximately equally divided over the vintages. Table 3 provides an overview of the wines categorized per subregion. The average ratings per subregion range from 90.9 (Saint-Julien) to 95.3 (Sauternes). The LDDR and TT_MDDR stand for "Length Drink Date Range" and "Time To Midpoint of Drink Date Range" respectively. These variables are discussed in more detail in section 5.2.[8] The LDDR signals the length of the drink date as is estimated by The Robert Parker Wine Advocate (i.e., optimal drink date lies within (2020-2040). The LDDR ranges form 12.5 for the region Côte de Beaunne 36.0 wines from Sauternes. The TTMDDR provides information about the time between the vintage year and the midpoint of the drink date range (MDDR). We observe the highest (lowest) TTMDDR for Sauternes (Côte de Beaune). Regarding these variables, we observe that a high average rating per subregion is associated with a high LDDR and TT_MDDR (e.g., Saint-Julien: 19.1 and 16.9, Sauternes: 36.0 and 30.3). Figure 1 shows the relation between the average rating and the LDDR. To control for outliers, this paper winsorizes the LDDR at the 99th percentile. As can be observed, the LDDR is positively correlated to the average rating. The graph also a potential non-linear relation between the variables. The same holds for figure 2. The graph also shows a potentially positive non-linear relation between the average rating and the TTMDDR. This is preliminary evidence for the interaction effect stated in hypotheses 2 and 3.

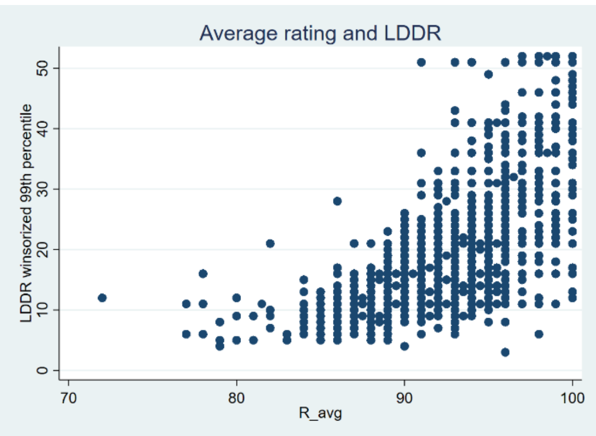

Figure 1: Average rating and LDDR

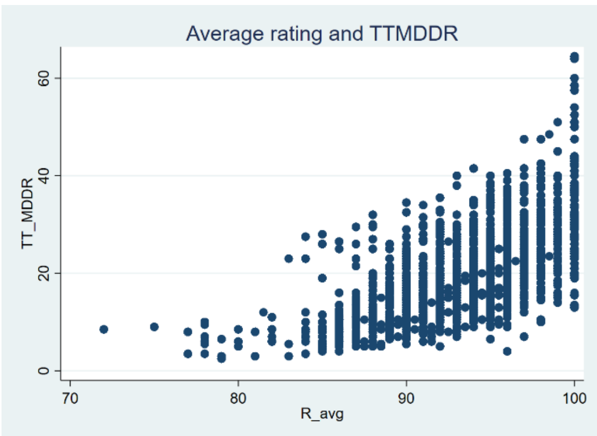

Figure 2: Average rating and TTMDDR

[8] For a better understanding of these variables, it is recommended to first read section 5.2 regarding the construction of these variables.

	WINES PER VINTAGE				WINES PER RATING CATEGORY				RATING		LDDR		TT_MDDR	
SUBREGIONS IN BORDEAUX	Wines	1990 - 1999	2000 - 2009	2010 - 2015	96-100	90-95	80-89	70-79	Avg.	σ	Avg.	σ	Avg.	σ
Margaux	52	20	20	12	14	28	10	0	93.0	(4.06)	22.4	(9.12)	19.1	(6.73)
Pauillac	249	96	100	53	41	122	85	1	91.5	(3.94)	19.7	(9.69)	16.9	(8.05)
Pessac-Leognan	78	30	30	18	25	37	16	0	93.5	(3.94)	22.3	(10.57)	18.7	(7.43)
Pomerol	126	46	50	30	31	66	27	2	92.6	(4.35)	20.6	(9.66)	17.6	(8.04)
St.-Estephe	77	29	30	18	9	47	21	0	91.7	(3.77)	20.2	(8.50)	18.9	(7.01)
St.-Julien	154	59	59	36	16	83	53	2	90.9	(3.99)	19.1	(7.55)	16.9	(6.92)
St.-Émilion	125	45	50	30	37	63	21	4	93.2	(4.96)	23.0	(12.40)	19.3	(9.26)
Sauternes	20	6	10	4	8	12	0	0	95.3	(2.97)	36.0	(15.90)	30.3	(8.50)
Subtotal	**881**	**331**	**349**	**201**										
BURGUNDY														
Côte de Beaune	15	8	5	2	6	9	0	0	94.5	(2.39)	12.5	(5.68)	10.4	(5.55)
Côte de Nuits	189	64	66	59	51	129	9	0	94.0	(2.60)	18.2	(7.43)	17.5	(7.23)
Subtotal	**204**	72	71	61										
RHÔNE														
Northern Rhône	74	28	28	18	30	33	11	0	94.5	(3.73)	19.9	(8.43)	17.5	(6.29)
Southern Rhône	23	8	9	6	4	16	2	1	92.5	(4.13)	18.5	(5.30)	14.5	(4.29)
Subtotal	**97**	**36**	**37**	**24**										
TOTAL	**1182**	**439**	**457**	**286**										

Table 2: Descriptive statistics

Our price dataset consists of approximately 103,000 price observations ranging between 1997 and 2020. We have substantially fewer observations for early years. This is a logical consequence of the dynamics in the wine market. In 1997, there exists no price data of vintages after 1997 since these do not yet exist. Only price data of vintages before 1997 exists. In our datasets, 1997 comprises only observations of the vintages 1990-1996. In 2020, price data is collected of the vintages 1990-2019. The density of observations per year is shown in figure 3. As can be observed, there are substantially more observations for recent years. Figure 2 shows the density of observations per vintage year. The rationale behind this graph is oppositive from the density graph per year (figure 2). Vintages of early years are more represented in our dataset. Exceptions occur when certain vintages are very popular (unpopular) when these are of high (low) quality.

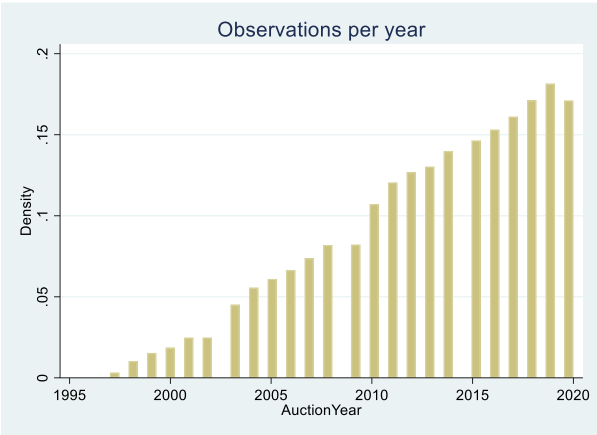

Figure 2: density of observations per year

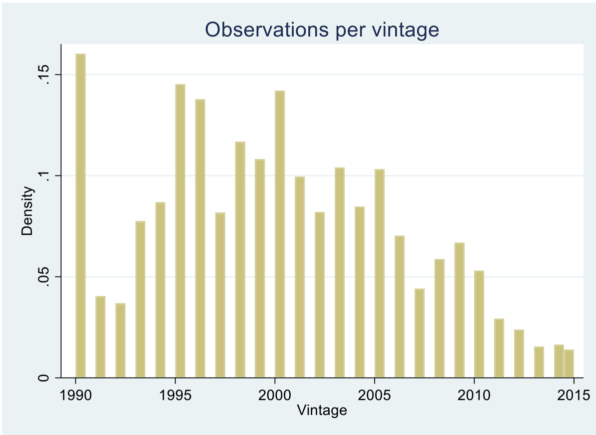

Figure 3: density of observations per vintage

Table 3 shows the descriptive statistics related to the price. The first column shows the number of price observations per subregion and rating category. The dataset contains most observations for the subregion Pauillac and Côte de Nuits (24,034 and 19,448, respectively). The rest of the subregions contain between approximately 5,000 and 10,000 observations except the subregions Sauternes, Côte de Beaune and Southern Rhône. This paper finds the observations for these subregions sufficiently large to include them in our analysis. The observations per rating category are more equally divided. The rating category 94-97 includes the most observations. The lowest rating category 70-88 contains the lowest number of observations. This distribution across the rating categories follows the natural division of wines within the spectrum of investment-grade wines.

The average prices across the subregions differ substantially. The highest average price (4359.37 USD) can be found in the subregion Côte de Beaunne. Referring to table 2, this is in line with the average rating of wines originating from this subregion. Côte de Beaunne, in comparison with the other subregions, has the highest average rating. The same relation holds for the subregion of Saint-Julien, Saint-Estephe, and Southern Rhône, which exhibit relatively low average prices. The relation between the average rating and the average price is more clearly visible when examining the average prices across the different rating categories. This is preliminary evidence for our hypothesis 1.

The standard deviation varies between 84.83 and 1708.65 across the subregions and rating categories. It is important to note that each subregion or rating category contains wine of various ages. Young wines, in general, entail a substantially lower average price than old wines. The wines in our dataset vary in age between 5 and 30 years old. The study of Cardebat et al. (2017) reports a standard deviation of 780.88 for their whole sample. Their minimum and maximum prices can explain a relatively high standard deviation for certain subregions. Furthermore, the average rating within a subregion can differ considerably, explaining the high standard deviation. This explanation is supported by the standard deviation that we report across the rating categories. Except for the category 97-100, the standard deviations are in line with the findings of Cardebat et al. (2017). This also holds for skewness and kurtosis.

Subregions	**Obs.**	**Mean (USD)**	**Std. Dev.**	**Min. (USD)**	**Max. (USD)**	**Skewness**	**Kurtosis**
Bordeaux							
Margaux	5,514	382.90	382.90	35.16	2000.79	1.58	5.84
Pauillac	24,034	328.11	333.58	18.49	6710.28	2.55	16.83
Pessac-Leognan	7,075	311.49	206.65	20.12	1663.32	1.07	3.95
Pomerol	9,163	905.31	1104.93	12.27	12343.79	1.70	6.23
St.-Estephe	6,375	137.74	95.84	26.73	764.48	2.89	13.76
St.-Julien	11,892	124.07	71.28	20.48	1894.78	2.69	37.41
St.-Émilion	9,757	372.98	330.60	18.35	4850.60	2.98	18.01
Sauternes	1,647	308.02	135.13	107.86	1017.69	1.63	5.76
Burgundy							
Côte de Beaune	1,367	4359.37	1960.53	687.97	14171.31	0.62	3.80
Côte de Nuits	19,448	2707.35	3899.09	101.10	32602.63	3.03	12.54
Rhône							
Northern Rhône	5,370	301.32	135.13	29.96	3412.50	2.14	13.20
Southern Rhône	2,114	84.83	39.96	25.98	443.83	2.51	12.73

Rating category	Obs.	Mean (USD)	Std. Dev.	Min. (USD)	Max. (USD)	Skewness	Kurtosis
97-100	19,599	1708.65	3395.64	45.70	32602.63	4.00	20.57
94-97	32,528	858.50	1717.85	33.08	27462.83	5.58	43.58
91-94	27,093	640.10	1440.93	19.44	27983.23	7.03	69.46
88-91	18,119	409.66	1175.01	18.50	30698.33	10.25	140.08
70-88	6,416	197.59	354.66	12.27	4897.08	5.80	45.53

Table 3: Descriptive statistics concerning the price

5. Methodology

This section discusses the methodology of the performed analysis. The introduction starts with the suitability to apply the technique on several types of assets, after which the fundamentals and underlying principles will be covered. Thereafter, this section relates the methodology with the methodologies used in the paper of our literature review.

5.1 Introduction of the hedonic regression technique

In essence, hedonic regressions explain variations in price using observable attributes of the respective real asset. It provides insight into the contribution of an attribute to its price by relating the price to the assumed value-determining characteristics (Rosen, 1974). Due to the relative infrequently traded and illiquid nature of the wine market, hedonic pricing techniques are appropriate for studying wine prices. Therefore, this method is applied in all studies that examine price determinants. The hedonic regression technique is also commonly used in other real assets infrequently traded on illiquid markets, including art (Li, Ma and Renneboog, 2018) and real estate (e.g., Sirmans and Macpherson, 2005).

The general specification of a hedonic price function is denoted by (1). The implication of this technique rests on the assumption that a consumer's utility does not depend on the asset as a whole but the underlying observable attributes of the asset (Fogarty, 2005). Thus, the asset is 'split up' into vectors of observable attributes separately included in the price equation. Fogarty (2005) adds that the consumer's utility function related to the asset must be weakly separable, and consumers must engage in two-stage budgeting. A weakly separable utility function with *m* denotes a vector of a standard consumption good, and u(z) representing a sub-utility function is denoted by (2). Derivations of this function are provided in the research paper Triplett (2004). This implies that the preference ordering across attributes is not related to the consumption of other goods. In practice, this means that the consumption of food that suits a certain type of wine is not considered in the utility function of the respective wine. Although the assumption regarding separability is strong, as Clements et al. (1997) claimed, the potential limitation of the technique is not insuperable.

$$Price = P(\text{vector of observable attributes}) \quad (1)$$

$$Utility = U(\text{u(z), m}) \quad (2)$$

The abovementioned underlying theory provides, however, no fundament for the exact model specification. Only the data considered can provide any directions for the exact model specification (Tripplet, 2004). A Box-Cox test can be used to determine the optimal functional form of the hedonic regression (e.g., linear-linear, log-linear, log-log). Diewert (2003) states that the linear-linear equation is not appropriate since it cannot meet the requirement regarding the Fisher's time reversal test of the implied heterogeneity condition. Fogarty (2005) agrees with Diewert that the log-linear equitation is most appropriate for estimating wine returns. This finding is supported by the research papers in the literature review. Furthermore, this paper has not found any other paper that uses the linear-linear specification.

5.2 Construction of variables

This section discusses the construction of variables. The variables relate to the age, rating and drink date variables. The first variable, constructed by formula (3), refers to the average rating of a single tasting note of a particular wine vintage. In some cases, the rating is indicated by a range (e.g., "93-95"). The average rating refers to the midpoint of the range, which is calculated as follows:

$$Average\ Rating = \frac{Rating\ Left\ Bound + Rating\ Right\ bound}{2} \quad (3)$$

Second, the construction of the variable relating to the age is straightforward, as is shown in formula (4). The age is defined as the difference between the year of sale and the vintage year.

$$Age = Year\ of\ Sale - Vintage\ Year \quad (4)$$

Third, the construction of the variables relating to the drink date is slightly more complex. Besides a rating, each tasting note is provided with an estimated ideal drink date. This is in most of the cases indicated by a range (e.g., 2030-2050). In this case, "2030" is labeled as the "Begin of Drink Date Range" and "2050" as the "End of Drink Date Range." The length of the drink date range ("LDDR") is defined in formula (5). In the case of the range “2030-2050”, the length is 20 years. The midpoint of the drink date range (“MDDR”) is defined in formula (6). In the former case, this midpoint of the range is the year “2040”.

$$LDDR = \ End\ of\ Drink\ Date\ range - Begin\ of\ Drink\ date\ Range \tag{5}$$

$$MDDR = \frac{Begin\ of\ Drink\ Date\ Range + End\ of\ Drink\ Date\ Range}{2} \tag{6}$$

To measure the time between the vintage year and the midpoint of the drink date range, this paper constructs the variable “TimeToMDDR” defined in formula (7). At each point in time, a wine is a certain time unit away from the midpoint of the drink date range. This is an alternative measure for the age. However, the age does not take into account differences in the TimeToMDDR between wines. The variable CurrentTimeToMDDR, as is defined by formula (8), takes the differences of TimeToMDDR into account. The sign options are provided in formula (9). If the current year is yet before the midpoint year of the drink date range, each additional year increases the CurrentTimeToMDDR and vice versa.

$$TimeToMDDR = MiddleOfDrinkDate - Vintage\ Year \tag{7}$$

$$CurrentTimeToMDDR = MDDR - Current\ Year \tag{8}$$

$$CurrentTimeToMDDR \begin{cases} > 0 & \text{if } Current\ Year\ < \ MDDR \\ = 0 & if\ Current\ Year\ = \ MDDR \\ < 0 & if\ Current\ Year\ > \ MDDR \end{cases} \tag{9}$$

To control for the length of the drink date, formula (7) is divided by (5) the LDDR. The ratio behind this standardization is as follows. If a certain wine has a very wide drink date range (e.g., “2020-2060”; MDDR=2040) compared to a short drink date range (e.g., “2030-2050”; MDDR=2040), comparing the midpoint of the drink date range might be more appropriate when standardized. The rationale behind this can be illustrated by the following example: a wine is at a particular moment at the exact optimal drink date. An additional year, further away from this optimal point, has a different implication regarding the drinkability for a wine with a narrow range (2040-2060; optimal drink date:

2050) than for a wine with a wide range (2030-2070; optimal drink date: 2050). An additional year is relatively closer towards the end of the drink date range for a wine with a more narrow range. To account for this possible effect, this paper controls for the length of the drink date range by constructing the standardized time to the midpoint of the drink date (“Std.CurrentTimeToMDDR”) in formula (10).

$$Std.CurrentTimeToMDDR = \frac{MDDR - Current\ Year}{LDDR} \quad (10)$$

5.3 Hedonic regression formulas

5.3.1 General set up regression formulas

This study applies a log-linear OLS regression technique similar to the studies of, e.g., Dimson et al. (2015), Cardebat et al. (2016), Fogarty (2005)). The log-linear is applied to control for heteroskedasticity. Dimson et al. (2015) cluster the standard errors by year of sale. This paper also clusters the standard errors by time but finds that the results are more significant when the standard errors are clustered by year month of sale. Most papers include fixed effects to the regression formula using dummy variables regarding the respective wine, vintage year of sale. In addition, to appendix A, table 4 shows the model specification of the studies in the literature review. At last, the prices used in this paper are denominated in USD and corrected for inflation using US inflation rates.

Research paper	Model specification		Fixed effects
Cardebat et al. (2017)	Log-Linear	Pooled OLS	chateau, year and vintage
Dimson et al. (2015)	Log-Linear	OLS	chateau and year dummies
Masset et al. (2016)	Log-Linear	Pooled OLS	chateau, year and vintage
Di Vittorio and Ginsburgh (1996)	Log-Linear	n.a.	chateau, year and vintage
Ashenfelter et al. (1995)	Log-Linear	n.a.	not disclosed
Jones and Storchmann (2001)	Log-Linear	OLS	not disclosed
Combris et al. (1997)	Log-Linear	OLS	vintage

Research paper	Model specification		Fixed effects
Combris et al. (2000)	Log-Linear	OLS	vintage
Wood and Anderson (2006)	Log-Linear	SUR OLS	not disclosed
Fogarty (2005)	Log-Linear	OLS	year
Byron and Ashenfelter (1995)	Log-Linear	OLS and SUR	not disclosed

Table 4: Model specifications

5.3.2 Baseline regression

Formula (11) shows the formal notation of the baseline regression. The dependent variable P_{it} refers to the hammer price denoted in US dollars and corrected for worldwide inflation. The price is a weighted monthly average of several auction houses of a single wine vintage. $Wine_{it}$ refers to the wine fixed effect and consists of 49 dummy variables. Each variable refers to wine irrespective of its vintage (e.g., 'Lafite Rothschild'). YMr_{it} indicates the year of sale fixed effects of the respective price data at time *t.* At last, the variable $Vintage_{it}$ refers to the vintage of the wine. The next sections extend the baseline regression, and each regression formula refers to the baseline regression as 'BLR'.

$$Ln(P_{it}) = \alpha_0 + \alpha_1 \sum_{j=1}^{50} Wine_{it} + \alpha_2 \sum_{j=1}^{276} YM_{it} + \alpha_3 \sum_{j=1}^{25} Vintage_{it} + \varepsilon_{it} \quad (11)$$

5.3.3 Methodology to examine the effect of rating and aging on price

Regression formula (12) is used to examine the effect of the Parker rating on price and the aging effect. Regression formula (13) extends the previous regression formula by applying interaction effects between the Parker rating and age. In case the linear relation is examined, the squared and cubic coefficients do not apply.

$$Ln(P_{it}) = BLR + \beta_1 * Avg.\ Rating_{it} + \beta_2 * Age_{it} + \beta_3 * Age_{it}^2 + \beta_4 * Age_{it}^3 + \varepsilon_{it} \quad (12)$$

$$\begin{aligned} Ln(P_{it}) = BLR &+ \beta_1 * Avg.\ Rating_{it} + \beta_2 * Age_{it} + \beta_3 * Age_{it}^2 + \beta_4 * Age_{it}^3 \\ &+ \gamma_2 * Avg.Rating * Age_{it} + \gamma_3 * Avg.Rating * Age_{it}^2 + \varepsilon_{it} \end{aligned} \quad (13)$$

5.3.4 Methodology to examine the effect of rating and aging measured by CTTMDDR on price

Regression formula (14) is used to examine the effect of (std)CTTMDDR on price. Similar to (14), regression formula (15) examines the interaction effects between the Parker rating and (std)CTTMDDR. However, in case the linear relation is examined, the squared and cubic coefficients do not apply. The same logic holds for when the squared or cubic relation is examined.

$$Ln(P_{it}) = BLR + \beta_1 * Avg.\ Rating_{it} + \beta_2 * (std)CTTMDDR_{it} + \beta_3 * (std)CTTMDDR_{it}^2 + \beta_4 * (std)CTTMDDR_{it}^3 + \varepsilon_{it} \quad (14)$$

$$\begin{aligned} Ln(P_{it}) = BLR &+ \beta_1 * Avg.\ Rating_{it} + \beta_2 * (std)CTTMDDR_{it} + \beta_3 * (std)CTTMDDR_{it}^2 \\ &+ \beta_4 * (std)CTTMDDR_{it}^3 + \gamma_2 * Avg.Rating * (std)CTTMDDR_{it} \\ &+ \gamma_3 * Avg.Rating * (std)CTTMDDR_{it}^2 \\ &+ \gamma_4 * Avg.Rating * (std)CTTMDDR_{it}^3 + \varepsilon_{it} \end{aligned} \quad (13)$$

5.4 Visualization techniques

To examine the predicted life price patterns of wines of various quality categories, this paper transforms the predicted log-transformed price Ln(P_{it}), as implied by the coefficients of the variables used in the regression formulas, to P_{it}. The predicted price is aggregated by collapsing the dataset over the respective quality category of the wine and *Age* or *CurrentTimeToMDDR*. In other words, the average predicted price is calculated per age or CTTMDDR and rating category. The visualization is used in section 7 to show the price paths of different illustrative wines.

Hypotheses 2 and 3 make use of the terminology 'high-' and 'low-quality wines. Based on the Robert Parker rating scale shown in appendix B, this paper defines high-quality wines as wines with a Parker rating higher than 90. Wines with a Parker rating below 90 are considered low-quality wines. This paper examines five ratings (i.e., 100, 95, 90, 85 and 80) to answer the hypotheses. To prevent the calculation of the average predicted price per age or CTTMDDR per rating, excluding too many observations, the calculation also takes the rating +1 and -1 of the respective rating into account.

6. Extension of the literature

This section discusses the extension of the literature. First, it briefly discusses the main papers of the literature review. Second, the extension regarding the dataset and methodology is linked to the literature review. First, this paper aims to confirm the findings related to the effect of the Parker rating as an indication for the quality of the wine and extent the literature using a more extensive dataset. Cardebat et al. (2017) Masset et al. (2015) examine a dataset containing 38,941 and 92,538 observations, respectively, on auction level. They both consider the same top 5 ranked wines from Bordeaux of vintages between 1945-2009. This paper studies a dataset containing 50 wines of the vintages 1990-2015, consisting of approximately 103,000 monthly average price observations. It includes 1,182 unique wines versus approximately 250 unique wines in the paper of Cardebat et al. (2017) and Masset et al. (2015). Furthermore, this study also examines wines from other than Bordeaux (i.e., Burgundy and Rhône).

Second, this study aims to confirm the findings related to the effect of age on price and the interaction effect between age and the quality of the wine indicated by the Parker rating. Besides the papers Cardebat et al. (2017) and Masset et al. (2015), the papers of Wood and Anderson (2006), Di Vittorio and Ginsburgh (1996), Ashenfelter et al. (1995), and Byron and Ashenfelter et al. (1995) examine the age. These papers examine the linear effect of age on price. The number of observations in these studies is also relatively limited. Di Vittorio and Ginsburgh (1996) examine a dataset of 240 unique wines and 29,991 observations which is the most extensive among these papers.

Furthermore, this study extends the existing literature by examining wines from Burgundy and Rhône. Dimson et al. (2015) is the only paper that examines the squared and cubic relation between age and price. They study 5 wines from the Bordeaux region of the vintages 1945-2009 using a dataset containing 9,492 observations. Their main contribution to the literature is examining interaction effects between age and the quality of the wine. This paper extends their analysis by examining a more extensive dataset, which also contains wines from the Burgundy and Rhône region.

Third, this paper introduces a new variable related to the wine's optimal drink date, which is not yet examined in the existing literature to the best of our knowledge. However, this contribution is based on the findings of Dimson et al. (2015), who find that wines of high quality stabilize when they reach maturity. However, they do not explicitly incorporate a measure for this maturity of the wine (i.e., when it is close to the optimal drink date).

7. Results

7.1 Results related to the effect of age, Parker rating and interaction effects

This section discusses hypotheses 1 and 2 regarding the effect of the quality of the wine, indicated by the Parker rating, the effect of aging, and interaction effects. This section is organized as follows. At first, this section discusses the output related to the effect of the quality. Second, the aging effect is discussed. Third, this section considers the interaction effect between the age and the quality of the wine.

7.1.1 The effect of the Parker rating on price

The coefficients of the average rating (R_avg_{it}) in regressions (1) to (6) indicate a positive relation between the Parker rating and the price of the wine (P_{it}). The coefficients for the Parker rating are significant at a 1% significance level. The results are presented in table 5. This paper finds that in our sample, a Parker-point is on average associated with a 9.79% to 10.22% higher price when controlled for age and, in some cases, interaction effects between age and the quality indicated by the Parker rating. The size of this effect is approximately equal across the six regression models and therefore found to be robust. Hypothesis 1 states that the quality of the wine, indicated by the Parker rating, positively affects the price. Based on the results of regressions (1) to (6), this paper confirms hypothesis 1.

The study of Cardebat et al. (2017) reports an average increase in the price of 3.40% per Parker-point. This effect is remarkably lower than our data and regression models indicate. Cardebat et al. (2015) examine five wines from Bordeaux (vintages 1945-2000) of the highest quality. They include worldwide auction data between 2000-2012, which is approximately similar to our dataset. Besides the fixed effects regarding the auction house, location, vintage, year of sale, chateau, they also include age, lot and case size. The smaller effect could be due to the inclusion of fixed effects regarding the auction house and location. It is possible that certain auction houses only auction wines of a certain Parker rating (e.g., Parker ratings > 95). The information about the specific auction house and location is of significant influence on the price (Cardebat et al. (2017), Masset et al. (2015)). Including this information using dummy variables can therefore interfere with the effect of the Parker rating.

Masset et al. (2015) do not include the Parker rating using a continuous variable. Therefore, it is not appropriate to compare the results. Nevertheless, the significance and the sign of the coefficients are in line with our findings. The next section discusses the effect of aging on prices.

VARIABLES	(1) lnPrice	(2) lnPrice	(3) lnPrice
R_avg	**0.0939******	**0.0934******	**0.0934******
	(0.00106)	(0.00105)	(0.00108)
Age	**0.0237******	**0.0213******	**0.0208******
	(0.000314)	(0.000471)	(0.000928)
Age^2		**0.000741******	**0.000693******
		(4.26e-05)	(8.09e-05)
Age^3			**0.6.77e-06**
			(8.05e-06)
Chateau FE	Yes	Yes	Yes
Vintage FE	No	No	No
Year month of sale FE	Yes	Yes	Yes
Constant	**-3.720******	**-4.026******	**-4.013******
	(0.100)	(0.103)	(0.116)
Observations	103,755	103,755	103,755
R-squared	0.926	0.927	0.927

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: output of regression (1) to (3)

7.1.2 The effect of aging on wine prices

Table 5 shows the output relating to the aging effect. Regressions (1) to (3) cover the effect of the rating and the linear, squared and cubic relation between age (Age_{it}, Age^2_{it} and Age^3_{it} , respectively) and price. Regressions (4) to (6), shown in table 6 in the next section, also include interaction effects. These will be discussed in the next section. The linear coefficient of age in regression (1) indicates a significant positive effect on the price of the wine. The price of wine increases by 2.40% per year when it is controlled for the rating of the wine and the fixed effects. Sub-hypothesis 2A states that the return to age is linear and positive with respect to the wines in our dataset (i.e., with ages between 5 and 30 years old). Based on the significant positive coefficient in regression (1), this paper confirms sub-hypothesis 2A.

Our results are in line with existing literature. Only the study of Cardebat et al. (2017) finds notably higher results for the aging effect. They find an average effect of aging varying between 8.3% and 8.7% per year. They explain this relatively high effect by the time frame in which they examine the prices. The period between 2001 and 2012 is considered the peak of the fine-wine pricing curve. The other papers have more similar effect sizes. For example, Di Vittorio and Ginsburgh (1996) find an average aging effect of 3.7% per year when controlling for the chateau, transactional and temporal factors and subjective quality measures. Other studies (i.e., Wood and Anderson (2006), Fogarty (2005) and Ashenfelter et al. (1995)) find aging effects of 2.2%, 3.1% and 2.4%-3.6%, respectively.

Regression (2) shows a significant squared relation between age and price. The coefficients demonstrate a linear increase of 2.15% per year in combination with a positive quadratic coefficient of age. This positive squared term implies that wines experience larger marginal price increases per year when they are older. In other words, the return to age is convex. Sub-hypothesis 2B states that the positive rate of return diminishes when wines become older (i.e., a concave return to age). Based on the output of regression (2), this paper rejects sub-hypothesis 2B. Dimson et al. (2015) s the only paper that examines the non-linear aging effect. They find significant coefficients for a third-degree polynomial function of age. The findings of this paper are not in line with their results which indicate a concave return to age regarding wines with ages between zero and 30 years. No other papers examine the non-linear relation between age and prices.

Although no hypothesis regarding a polynomial function of age is formulated, this paper has included the regression results of this polynomial function of age in regression (3). The third-degree polynomial coefficient is not significant, indicating that in our dataset, containing wines with ages between 5 and 30, there is no effect according to the stylized model of Dimson et al. (2015). Furthermore, it is noteworthy that both regression (1) and (2) show significant coefficients at a 1% level. Since the coefficients represent the average effect of age on price and both regressions show highly significant results, it is without further examination not possible to determine if the effect of age on price is either linear or quadratic. Figures 4 and 5 presented below show the predicted price over age and CTTMDDR and help further to understand the relation between age and price.

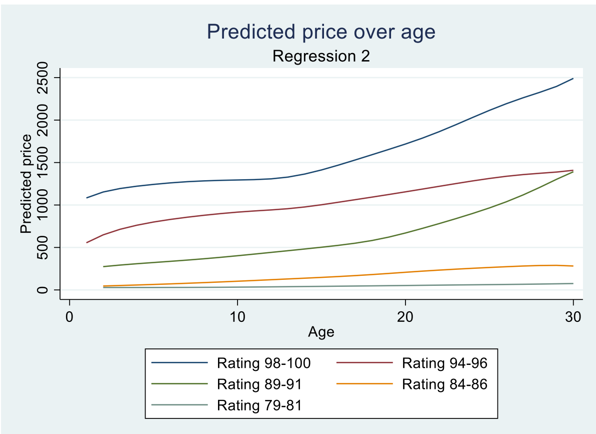

Figure 4: Predicted price over age (regression 2)

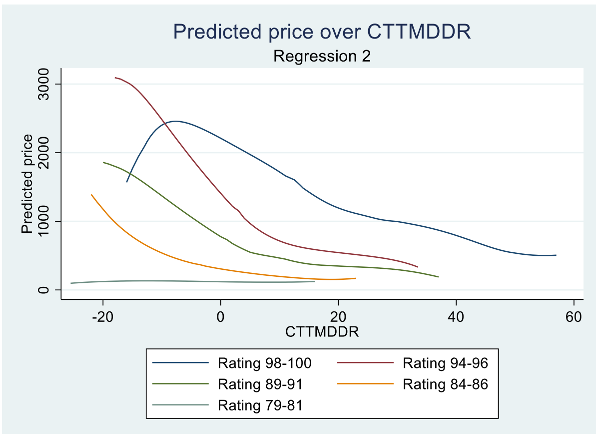

Figure 5: Predicted price over age (regression 3)

Previously, this section discussed the effect of age on the prices without considering the fixed effects included in regression (2). Figures 4 and 5 incorporate these fixed effects. They show the predicted price based on regression (2). The predicted price is plotted against age and CTTMDDR, respectively. It is noteworthy to mention that both regression formulas result in a $R^2 > 0.92$. This implies that > 92% of the variance in Ln(P_{it}) is explained by the independent variables in the regression. Also, the coefficients of the fixed effects are significant at a 1% level. These are shown in appendix E. Thus, the independent variables are considered accurate predictors. Figure 4 shows the predicted price path over age. It considers 5 rating categories (i.e., wines with a rating between 98-100, 94-96, 89-91, 84-86 and 79-81). As can be observed in the figure, the wines with the highest average predicted price comprise the category of the highest average rating and vice versa. The categorization provides, however, no statistical evidence to answer hypothesis 1. Nevertheless, the results point in the same direction.

Wines in the highest rating category are predicted to have an average price of 1100 USD when first auctioned. Until approximately 12 years old, when these wines sell on average for 1400 USD, their prices remain relatively stable. Thereafter, wines within this rating category experience large increases in price over time. At the age of 30 years, these wines are on average auctioned at 2500 USD. The starting price of the other categories is substantially lower (i.e., <500 USD). Wines within the rating category 94-96 experience near-linear price appreciations. Around the age of 30 years, they are on average auctioned at 1300 USD. Wines within the rating category 89-91 and 84-86 experience higher rates of return after the age of approximately 18 years old. Based on the figure, it is impossible to conclude if the price path is non-linear or that around 18 years, there is a breakpoint after which they experience a higher linear return. Although the categorization presented in figure 4 provides no statistical evidence for hypotheses 2A and 2B, the results contribute to a better understanding of the (non-)linear relation between age and price. Moreover, it helps to understand better why the linear and quadratic coefficients in regression (1) and (2) are significant. Based on the figure, this paper finds evidence that both the linear and quadratic effect is appropriate to describe wines with age between 5 and 30 years old. It also provides a reason to examine the interaction effects. These will be discussed in section 7.1.3.

Figure 5 is based on the same predicted price as figure 4. However, the predicted price is plotted against the CTTMDDR. It is important to note that the x-axis is mirrored. A positive CTTMDDR indicates a young wine. If a wine becomes older, the CTTMDDR decreases. A value below zero indicates that the wine is after the MDDR. Two practical issues need to be discussed. First, the x-axis ranges from -25 to 60 and is much larger than the x-axis of figure 4. Please note that irrespective of the rating category, the wines at CTTMDDR = 20 do not have the same age. In other words, the average predicted price at, for example, CTTMDDR = 20 consists of different data points than the average predicted price at 20 years old. Second, as can be observed, only wines within the highest rating category have values of CTTMDDR between 40 and 60. This is not due to a sample selection bias. As discussed in the literature review, high-quality wines have a different aging potential than low-quality wines. For high-quality wines, this implies that the TTMDDR is large. This relation is also shown in figure 2 in section 4.4 regarding the descriptive statistics. According to figure 4, wines of the lowest rating category do not experience a price increase nor decrease. In other words, their prices remain stable between 20 years before and after the MDDR. The rating categories 84-86, 89-91 and 94-96 experience exponential growth even when they passed the MDDR. This is in line with the stylized model of Dimson et al. (2015). According to their mode, wines that are not drinkable anymore can still increase because of the discounted value of lifelong storage perceiving the wine as a collectible. The rating categories 89-91 and 94-96 seem to stabilize when they are 20 years past their MDDR. The most notable price path is of the rating category 98-100. These wines show a substantial price decrease when they are passed the MDDR. Their value even drops below the value of the two lower rating categories. As emphasized earlier, this graph shows the predicted price of the age and rating variables and the fixed effects. The predicted price path shown in figures 4 and 5 represents the average of the predicted price per CTTMDDR over various rating categories. The fixed effects can cause the price path to differ from the implied price path based on the coefficients shown in table 5. Since no statistical information is provided along with these graphs, they only serve as an indication.

7.1.3 Interaction effects between the quality and age of the wine

Table 6 shows the output of regression (4) to (6) related to the interaction effects between age and the Parker rating. Regression (4) shows coefficients at a 1% significance level. This means that both the aging effect and the interaction between the average rating and age significantly affect the price. The linear coefficient implies that the return to age is on average 21.77 per year%. This coefficient is substantially higher than the return to age in regression formulas (1) to (3).

VARIABLES	(4) lnPrice	(5) lnPrice	(6) lnPrice
R_avg	**0.0973*** **	**0.0953*** **	**0.0948*** **
	(0.000915)	(0.000874)	(0.000967)
Age	**0.197*** **	**0.197*** **	**0.189*** **
	(0.00904)	(0.0120)	(0.0107)
Age^2		**-0.00261*** **	**-0.00413** **
		(0.000963)	(0.00182)
Age^3			0.000152
			(0.000127)
R_avg # Age	**-0.00184*** **	**-0.00187*** **	**-0.00180*** **
	(9.52e-05)	(0.000126)	(0.000112)
R_avg # Age^2		**3.43e-05*** **	**4.90e-05** **
		(1.03e-05)	(1.95e-05)
R_avg # Age^3			**-1.41e-06**
			(1.37e-06)
Chateau FE	Yes	Yes	Yes
Vintage FE	No	No	No
Year month of sale FE	Yes	Yes	Yes
Constant	**-3.975*** **	**-3.838*** **	**-3.780*** **
	(0.0846)	(0.0824)	(0.0960)
Observations	103,755	103,755	103,755
R-squared	0.928	0.928	0.928

Table 6: output of regression (4) to (6)

To examine the total effect of an increase in age, coefficients regarding the Parker rating and the interaction should also be considered. The small but significant negative interaction coefficient implies that the return to age is negatively affected by the Parker rating. In other words, wines with a high Parker rating experience a smaller return to age. Sub-hypothesis 2C states that the quality of the wine, measured by the Parker rating, positively influences the linear aging effect. Based on the results of regression (4), this paper rejects sub-hypothesis 2C. This implies that the quality of the wine, measured by the Parker rating, negatively affects the linear aging effect. However, the overall effect is also based on the coefficient of the Parker rating without interaction. Concerning this variable, a higher Parker rating compensates for the diminishing return to age. This indicates that there is a tradeoff. Figure 6 shows the overall effect of the coefficients regarding the Parker rating, age and the interaction effect. The wines in the graph are illustrative. As can be observed, the wines in the lowest rating category experience the highest return to age. Nevertheless, the relative prices of wines in the rating category are the highest.

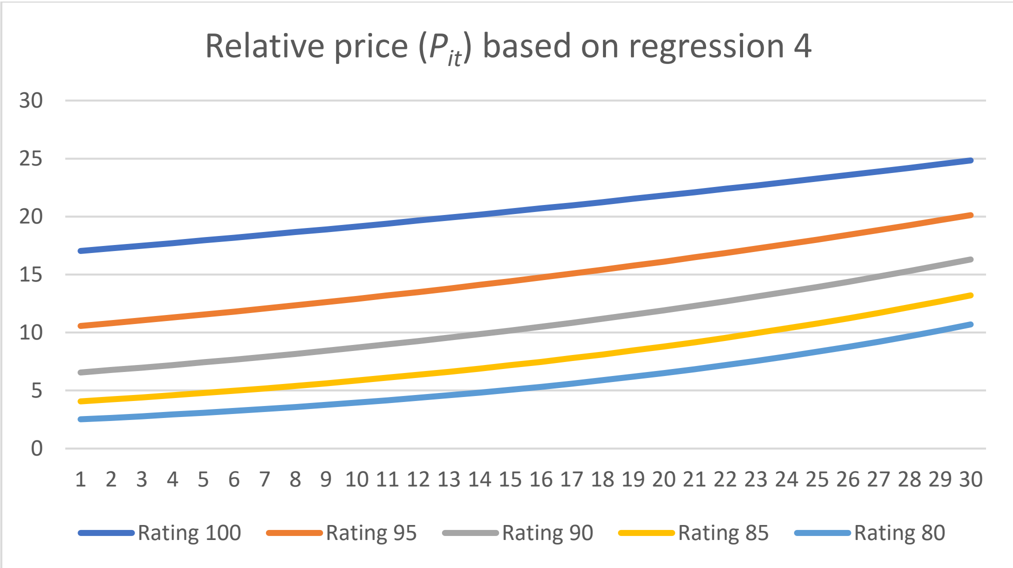

Figure 6: Relative prices based on the age and rating coefficients of regression (4)

No literature discusses regression output regarding the linear interaction effect between age and the Parker rating. Dimson et al. (2015) their paper present a stylized model that describes the price path of low- and high-quality wines. However, this stylized model does not discuss the return to specific price determinants. Appendix C shows the predicted price paths based on regression (4). As can be observed, the predicted price path is approximately similar to the predictions based on regression (2) shown in figures 4 and 5. These indicate that certain wines experience a non-linear price path.

Regression (5) examines the interaction effect between age and the Parker rating in a quadratic relationship. All coefficients in this regression are found to be significant at a 1% level. Figure 7 shows the relative price based on the coefficients of regression (5). It does not take the fixed effects into account. Sub-hypothesis 2D states that high-quality wines exhibit a concave return to age for the first 30 years, after which the price stabilizes. Based on the Robert Parker Wine Advocate rating scale, shown in appendix B, this paper defines high quality as a Parker rating above 90. Below 90 is considered low-quality. Based on the return to age of the illustrative wines with a Parker rating of 100 and 95, shown in figure 7, this paper rejects sub-hypothesis 2D. Also, the convex return to age does not indicate a potential stabilization after the age of 30. An illustrative wine with a Parker rating of 90, which can be considered as both a high- and low-quality wine, supports the rejection of sub-hypothesis 2D. Sub-hypothesis 2E states that low-quality wines experience little price appreciations over the first 30 years, after which the prices increase linearly. Based on figure 7, this paper supports the part of the hypothesis that low-quality wines experience little return to age the first 30 years. The direction of the return to age at the age of 30 years provides reason to assume that the price afterward increases linearly. Therefore, this paper supports sub-hypothesis 2D.

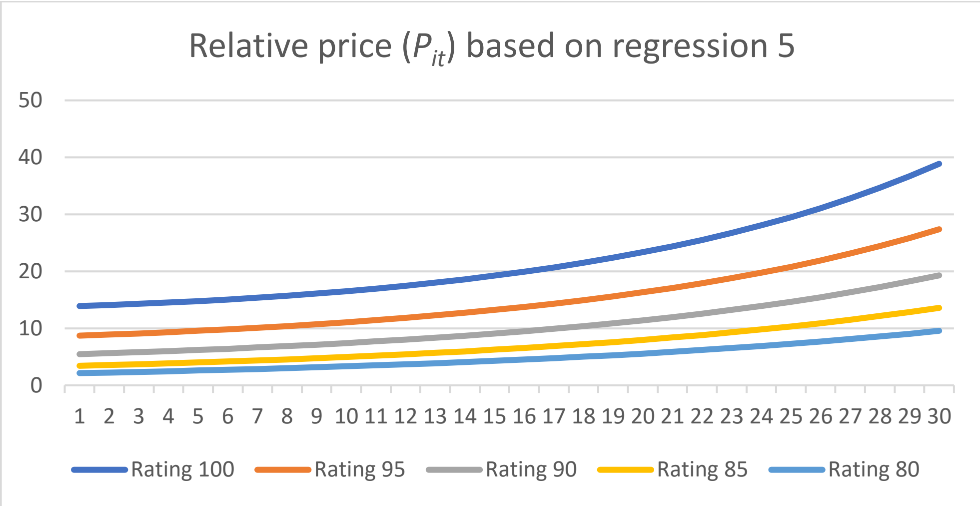

Figure 7: Relative price based on the CTTMDDR and rating coefficients of regression (5)

Figures 8 and 9 show the predicted price over age and CTTMDDR, respectively. First, this paper concludes that the figures show approximately the same price paths as figures 4 and 5. However, one major difference can be observed when comparing figures 4 and 5. Figure 6 indicates that wines in the rating category 89-91 increase in value in such a way that they are on average auctioned at higher prices than wines in the rating category 94-96. In figure 4, these wines are equally prices at the age of 30. Figures 4 and 8 are based on regression (2) and (5), respectively. Both regressions have very high R^2 values (i.e.,> 0.92) and highly significant coefficients. Therefore, it is not possible to determine which graph is more representative for the dataset.

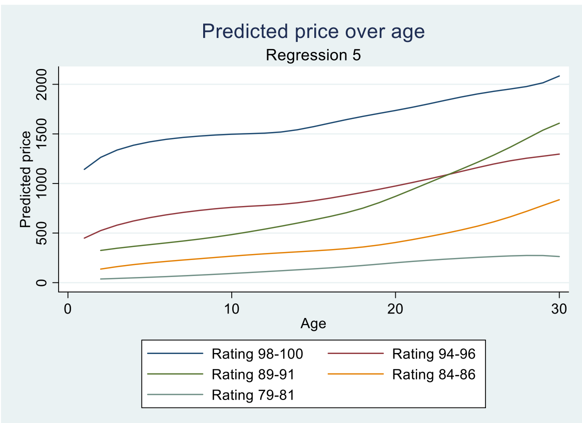

Figure 8: Predicted price over age (regression 5)

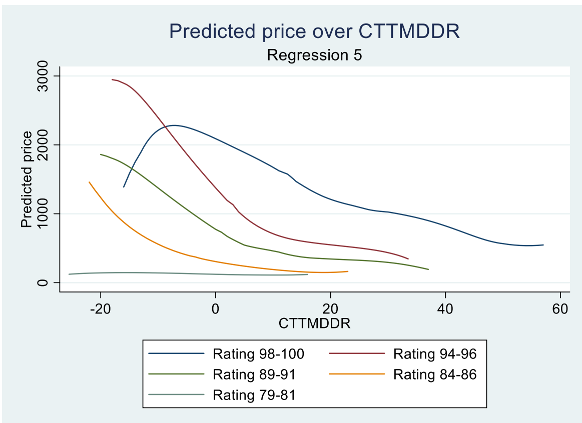

Figure 9: Predicted price over age (regression 5)

7.2 Results related to the effect of age measured by CTTMDDR, Parker rating and interaction effects

This section discusses hypotheses 1 and 3 regarding the effect of the quality of the wine indicated by the Parker rating and the interaction effects between the aging effect, measured by CTTMDDR and the quality of the wine. This section is organized as follows. At first, this section discusses the output related to the effect of the quality of the wine indicated by the Parker rating. Second, the interaction effects are discussed in section 7.2.2.

7.2.1 The effect of the Parker rating on price

The coefficients in regressions (7) and (8) of the average Parker rating indicate a significant positive relation between the quality of the wine. The results are shown in table 7. Across the two regressions, the effect differs on average from 6.07% to 6.49% per Parker-point. The effects are also significant at a 1% level. These results are lower than the results of regression (1) to (6). However, the effect is again higher than found in the literature. For the comparison with the literature, this study refers to section 7.1.1. Based on regression (7) and (8), this paper supports hypothesis 1.

6.2.2 Interaction effects between the quality and CTTMDDR of the wine

Table 7 shows the output related to the interaction effects between the age measured by CTTMDDR and the Parker rating. Both regression (7) and (8) show coefficients at a 1% significance level. This confirms that the quality of the wine, measured by the Parker rating, significantly influences the aging effect measured by CTTMDDR. This effect holds for both the CTTMDDR and the standardized CTTMDDR in regression (8) and (9), respectively. Both the linear and quadratic terms of (STD_)CTTMDDR indicate via a negative coefficient that a decrease in (STD_)CTTMDDR, which signals an increase in age, results in a price increase. The positive third-degree coefficient of (STD_)CTTMDDR has an opposite sign indicating that for large values of (STD_)CTTMDDR, the effect diminishes. Since both regressions show coefficients at a 1% significance level, this paper prefers using the CTTMDDR instead of the STD_CTTMDDR since the latter is more difficult to interpret.

VARIABLES	(7) lnPrice	(8) lnPrice
	CTTMDDR	**(STD_CTTMDDR)**
R_avg	**0.0589*** **	**0.0629*** **
	(0.000669)	(0.000706)
CTTMDDR	**-0.0682*** **	**-0.179*** **
	(0.00750)	(0.0102)
CTTMDDR2	**-0.00323*** **	**-0.0152*** **
	(0.000236)	(0.00428)
CTTMDDR3	**2.08e-05** **	**0.00197** **
	(8.43e-06)	(0.000783)
R_Avg # (STD)_CTTMDDR	**0.000715*** **	**9.58e-05*** **
	(8.00e-05)	(6.60e-06)
R_Avg # (STD)_CTTMDDR2	**4.02e-05*** **	**4.26e-06*** **
	(2.74e-06)	(2.67e-07)
R_Avg # (STD)_CTTMDDR3	**-3.28e-07*** **	**-5.72e-08*** **
	(8.53e-08)	(4.66e-09)
Chateau FE	Yes	Yes
Vintage FE	Yes	Yes
Month of sale FE	Yes	Yes
Constant	**-0.349*** **	**-0.728*** **
	(0.0622)	(0.0672)
Observations	100,447	99,616
R-squared	0.917	0.940

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Output of regression (7) to (8)

Hypothesis 3 states that the quality of the wine, measured by the Parker rating, significantly affects the return to age, measured by the (STD_)CTTMDDR. Based on the significant coefficients shown in table 6, this paper supports hypothesis 3. However, it is difficult to support or reject sub-hypothesis 3A and 3B based on the regression output. Therefore, to answer the sub-hypotheses, this paper examines Figure 8. The lines in the graph are based on the coefficients of regression formula (8) without considering the fixed effects. Figure 5 shows illustrative wines with ratings varying between 100 and 80. During the first 20 years, wines with a rating higher rating experience a higher return to CTTMDDR. This is especially pronounced for the illustrative wines with a Parker rating of 100 and 95 and 90. After 10-20 years, both wines with a Parker rating of 100 and 95 decreases in value while the value of the wine with a Parker rating of 90 clearly stabilizes. The wines of the lowest two rating categories show an equal price path. The relative prices show a more linear price increase both before and after the MDDR. This figure also shows that wines with a higher Parker rating have a relatively higher price. This also supports hypothesis 1 regarding the positive effect of the quality of the wine, indicated by the Parker rating and on the price.

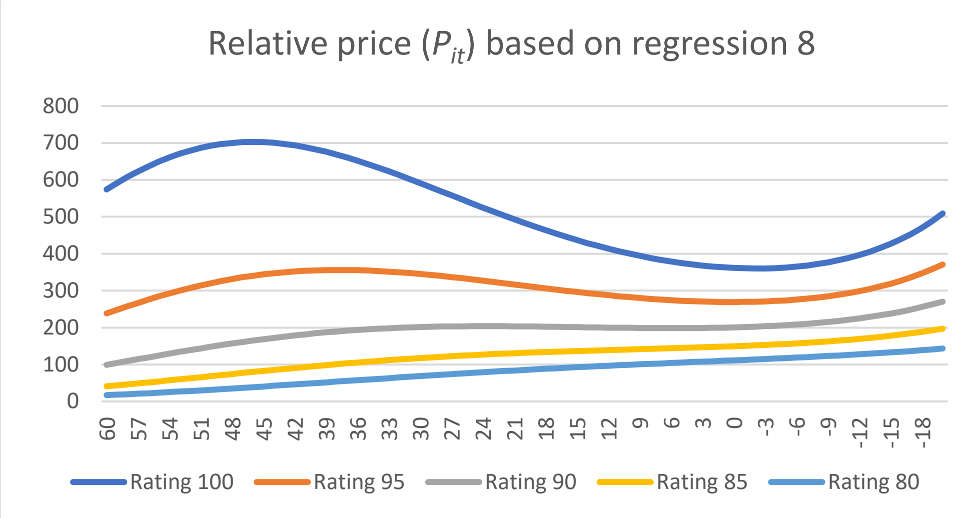

Figure 10: Relative price based on the CTTMDDR and rating coefficients of regression (8)

Hypothesis 3 states that the quality of the wine, measured by the Parker rating, significantly affects the return to age, measured by the (STD_)CTTMDDR. Based on the significant coefficients shown in table 6, this paper supports hypothesis 3. However, it is difficult to support or reject sub-hypothesis 3A and 3B based on the regression output. Therefore, to answer the sub-hypotheses, this paper examines Figure 10. The lines in the graph are based on the coefficients of regression formula (8) without considering the fixed effects. Figure 10 shows illustrative wines with ratings varying between 100 and 80. During the first 20 years, wines with a rating higher rating experience a higher return to CTTMDDR. This is especially pronounced for the illustrative wines with a Parker rating of 100 and 95 and 90. After 10-20 years, both wines with a Parker rating of 100 and 95 decreases in value while the value of the wine with a Parker rating of 90 clearly stabilizes. The wines of the lowest two rating categories show an equal price path. The relative prices show a more linear price increase both before and after the MDDR. This figure also shows that wines with a higher Parker rating have a relatively higher price. This also supports hypothesis 1 regarding the positive effect of the quality of the wine, indicated by the Parker rating and on the price.

To recall, hypothesis 3 is based on the findings of Dimson et al. (2015. They find that high-quality wines experience large price increases while they mature and stabilize after approximately 30 years. Thereafter the prices increase again when the wine becomes antique, and the value represents the discounted value of lifelong storage perceiving the wine as a collectible.). Sub-hypothesis 3A relates to high-quality wines. It states that high-quality wines experience a concave return to CTTMDRR until the price stabilizes around the MDDR, after which the price increases again. The findings of this study regarding high-quality wines (i.e., Parker rating > 90) in the perspective of sub-hypothesis 3A are ambiguous. Based on the illustrative wine with a Parker rating of 90, this paper would support sub-hypothesis 3A. However, the return to CTTMDDR of illustrative wines with a Parker rating of 100 and

95 provides evidence to reject sub-hypothesis 3A. These wines show a decrease in the price instead of stabilization. Both findings considered, this paper rejects sub-hypothesis 3A. Since the paper of Dimson et al. (2015) considers only two categories (i.e., high and low-quality wines) and uses age instead of CTTMDDR in their analysis, our results can not disprove their findings. In the meantime, it provides a reason to further examine the relation between CTTMDDR and the price. Sub-hypothesis 3B relates to low-quality wines. Dimson et al. (2015) find that wines low-quality wines (i.e., a Parker rating < 90) experience little price increases in the first years and show near-linear price increases thereafter. The two illustrative wines with a Parker rating below 90 exhibits a highly comparable price path. This paper therefore supports sub-hypothesis 3B.

Figures 11 and 12 show the predicted price paths based on regression (7) and plot them against the age and CTTMDDR. Referring to figure X, these graphs also include the fixed effects. As can be observed, these figures correspond to a very high extent with figures 6 and 7. For discussion of these graphs, this paper refers to section 7.1.3.

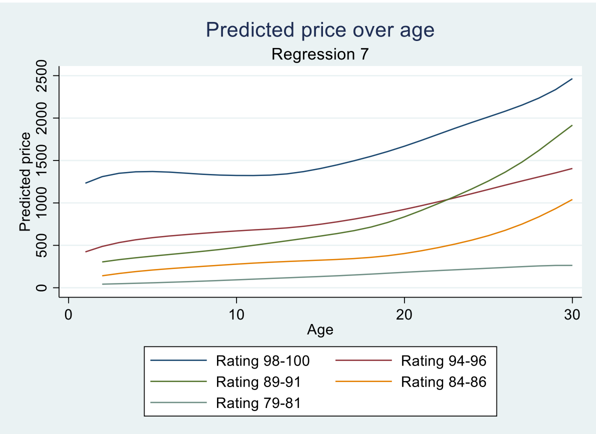

Figure 11: Predicted price over age (regression 7)

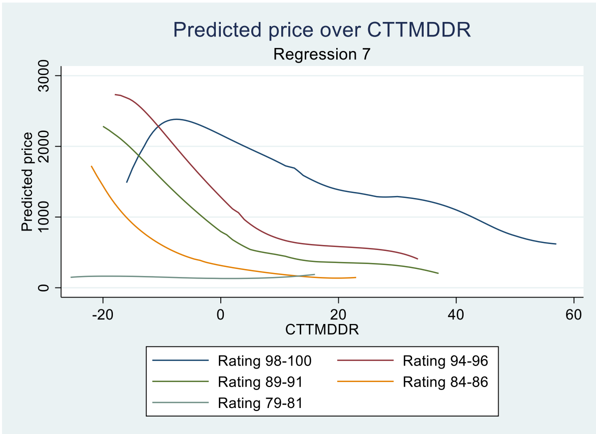

Figure 12: Predicted price over age (regression 7)

7.3 Robustness check

This section discusses the robustness check of regression (1), (2), (4), (5) and (7). In case the residuals of the regression formula are correlated with each other, the OLS standard errors will be biased. The dataset used in this analysis consists of approximately 103,000 price observations for 1,182 unique wines and thus can be considered as panel data. Regressions on this type of data often result in biased standard errors. This is the case if observations in the dataset are correlated. In other words, this happens when a time effect (e.g., the current year of the observation) or the effect of a chateau (e.g., wines of the Chateau Margaux) is similar for groups of observations within clusters. In practice, this is, for example, the case if the aging effect depends on a certain cluster of wines. The aging effect can also have a different impact over time. Incorrect standard errors violate the assumption of the OLS regression. Therefore, this paper verifies the results by clustering the standard errors over various id and time factors, including the year of sale, year month of sale, the chateau and the chateau and vintage year. The results are shown in appendix D.

Concerning regression (1), (2) and (4), the results indicate that the coefficients are significant at a 1% level at each of the specifications of the clustered standard errors. It can be observed that the standard errors clustered by the year month are the lowest. Clustered standard errors by year result in higher standard errors. This indicates that fixed effects in the regression formula do not control for all the non-constant chateau or time effects. In practice, this implies that a price observation in, e.g., the year 2005, has a different effect on a Mouton Rothschild than on a Margaux. The results of regression (5) and (8) presented in appendix D show significant results when the standard errors are clustered by White's standard errors, year and year month. The results are not significant when the standard errors are clustered by chateau or chateau + vintage. This indicates that there are still certain effects per chateau and chateau + vintage that are not controlled for by the fixed effects in the regression formula, leading to biased standard errors.

8. Limitation and discussion

The price data is derived from the Wine Market Journal database. The database includes worldwide price observations, both of physical auctions and online auctions of the major auction houses. It is, however, impossible to determine if the database contains price observations of all the auctions that took place. It is possible that some auctions are not included in the database. There exists a scenario in which a large number of auctions are not represented in the database. The conclusion of this paper is mainly focused on the price observations in our dataset. A conclusion of the price determinants regarding wines, in general, should be applied with caution. However, the worldwide auction market, including online auctions, can be considered a competitive market, an argument in favor of extrapolating the conclusion to price observations outside of the dataset.

Furthermore, this paper analyzes the average monthly prices. Hence, it is difficult to determine if certain monthly average price observations are an outlier since there is no information about the number of observations that comprise the monthly average. This paper has therefore not performed an outlier analysis. Other research papers (e.g., Cardebat et al. (2017)) incorporate price observations on a single transaction level. This provides the possibility to perform an outlier analysis. This paper assumes that outliers are likely since the price an investor is willingness-to-pay depends on the observable price determinants and other factors, including the composition of their collection. For example, suppose a wine collector misses one particular wine to complete his collection (e.g., all vintages of the wine Mouton Rothschild). In that case, this investor is likely to have a substantially higher willingness to pay than a wine consumer. Furthermore, the use of price observations in a single provides the possibility to control for transaction factors that are found to be significant (Cardebat et al. (2017) and Masset et al. (2015)). These effects are not considered in our analysis. Further research on our topic should be based on price observations on a transactional level and incorporate these effects.

This paper bases the quality of the wine only on the Parker rating. There are other established wine review databases, including The Wine Spectator. Further research should also examine other sources of subjective quality measures. In case of a significant discrepancy, further research is necessary. Nevertheless, the potential endogeneity problems will still be present. Another limitation of the Robert Parker database is that the ratings can slightly differ per tasting note. Certain high-quality wines entail more than five tasting notes, of which the Parker rating and the MDDR can slightly differ. This paper has not performed any corrections regarding this issue. At each price observation, it attached the Parker rating and MDDR of the most recent tasting note.

The extension of this paper is based on the optimal drink date presented in each tasting note. The optimal drink date is an estimation that is sometimes published more than 40 years before the MDDR. The Robert Parker Wine Advocate does not publish any information about the accuracy of their estimations. A wide range can signal uncertainty. Nevertheless, the results regarding the CTTMDDR are significant in our analysis. This paper has the following recommendation for further regarding this variable. First, oenological research concerning drinkability should be performed. Based on a large set of (non-)drinkable wines and consumer preferences, a relation between chemical aspects and drinkability can be quantified. This provides the possibility to apply the knowledge regarding chemical substances and drinkability on young wines and estimate their optimal drink date. The estimated optimal drink date can thereafter be used as independent variable in the hedonic regression. This methodology provides a more objective measure of drinkability.

9. Conclusion

Understanding price determinants of fine wines is increasingly important for both fine wine investors and consumers. Investors seeking diversification benefits need to understand the price dynamics of fine wines. Especially the predicted price paths over age and CTTMDDR provide insights into the price behavior of fine wines. Furthermore, fine wine consumers and collectors need quantitative models to produce a reliable valuation of auctioned fine wines.

This study examines approximately 103,000 monthly price observations of fine wines of the French regions Bordeaux, Burgundy and Rhône between 1997 and 2020. It considers vintages between 1990 and 2015. The use of hedonic regressions provides insight into the effect of the quality of the wine, measured by the Parker rating, the return to age, measured in years and CTTMDDR and interaction effects. The conclusion of the results is as follows.

The results indicate a positive relation between the Parker rating and the price when controlled for various fixed effects as well as the age, CTTMDR and interaction effects. This paper supports the hypothesis that the quality of the wine, measured by the Parker rating, positively affects the price. In practice, this implies that high-quality wines are, on average, more expensive. This result is robust to various model specifications.

Furthermore, this study examines the effect of aging. The results indicate a significant positive return to age both in the linear and quadratic function of age. Therefore, sub-hypothesis 2A concerning the linearly positive effect is supported. However, this paper finds no evidence for a concave return to age concerning wines between the age of 0 and 30. Therefore, it rejects sub-hypothesis 2B. On the other hand, it finds significant evidence for a convex return to age. These results only apply to wine between the age of 0 and 30. The predicted price paths plotted against the age based on the regression formulas that contributed to answering sub-hypothesis 2A and 2B confirm our findings. The predicted price paths plotted against the CTTMDDR confirm the linear and quadratic relation between age, measured in CTTMDDR and the price. However, wines in the highest rating category exhibit a different price path. Their predicted prices indicate a price decrease after the MDDR. Further statistical research must be performed to examine the statistical relevance of this predicted price path. This study also finds significant interaction effects between the age and the quality of the wine, measured by the Parker rating. The results indicate that high-quality wines exhibit a convex return to age for the first 30 years. The direction of the price increase does not suggest that the prices stabilize around the age of 30 years. This study, therefore, rejects sub-hypothesis 2D. Low-quality wines experience little return to age the first 30 years, after which the prices increase linearly. This lead to the support of sub-hypothesis 2E. In practice, this implies that high-quality wines experience a more positive return to age than low-quality wines.

At last, this study examined the return to CTTMDDR and the interaction effect with the quality of the wine, measured by the Parker rating. For both the CTTMDDR and the STD_CTTMDDR, this study finds highly significant results. This leads to the support of hypothesis 3. The findings of this study concerning high-quality wines and the return to CTTMDDR and the interaction effects are ambiguous. High-quality wines with a Parker rating seem to decrease in value around the MDDR. However, the results concerning high-quality wines with a Parker rating between 90 and 95 support sub-hypothesis 3A. The results indicate that low-quality wines experience little price appreciations until the MDDR, after which the prices increase linearly. This outcome leads to the support of sub-hypothesis 3B.

The significant findings regarding this new variable can greatly impact the literature concerning price determinants of fine wines. To date, the literature has only examined the return to age across different rating categories. These studies do not consider that wines within the same rating category can have different values for TTMDDR. This can result in a biased measure of age. The CTTMDDR variable provides an outcome. As is discussed in the previous section, this paper recommends performing further research on the drinkability of fine wines to quantify the TTMDDR based on objective oenological measures.

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Appendix A: Overview of relevant literature

AUTHOR	YEAR	R^2	REGION	WINERIES	TYPE	VINTAGES	PRICE GRANULARITY	SOURCE	DEPENDENT VARIABLES USED IN MODEL SPECIFICATION	
CARDEBAT	2017	0.74	Bordeaux (France)	5	IG	1945 - 2009	Yearly average	Auction	Objective	Year of sale, age, lot size, case size, vintage, chateau and city, company the auction took place;
									Subjective	Parker rating
									Sensory	None
DIMSON ET AL.	2015	0.74	Bordeaux (France)	5	IG	1900-2012	Quarterly average	Auction	Objective	Year of sale, age, chateau, weather/wine quality, production yield, dealer + interaction terms
									Subjective	None
									Sensory	None
MASSET ET AL.	2016	0.87	Bordeaux (France)	14	IG	1945-2009	Price per transaction	Auction	Objective	Year of sale, lot size, case size, vintage, chateau, auction house and location and interaction terms
									Subjective	Parker rating
									Sensory	None
DI VITTORIO AND GINSBURGH	1996	0.90	Bordeaux (France)	60	IG + HEFW	1949-1989	Price per transaction	Auction	Objective	Year of sale, age, lot size, case size, bottle size, vintage, chateau, weather conditions
									Subjective	None
									Sensory	None
	1995	0.83		14	IG			Auction	Objective	Age, weather conditions

ASHENFELTER ET AL.			Bordeaux France			1960-1969	Price per transaction		Subjective	None
									Sensory	None
JONES AND STORCHMANN	2001	na	Bordeaux (France)	21	IG	1980-1994			Objective	Age, Chateau, Grape composition
									Subjective	Parker Points
									Sensory	
COMBRIS ET AL.	1997	0.66	Bordeaux (France)	na	All	na	na	Experimental study	Objective	Ranking, color vintage, chateau, group
									Subjective	Jury rating
									Sensory	Including finesse and complexity of aromas, harmony between components and finish
COMBRIS ET AL.	2000	0.61	Burgundy (France)	na	All	na	na	Experimenta l study	Objective	Ranking, color and vintage
									Subjective	Jury rating
									Sensory	Including finesse and complexity of aromas, harmony between components and finish
WOOD AND ANDERSON	2006	0.80	Australia	3	HEFW	Various	Price per transaction	Auction	Objective	Age, weather variables including temperature, wind, rain, sun hours
									Subjective	None
									Sensory	None
FOGARTY	2005	0.92	Australia	84	HEFW	1965-2000	Quarterly average	Auction	Objective	Year of sale, vintage and a brand variable
									Subjective	None
									Sensory	None
BYRON AND ASHENFELTER	1995	0.84	Australian	13	HEFW + Table	Various	Price per transaction	Auction	Objective	Age and weather variables
									Subjective	None
									Sensory	None

Appendix B: The Wine Advocate Rating System

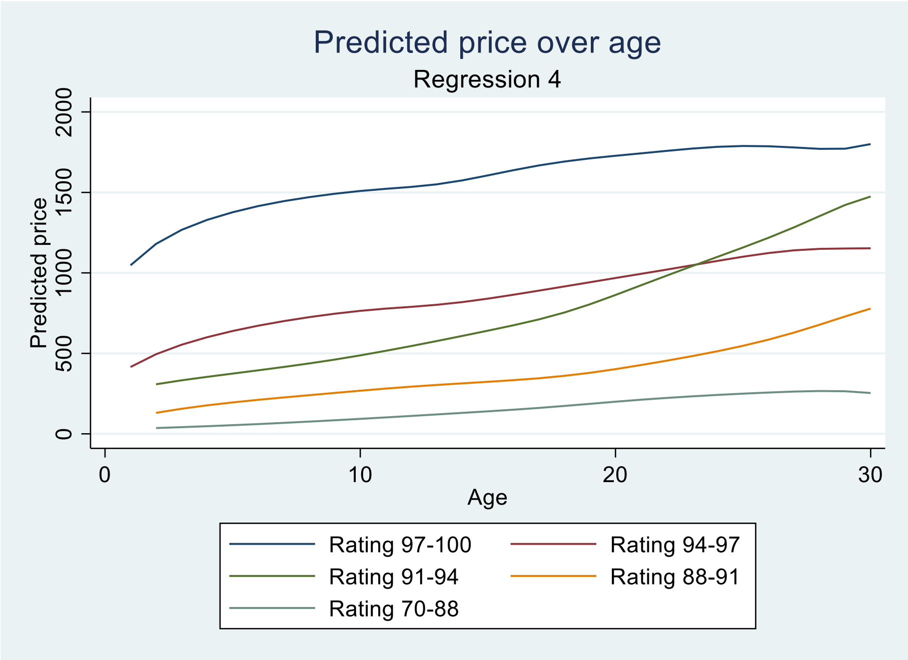
Throughout the database, each rating is based on this rating system. The rating system entails a 100-point scale in which wines can be rated from 50 to 100 points. Compared to other rating systems that use a 20-point scale, the TWA Rating system provides more room for accuracy. *As a result, the Wine Advocate* claims to be the industry's standard. Please find in the table below the rating system and the correlation between the scores and the assessments.

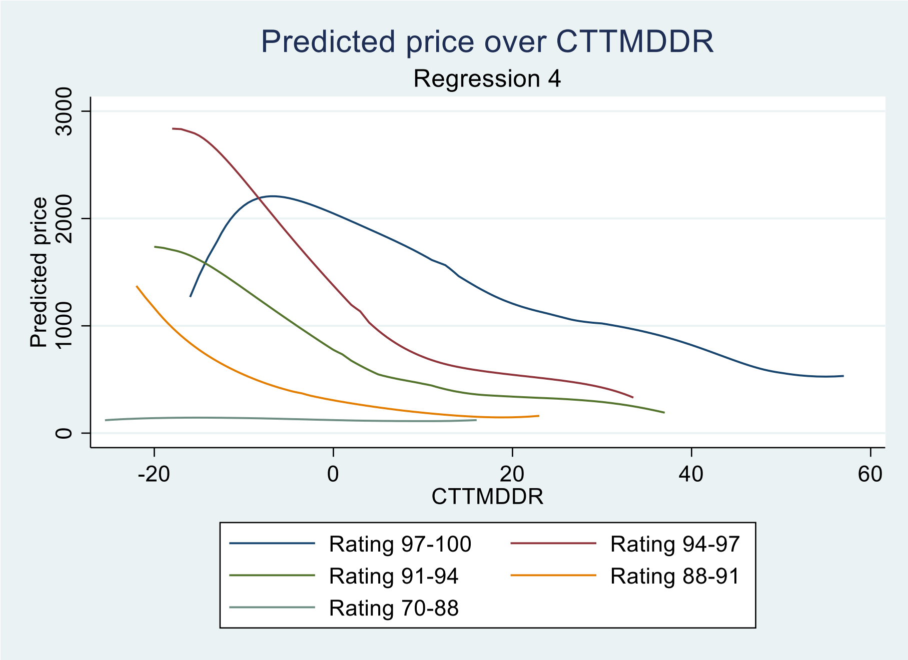
Score	Assessment
96-100	An **extraordinary** wine of profound and complex character displaying all the attributes expected of a classic wine of its variety. Wines of this caliber are worth a special effort to find, purchase and consume.
90-95	An **outstanding** wine of exceptional complexity and character. In short, these are terrific wines.
80-89	A **barely above average to very good** wine displaying various degrees of finesse and flavor as well as character with no noticeable flaws.
70-79	An **average** wine with little distinction except that it is soundly made. In essence, a straight forward, innocuous wine.
60-69	A **below average** wine containing noticeable deficiencies, such as excessive acidity and/or tannin, an absence of flavor or possibly dirty aromas or flavors.
50-59	A wine deemed to be unacceptable.

Apart from a numerical part of the rating, the TWA Rating System also provides symbols that can accompany the scores. A score placed in parentheses, i.e., "(90 - 93)," indicates that the wine is tasted from the barrel and signals the estimated range for when the wine is bottled. Parentheses or a single score combined with a plus sign, i.e., "92+" or "(90 - 93)," indicates that the reviewer believes the wine will improve and rated higher the next tasting. Besides, a plus sign can also be accompanied by a single numerical score. Wines can, in some cases, also be rated with a question mark when the wine was faulty or showing unusual characteristics. In such cases, further tasting is required. Many of the wines are tasted and rated more than once. The following score represents a cumulative average of the wine performance in tastings to date. This implies that the actual rating is higher than denoted because prior ratings are also considered. At last, some bottles which are arguably not drinkable anymore will receive no score.

Relating to the scope of this research, the most important aspect entails the fact that reviewers rate wines vis-à-vis its peer group based on, for example style, region or grape variety. The rationale behind this comes down to the basic rule not to compare apples with pears.

Appendix C: Predicted price path of regression (4)





Appendix D: Robustness check

The table below shows the output of the regressions (1) - (2), (4) – (5) and (8) using various (clustered) standard errors. The first column reports the White standard errors. The other columns report the clustered standard errors clustered by year, year-month, chateau and chateau + vintage, respectively.

Clustered Standard errors

	White	**Year**	**YM**	**Chateau**	**Chateau + Vintage**
Regression 1					
R_avg	**0.0939*****	**0.0939*****	**0.0939*****	**0.0939*****	**0.0939*****
	(0.000419)	(0.00338)	(0.00106)	(0.00392)	(0.00392)
Age	0.0237***	0.0237***	0.0237***	0.0237***	0.0237***
	(0.000198)	(0.000825)	(0.000314)	(0.00152)	(0.00152)
Regression 2					
R_avg	**0.0934*****	**0.0934*****	**0.0934*****	**0.0934*****	**0.0934*****
	(0.000416)	(0.00335)	(0.00105)	(0.00386)	(0.00386)
Age	**0.0213*****	**0.0213*****	**0.0213*****	**0.0213*****	**0.0213*****
	(0.000214)	(0.00141)	(0.000471)	(0.00150)	(0.00150)
Age2	**0.000741*****	**0.000741*****	**0.000741*****	**0.000741*****	**0.000741*****
	(2.74e-05)	(0.000105)	(4.26e-05)	(0.000140)	(0.000140)
Regression 4					
R_avg	**0.0973*****	**0.0973*****	**0.0973*****	**0.0973*****	**0.0973*****
	(0.000413)	(0.00268)	(0.000915)	(0.00351)	(0.00351)
Age	**0.197*****	**0.197*****	**0.197*****	**0.197*****	**0.197*****
	(0.00517)	(0.0230)	(0.00904)	(0.0307)	(0.0307)
R_avg # age	**-0.00184*****	**-0.00184*****	**-0.00184*****	**-0.00184*****	**-0.00184*****
	(5.49e-05)	(0.000241)	(9.52e-05)	(0.000329)	(0.000329)

Regression 5	White	Year	YM	Chateau	Chateau + Vintage
R_avg	**0.0953*****	**0.0953*****	**0.0953*****	**0.0953*****	**0.0953*****
	(0.000530)	(0.00257)	(0.000874)	(0.00390)	(0.00390)
age	**0.197*****	**0.197*****	**0.197*****	**0.197*****	**0.197*****
	(0.00628)	(0.0285)	(0.0120)	(0.0338)	(0.0338)
age2	**-0.00261*****	**-0.00261**	**-0.00261*****	**-0.00261**	**-0.00261**
	(0.000735)	(0.00182)	(0.000963)	(0.00259)	(0.00259)
R_avg # age	**-0.00187*****	**-0.00187*****	**-0.00187*****	**-0.00187*****	**-0.00187*****
	(6.66e-05)	(0.000297)	(0.000126)	(0.000360)	(0.000360)
R_avg # age2	**3.43e-05*****	**3.43e-05***	**3.43e-05*****	**3.43e-05**	**3.43e-05**
	(7.81e-06)	(1.93e-05)	(1.03e-05)	(2.77e-05)	(2.77e-05)
Regression 8					
R_avg	**0.0589*****	**0.0589*****	**0.0589*****	**0.0589*****	**0.0589*****
	(0.000583)	(0.00163)	(0.000669)	(0.00407)	(0.00407)
CTTMDDR	**-0.0682*****	**-0.0682*****	**-0.0682*****	**-0.0682****	**-0.0682****
	(0.00557)	(0.0180)	(0.00750)	(0.0334)	(0.0334)
CTTMDDR2	**-0.00323*****	**-0.00323*****	**-0.00323*****	**-0.00323****	**-0.00323****
	(0.000249)	(0.000395)	(0.000236)	(0.00128)	(0.00128)
CTTMDDR3	**2.08e-05****	**2.08e-05**	**2.08e-05****	**2.08e-05**	**2.08e-05**
	(8.39e-06)	(1.74e-05)	(8.43e-06)	(3.88e-05)	(3.88e-05)
R_avg # CTTMDDR	**0.000715*****	**0.000715*****	**0.000715*****	**0.000715****	**0.000715****
	(5.99e-05)	(0.000189)	(8.00e-05)	(0.000361)	(0.000361)
R_avg # CTTMDDR2	**4.02e-05*****	**4.02e-05*****	**4.02e-05*****	**4.02e-05*****	**4.02e-05*****
	(2.78e-06)	(4.81e-06)	(2.74e-06)	(1.45e-05)	(1.45e-05)
R_avg # CTTMDDR3	**-3.28e-07*****	**-3.28e-07***	**-3.28e-07*****	**-3.28e-07**	**-3.28e-07**
	(8.43e-08)	(1.80e-07)	(8.53e-08)	(3.94e-07)	(3.94e-07)

Appendix E: Results including fixed effects

VARIABLES	(1) lnPrice	(2) lnPrice	(3) lnPrice	(4) lnPrice	(5) lnPrice	(6) lnPrice	(7) lnPrice	(8) lnPrice
R_avg	0.0939***	0.0934***	0.0934***	0.0973***	0.0953***	0.0948***	0.0589***	0.0629***
	(0.00106)	(0.00105)	(0.00108)	(0.000915)	(0.000874)	(0.000967)	(0.000669)	(0.000706)
agec	0.0237***	0.0213***	0.0208***	0.197***	0.197***	0.189***		
	(0.000314)	(0.000471)	(0.000928)	(0.00904)	(0.0120)	(0.0107)		
age2c		0.000741***	0.000693***		-0.00261***	-0.00413**		
		(4.26e-05)	(8.09e-05)		(0.000963)	(0.00182)		
age3c			6.77e-06			0.000152		
			(8.05e-06)			(0.000127)		
R_avg_agec				-0.00184***	-0.00187***	-0.00180***		
				(9.52e-05)	(0.000126)	(0.000112)		
R_avg_age2					3.43e-05***	4.90e-05**		
					(1.03e-05)	(1.95e-05)		
R_avg_age3						-1.41e-06		
						(1.37e-06)		
CTTMDDR							-0.0682***	-0.179***
							(0.00750)	(0.0102)
CTTMDDR2							-0.00323***	-0.0152***
							(0.000236)	(0.00428)
CTTMDDR3							2.08e-05**	0.00197**
							(8.43e-06)	(0.000783)
R_avg_(STD_)CTTMDDR							0.000715***	9.58e-05***
							(8.00e-05)	(6.60e-06)
R_avg_(STD_)CTTMDDR2							4.02e-05***	4.26e-06***
							(2.74e-06)	(2.67e-07)
R_avg_(STD_)CTTMDDR3							-3.28e-07***	-5.72e-08***
							(8.53e-08)	(4.66e-09)
2. Ausone	0.753***	0.754***	0.754***	0.733***	0.736***	0.735***	0.638***	0.603***
	(0.0167)	(0.0166)	(0.0166)	(0.0158)	(0.0157)	(0.0158)	(0.0118)	(0.0112)
3. Beaucastel Chateauneuf du Pape	-0.984***	-0.986***	-0.986***	-0.987***	-0.988***	-0.988***	-0.988***	-0.995***
	(0.0202)	(0.0202)	(0.0203)	(0.0200)	(0.0200)	(0.0201)	(0.0203)	(0.0201)
4. Beychevelle	-0.480***	-0.482***	-0.483***	-0.472***	-0.475***	-0.476***	-0.710***	-0.704***
	(0.0229)	(0.0229)	(0.0231)	(0.0233)	(0.0233)	(0.0235)	(0.0178)	(0.0186)
5. Calon Segur	-0.737***	-0.738***	-0.738***	-0.729***	-0.730***	-0.730***	-0.844***	-0.877***
	(0.0170)	(0.0168)	(0.0168)	(0.0168)	(0.0167)	(0.0167)	(0.0147)	(0.0141)
6. Carruades de Lafite	0.370***	0.368***	0.368***	0.383***	0.380***	0.380***	0.202***	0.210***
	(0.0300)	(0.0299)	(0.0299)	(0.0306)	(0.0306)	(0.0306)	(0.0316)	(0.0316)

7. Cheval Blanc	0.708***	0.706***	0.707***	0.704***	0.703***	0.703***	0.685***	0.681***
	(0.0123)	(0.0124)	(0.0123)	(0.0124)	(0.0125)	(0.0125)	(0.0121)	(0.0124)
8. Cos d`Estournel	-0.485***	-0.486***	-0.486***	-0.486***	-0.488***	-0.488***	-0.508***	-0.510***
	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0130)	(0.0130)	(0.0132)	(0.0130)
9. DRC Echezeaux	1.696***	1.688***	1.688***	1.706***	1.699***	1.699***	1.617***	1.618***
	(0.0268)	(0.0267)	(0.0267)	(0.0272)	(0.0271)	(0.0271)	(0.0268)	(0.0270)
10. DRC Grands Echezeaux	1.761***	1.755***	1.755***	1.765***	1.760***	1.759***	1.712***	1.718***
	(0.0238)	(0.0236)	(0.0236)	(0.0239)	(0.0237)	(0.0237)	(0.0230)	(0.0228)
11. DRC La Tache	2.285***	2.280***	2.280***	2.276***	2.272***	2.272***	2.291***	2.290***
	(0.0188)	(0.0185)	(0.0186)	(0.0184)	(0.0183)	(0.0183)	(0.0187)	(0.0186)
12. DRC Montrachet	2.765***	2.763***	2.763***	2.756***	2.755***	2.755***	2.801***	2.764***
	(0.0168)	(0.0167)	(0.0168)	(0.0170)	(0.0169)	(0.0170)	(0.0163)	(0.0155)
13. DRC Richebourg	1.910***	1.904***	1.904***	1.907***	1.902***	1.902***	1.906***	1.915***
	(0.0195)	(0.0192)	(0.0193)	(0.0194)	(0.0192)	(0.0192)	(0.0185)	(0.0181)
14. DRC Romanee Conti	3.708***	3.703***	3.703***	3.695***	3.691***	3.691***	3.777***	3.780***
	(0.0172)	(0.0169)	(0.0170)	(0.0169)	(0.0167)	(0.0168)	(0.0158)	(0.0154)
15. DRC Romanee St. Vivant Marey Monge	1.802***	1.795***	1.795***	1.799***	1.793***	1.793***	1.750***	1.752***
	(0.0172)	(0.0172)	(0.0172)	(0.0173)	(0.0173)	(0.0172)	(0.0198)	(0.0195)
16. Ducru Beaucaillou	-0.488***	-0.488***	-0.488***	-0.493***	-0.493***	-0.493***	-0.531***	-0.532***
	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0115)	(0.0107)	(0.0106)
17. Duhart Milon	-0.821***	-0.824***	-0.824***	-0.818***	-0.821***	-0.822***	-0.926***	-0.925***
	(0.0246)	(0.0245)	(0.0246)	(0.0249)	(0.0248)	(0.0250)	(0.0235)	(0.0237)
18. Georges Roumier Bonnes Mares	1.431***	1.426***	1.426***	1.427***	1.423***	1.423***	1.363***	1.361***
	(0.0198)	(0.0197)	(0.0197)	(0.0199)	(0.0198)	(0.0198)	(0.0202)	(0.0201)
19. Grand Puy Lacoste	-0.849***	-0.849***	-0.849***	-0.836***	-0.838***	-0.838***	-0.911***	-0.916***
	(0.0176)	(0.0176)	(0.0176)	(0.0173)	(0.0175)	(0.0175)	(0.0181)	(0.0181)
20. Gruaud Larose	-0.718***	-0.720***	-0.720***	-0.705***	-0.708***	-0.708***	-0.855***	-0.848***
	(0.0186)	(0.0185)	(0.0186)	(0.0186)	(0.0187)	(0.0188)	(0.0181)	(0.0186)
21. Guigal Cote Rotie La Mouline	0.216***	0.218***	0.218***	0.215***	0.217***	0.217***	0.347***	0.340***
	(0.0197)	(0.0198)	(0.0198)	(0.0192)	(0.0194)	(0.0194)	(0.0247)	(0.0246)
22. Haut Brion	0.456***	0.454***	0.454***	0.451***	0.449***	0.450***	0.474***	0.464***
	(0.00899)	(0.00907)	(0.00899)	(0.00904)	(0.00912)	(0.00907)	(0.00965)	(0.00961)
23. J.L. Chave Hermitage	0.00380	0.00154	0.00162	-0.00189	-0.00368	-0.00366	0.0292**	0.0207*
	(0.0122)	(0.0121)	(0.0121)	(0.0120)	(0.0119)	(0.0119)	(0.0117)	(0.0114)
24. Jaboulet Hermitage La Chapelle	-0.532***	-0.535***	-0.535***	-0.525***	-0.530***	-0.529***	-0.578***	-0.587***
	(0.0208)	(0.0209)	(0.0208)	(0.0210)	(0.0213)	(0.0213)	(0.0196)	(0.0194)
25. La Conseillante	-0.317***	-0.320***	-0.320***	-0.314***	-0.317***	-0.317***	-0.414***	-0.415***
	(0.0188)	(0.0189)	(0.0190)	(0.0191)	(0.0192)	(0.0193)	(0.0177)	(0.0183)
26. La Mission Haut Brion	0.0176	0.0152	0.0153	0.0171	0.0150	0.0150	-0.0214**	-0.0187*
	(0.0108)	(0.0109)	(0.0109)	(0.0110)	(0.0110)	(0.0110)	(0.0101)	(0.0101)
27. Lafite Rothschild	0.953***	0.950***	0.950***	0.938***	0.937***	0.937***	0.961***	0.936***
	(0.0188)	(0.0188)	(0.0188)	(0.0186)	(0.0187)	(0.0187)	(0.0193)	(0.0190)

28. Lafleur (Pomerol)	0.779***	0.779***	0.779***	0.777***	0.776***	0.777***	0.753***	0.740***
	(0.0159)	(0.0160)	(0.0159)	(0.0158)	(0.0159)	(0.0158)	(0.0145)	(0.0142)
29. Latour	0.693***	0.691***	0.692***	0.681***	0.681***	0.682***	0.685***	0.671***
	(0.0108)	(0.0108)	(0.0108)	(0.0106)	(0.0106)	(0.0106)	(0.0108)	(0.0106)
30. Leoville Barton	-0.765***	-0.767***	-0.767***	-0.761***	-0.763***	-0.763***	-0.825***	-0.853***
	(0.0174)	(0.0174)	(0.0174)	(0.0171)	(0.0172)	(0.0172)	(0.0162)	(0.0163)
31. Leoville Las Cases	-0.372***	-0.373***	-0.373***	-0.375***	-0.375***	-0.375***	-0.368***	-0.372***
	(0.0137)	(0.0139)	(0.0138)	(0.0135)	(0.0136)	(0.0135)	(0.0141)	(0.0143)
32. Leoville Poyferre	-0.723***	-0.724***	-0.724***	-0.724***	-0.726***	-0.726***	-0.774***	-0.779***
	(0.0181)	(0.0181)	(0.0181)	(0.0181)	(0.0180)	(0.0181)	(0.0161)	(0.0157)
33. Lynch Bages	-0.390***	-0.392***	-0.392***	-0.379***	-0.383***	-0.383***	-0.462***	-0.461***
	(0.0124)	(0.0125)	(0.0126)	(0.0124)	(0.0126)	(0.0126)	(0.0118)	(0.0119)
34. Margaux	0.620***	0.618***	0.618***	0.613***	0.612***	0.612***	0.636***	0.625***
	(0.0101)	(0.0102)	(0.0101)	(0.00992)	(0.0100)	(0.00999)	(0.0103)	(0.0103)
35. Montrose	-0.567***	-0.570***	-0.570***	-0.566***	-0.569***	-0.570***	-0.619***	-0.628***
	(0.0142)	(0.0143)	(0.0143)	(0.0141)	(0.0144)	(0.0144)	(0.0136)	(0.0140)
36. Mouton Rothschild	0.668***	0.664***	0.664***	0.653***	0.651***	0.650***	0.627***	0.620***
	(0.00934)	(0.00933)	(0.00933)	(0.00928)	(0.00930)	(0.00937)	(0.00952)	(0.00916)
37. Palmer	-0.0798***	-0.0813***	-0.0813***	-0.0857***	-0.0870***	-0.0873***	-0.151***	-0.154***
	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0110)	(0.00936)	(0.00962)
38. Pape Clement	-0.800***	-0.800***	-0.801***	-0.808***	-0.808***	-0.808***	-0.833***	-0.835***
	(0.0144)	(0.0145)	(0.0145)	(0.0147)	(0.0147)	(0.0148)	(0.0134)	(0.0135)
39. Pavie	-0.123***	-0.122***	-0.122***	-0.147***	-0.144***	-0.144***	-0.233***	-0.240***
	(0.00997)	(0.00982)	(0.00984)	(0.00987)	(0.00971)	(0.00974)	(0.00788)	(0.00816)
40. Petrus	2.019***	2.017***	2.017***	2.015***	2.014***	2.014***	2.025***	2.012***
	(0.00832)	(0.00828)	(0.00831)	(0.00844)	(0.00842)	(0.00849)	(0.00839)	(0.00874)
41. Pichon Baron	-0.552***	-0.554***	-0.554***	-0.550***	-0.553***	-0.553***	-0.606***	-0.604***
	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0124)	(0.0124)	(0.0114)	(0.0115)
42. Pichon Lalande	-0.345***	-0.347***	-0.347***	-0.355***	-0.355***	-0.356***	-0.436***	-0.442***
	(0.0176)	(0.0177)	(0.0177)	(0.0170)	(0.0170)	(0.0171)	(0.0162)	(0.0163)
43. Pontet Canet	-0.864***	-0.866***	-0.865***	-0.871***	-0.872***	-0.873***	-0.924***	-0.926***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0104)	(0.0104)	(0.00952)	(0.00908)
44. Rousseau Chambertin	1.747***	1.741***	1.741***	1.743***	1.737***	1.738***	1.726***	1.722***
	(0.0285)	(0.0282)	(0.0284)	(0.0287)	(0.0283)	(0.0285)	(0.0284)	(0.0281)
45. Rousseau Chambertin Clos de Beze	1.628***	1.621***	1.621***	1.622***	1.616***	1.616***	1.614***	1.633***
	(0.0264)	(0.0259)	(0.0260)	(0.0264)	(0.0260)	(0.0260)	(0.0268)	(0.0252)
46. Troplong Mondot	-0.851***	-0.852***	-0.852***	-0.852***	-0.854***	-0.854***	-0.878***	-0.872***
	(0.0194)	(0.0196)	(0.0196)	(0.0198)	(0.0200)	(0.0201)	(0.0189)	(0.0194)
47. Vieux Chateau Certan	-0.332***	-0.334***	-0.334***	-0.335***	-0.337***	-0.337***	-0.417***	-0.418***
	(0.0131)	(0.0132)	(0.0132)	(0.0134)	(0.0135)	(0.0135)	(0.0111)	(0.0111)
48. d`Yquem	-0.0106	-0.00913	-0.00910	-0.00993	-0.00890	-0.00899	-0.0873***	-0.125***
	(0.0175)	(0.0176)	(0.0175)	(0.0176)	(0.0176)	(0.0176)	(0.0152)	(0.0137)
49. de Vogue Musigny	0.854***	0.849***	0.849***	0.846***	0.842***	0.843***	0.864***	0.858***
	(0.0115)	(0.0118)	(0.0117)	(0.0113)	(0.0116)	(0.0115)	(0.0130)	(0.0131)
50. l`Evangile	-0.258***	-0.259***	-0.259***	-0.263***	-0.264***	-0.264***	-0.306***	-0.306***

	(0.0197)	(0.0198)	(0.0198)	(0.0197)	(0.0198)	(0.0198)	(0.0196)	(0.0198)
_IYM_458	0.0465***	0.0645***	0.0627***	0.0353***	0.0478***	0.0405***	-0.306***	-0.306***
	(0.00149)	(0.00198)	(0.00226)	(0.00159)	(0.00223)	(0.00282)	(0.0196)	(0.0198)
_IYM_461	0.0248***	0.0414***	0.0399***	-0.00954***	0.000906	-0.00650	0.0496***	0.0537***
	(0.00132)	(0.00159)	(0.00204)	(0.00280)	(0.00410)	(0.00523)	(0.00142)	(0.00131)
_IYM_464	0.127***	0.138***	0.137***	0.0989***	0.105***	0.0997***	0.0171***	0.0207***
	(0.00361)	(0.00371)	(0.00305)	(0.00396)	(0.00452)	(0.00461)	(0.00158)	(0.00136)
_IYM_467	-0.0318***	-0.0228***	-0.0235***	-0.0594***	-0.0548***	-0.0594***	0.123***	0.127***
	(0.00116)	(0.00122)	(0.00152)	(0.00232)	(0.00335)	(0.00436)	(0.00376)	(0.00348)
_IYM_470	0.0831***	0.104***	0.102***	0.0548***	0.0687***	0.0600***	-0.000503	0.00510***
	(0.00235)	(0.00274)	(0.00236)	(0.00298)	(0.00402)	(0.00468)	(0.00153)	(0.00160)
_IYM_473	0.0519***	0.0657***	0.0645***	0.0238***	0.0316***	0.0250***	0.141***	0.145***
	(0.00186)	(0.00213)	(0.00169)	(0.00254)	(0.00365)	(0.00460)	(0.00219)	(0.00186)
_IYM_476	0.0583***	0.0712***	0.0701***	0.0315***	0.0388***	0.0327***	0.102***	0.111***
	(0.00156)	(0.00175)	(0.00145)	(0.00238)	(0.00342)	(0.00438)	(0.00198)	(0.00157)
_IYM_479	-0.000184	0.0123***	0.0112***	-0.0234***	-0.0165***	-0.0226***	0.110***	0.116***
	(0.000938)	(0.00123)	(0.00164)	(0.00183)	(0.00304)	(0.00436)	(0.00200)	(0.00169)
_IYM_482	0.100***	0.123***	0.121***	0.0698***	0.0840***	0.0747***	0.0805***	0.0882***
	(0.00266)	(0.00319)	(0.00273)	(0.00321)	(0.00448)	(0.00534)	(0.00141)	(0.00135)
_IYM_485	-0.0126***	0.00696***	0.00528**	-0.0399***	-0.0275***	-0.0353***	0.186***	0.187***
	(0.00148)	(0.00201)	(0.00211)	(0.00234)	(0.00365)	(0.00469)	(0.00242)	(0.00210)
_IYM_488	0.0430***	0.0597***	0.0583***	0.0204***	0.0307***	0.0239***	0.0893***	0.0990***
	(0.00129)	(0.00168)	(0.00168)	(0.00202)	(0.00313)	(0.00408)	(0.00176)	(0.00146)
_IYM_491	-0.0446***	-0.0251***	-0.0267***	-0.0675***	-0.0551***	-0.0629***	0.147***	0.161***
	(0.00100)	(0.00163)	(0.00229)	(0.00181)	(0.00319)	(0.00455)	(0.00195)	(0.00173)
_IYM_494	0.0176***	0.0469***	0.0444***	-0.0106***	0.00840**	-0.00250	0.0569***	0.0670***
	(0.00154)	(0.00258)	(0.00334)	(0.00236)	(0.00422)	(0.00589)	(0.00181)	(0.00155)
_IYM_497	-0.0405***	-0.0144***	-0.0165***	-0.0691***	-0.0528***	-0.0627***	0.151***	0.159***
	(0.00114)	(0.00204)	(0.00294)	(0.00218)	(0.00406)	(0.00586)	(0.00194)	(0.00166)
_IYM_500	-0.0117***	0.0131***	0.0110***	-0.0401***	-0.0246***	-0.0341***	0.0920***	0.105***
	(0.00155)	(0.00228)	(0.00264)	(0.00242)	(0.00405)	(0.00549)	(0.00212)	(0.00179)
_IYM_503	-0.0156***	0.00752***	0.00568**	-0.0432***	-0.0286***	-0.0373***	0.109***	0.111***
	(0.00141)	(0.00216)	(0.00249)	(0.00227)	(0.00386)	(0.00523)	(0.00221)	(0.00182)
_IYM_506	-0.00241	0.0286***	0.0262***	-0.0351***	-0.0147***	-0.0255***	0.120***	0.131***
	(0.00264)	(0.00354)	(0.00331)	(0.00334)	(0.00497)	(0.00596)	(0.00205)	(0.00179)
_IYM_509	-0.0476***	-0.0167***	-0.0190***	-0.0826***	-0.0624***	-0.0730***	0.150***	0.155***
	(0.00158)	(0.00257)	(0.00356)	(0.00280)	(0.00486)	(0.00669)	(0.00267)	(0.00248)
_IYM_512	-0.0659***	-0.0359***	-0.0381***	-0.101***	-0.0808***	-0.0908***	0.0978***	0.110***
	(0.00214)	(0.00305)	(0.00300)	(0.00310)	(0.00488)	(0.00601)	(0.00269)	(0.00240)
_IYM_515	-0.0536***	-0.0253***	-0.0274***	-0.0865***	-0.0681***	-0.0779***	0.0891***	0.0945***
	(0.00164)	(0.00255)	(0.00295)	(0.00272)	(0.00456)	(0.00599)	(0.00250)	(0.00209)
_IYM_516	-0.0827***	-0.0356***	-0.0388***	-0.133***	-0.0997***	-0.113***	0.103***	0.116***
	(0.00525)	(0.00633)	(0.00520)	(0.00607)	(0.00782)	(0.00791)	(0.00251)	(0.00216)
_IYM_517	-0.0542***	-0.0137***	-0.0165***	-0.0992***	-0.0712***	-0.0834***	0.0527***	0.0581***
	(0.00359)	(0.00469)	(0.00411)	(0.00460)	(0.00657)	(0.00742)	(0.00464)	(0.00415)
_IYM_518	-0.0674***	-0.0267***	-0.0294***	-0.114***	-0.0861***	-0.0986***	0.101***	0.112***

	(0.00252)	(0.00362)	(0.00378)	(0.00412)	(0.00628)	(0.00770)	(0.00332)	(0.00297)
_IYM_519	-0.0803***	-0.0371***	-0.0401***	-0.127***	-0.0966***	-0.109***	0.0894***	0.0958***
	(0.00325)	(0.00440)	(0.00414)	(0.00455)	(0.00653)	(0.00747)	(0.00303)	(0.00239)
_IYM_520	-0.141***	-0.103***	-0.106***	-0.182***	-0.157***	-0.169***	0.0678***	0.0786***
	(0.00214)	(0.00324)	(0.00362)	(0.00357)	(0.00574)	(0.00728)	(0.00346)	(0.00296)
_IYM_521	-0.104***	-0.0717***	-0.0740***	-0.151***	-0.129***	-0.140***	0.0286***	0.0375***
	(0.00196)	(0.00270)	(0.00338)	(0.00388)	(0.00593)	(0.00759)	(0.00292)	(0.00230)
_IYM_522	-0.153***	-0.121***	-0.123***	-0.182***	-0.160***	-0.170***	0.0646***	0.0828***
	(0.00446)	(0.00517)	(0.00420)	(0.00469)	(0.00576)	(0.00571)	(0.00333)	(0.00262)
_IYM_524	-0.0535***	-0.0199***	-0.0222***	-0.0971***	-0.0751***	-0.0864***	0.0252***	0.0247***
	(0.00287)	(0.00378)	(0.00341)	(0.00401)	(0.00594)	(0.00713)	(0.00412)	(0.00404)
_IYM_525	-0.0555***	-0.0197***	-0.0222***	-0.101***	-0.0776***	-0.0894***	0.104***	0.112***
	(0.00315)	(0.00409)	(0.00361)	(0.00429)	(0.00630)	(0.00742)	(0.00301)	(0.00262)
_IYM_526	-0.00389	0.0288***	0.0267***	-0.0605***	-0.0398***	-0.0508***	0.0970***	0.105***
	(0.00339)	(0.00398)	(0.00326)	(0.00514)	(0.00720)	(0.00857)	(0.00312)	(0.00267)
_IYM_527	-0.00367	0.0255***	0.0235***	-0.0595***	-0.0411***	-0.0515***	0.117***	0.130***
	(0.00329)	(0.00393)	(0.00318)	(0.00494)	(0.00699)	(0.00821)	(0.00387)	(0.00314)
_IYM_528	0.00376	0.0450***	0.0423***	-0.0571***	-0.0293***	-0.0419***	0.139***	0.148***
	(0.00302)	(0.00413)	(0.00401)	(0.00516)	(0.00765)	(0.00911)	(0.00344)	(0.00279)
_IYM_529	-0.0705***	-0.0300***	-0.0326***	-0.127***	-0.0992***	-0.112***	0.175***	0.196***
	(0.00357)	(0.00459)	(0.00403)	(0.00521)	(0.00742)	(0.00853)	(0.00361)	(0.00284)
_IYM_530	0.0753***	0.113***	0.111***	0.0241***	0.0485***	0.0362***	0.134***	0.157***
	(0.00393)	(0.00492)	(0.00411)	(0.00506)	(0.00719)	(0.00821)	(0.00404)	(0.00331)
_IYM_531	0.0332***	0.0772***	0.0745***	-0.0194***	0.0106	-0.00227	0.231***	0.245***
	(0.00427)	(0.00543)	(0.00452)	(0.00546)	(0.00764)	(0.00843)	(0.00396)	(0.00357)
_IYM_532	0.0120***	0.0520***	0.0495***	-0.0436***	-0.0163**	-0.0283***	0.192***	0.203***
	(0.00304)	(0.00418)	(0.00392)	(0.00478)	(0.00712)	(0.00843)	(0.00407)	(0.00335)
_IYM_533	0.0585***	0.0994***	0.0967***	0.00735	0.0346***	0.0220***	0.177***	0.189***
	(0.00407)	(0.00516)	(0.00437)	(0.00517)	(0.00731)	(0.00817)	(0.00351)	(0.00283)
_IYM_534	5.93e-05	0.0361***	0.0336***	-0.0600***	-0.0361***	-0.0482***	0.227***	0.242***
	(0.00455)	(0.00516)	(0.00410)	(0.00606)	(0.00799)	(0.00881)	(0.00410)	(0.00360)
_IYM_536	-0.0293***	0.00715**	0.00477	-0.0811***	-0.0570***	-0.0685***	0.164***	0.177***
	(0.00259)	(0.00363)	(0.00359)	(0.00435)	(0.00667)	(0.00815)	(0.00477)	(0.00398)
_IYM_537	-0.0598***	-0.0262***	-0.0283***	-0.111***	-0.0893***	-0.0999***	0.141***	0.154***
	(0.00256)	(0.00340)	(0.00318)	(0.00438)	(0.00654)	(0.00789)	(0.00331)	(0.00269)
_IYM_538	-0.0402***	-0.00534	-0.00759**	-0.0881***	-0.0650***	-0.0760***	0.111***	0.128***
	(0.00314)	(0.00405)	(0.00349)	(0.00444)	(0.00643)	(0.00747)	(0.00350)	(0.00268)
_IYM_539	0.0207***	0.0583***	0.0558***	-0.0298***	-0.00523	-0.0173**	0.135***	0.147***
	(0.00234)	(0.00340)	(0.00357)	(0.00418)	(0.00660)	(0.00827)	(0.00351)	(0.00292)
_IYM_540	-0.0376***	0.00644	0.00368	-0.0924***	-0.0623***	-0.0752***	0.204***	0.217***
	(0.00433)	(0.00551)	(0.00465)	(0.00551)	(0.00772)	(0.00847)	(0.00337)	(0.00259)
_IYM_541	0.0865***	0.129***	0.127***	0.0200***	0.0498***	0.0375***	0.157***	0.171***
	(0.00361)	(0.00470)	(0.00426)	(0.00586)	(0.00826)	(0.00936)	(0.00420)	(0.00374)
_IYM_542	0.0335***	0.0788***	0.0760***	-0.0224***	0.00828	-0.00465	0.255***	0.280***
	(0.00314)	(0.00439)	(0.00415)	(0.00494)	(0.00744)	(0.00874)	(0.00412)	(0.00345)
_IYM_543	0.0142***	0.0584***	0.0558***	-0.0418***	-0.0116	-0.0239***	0.224***	0.236***

	(0.00337)	(0.00459)	(0.00412)	(0.00506)	(0.00744)	(0.00853)	(0.00407)	(0.00304)
_IYM_544	0.0138***	0.0540***	0.0515***	-0.0372***	-0.00993	-0.0215***	0.204***	0.213***
	(0.00389)	(0.00498)	(0.00420)	(0.00505)	(0.00711)	(0.00782)	(0.00391)	(0.00298)
_IYM_545	-0.0234***	0.0181***	0.0157***	-0.0790***	-0.0509***	-0.0625***	0.209***	0.219***
	(0.00315)	(0.00434)	(0.00392)	(0.00483)	(0.00721)	(0.00837)	(0.00391)	(0.00326)
_IYM_546	-0.0859***	-0.0538***	-0.0557***	-0.136***	-0.115***	-0.124***	0.167***	0.174***
	(0.00554)	(0.00622)	(0.00506)	(0.00620)	(0.00760)	(0.00766)	(0.00363)	(0.00284)
_IYM_548	0.0428***	0.0831***	0.0806***	-0.00734*	0.0201***	0.00841	0.0822***	0.0930***
	(0.00258)	(0.00381)	(0.00400)	(0.00425)	(0.00661)	(0.00806)	(0.00487)	(0.00457)
_IYM_549	0.0525***	0.0964***	0.0937***	-0.00760	0.0227***	0.0102	0.246***	0.258***
	(0.00280)	(0.00385)	(0.00445)	(0.00526)	(0.00775)	(0.00945)	(0.00353)	(0.00288)
_IYM_550	0.0797***	0.125***	0.122***	0.0239***	0.0548***	0.0418***	0.261***	0.282***
	(0.00289)	(0.00424)	(0.00428)	(0.00478)	(0.00736)	(0.00878)	(0.00421)	(0.00327)
_IYM_551	-0.00208	0.0374***	0.0350***	-0.0537***	-0.0271***	-0.0383***	0.275***	0.294***
	(0.00278)	(0.00389)	(0.00362)	(0.00445)	(0.00670)	(0.00788)	(0.00378)	(0.00292)
_IYM_552	0.0935***	0.142***	0.139***	0.0396***	0.0736***	0.0611***	0.194***	0.206***
	(0.00318)	(0.00468)	(0.00476)	(0.00484)	(0.00739)	(0.00873)	(0.00360)	(0.00285)
_IYM_553	0.0782***	0.124***	0.121***	0.0192***	0.0516***	0.0395***	0.310***	0.324***
	(0.00432)	(0.00559)	(0.00471)	(0.00576)	(0.00800)	(0.00860)	(0.00388)	(0.00308)
_IYM_554	0.0878***	0.135***	0.133***	0.0301***	0.0635***	0.0508***	0.297***	0.310***
	(0.00381)	(0.00523)	(0.00471)	(0.00538)	(0.00781)	(0.00879)	(0.00422)	(0.00358)
_IYM_555	0.0828***	0.131***	0.128***	0.0228***	0.0563***	0.0438***	0.300***	0.316***
	(0.00293)	(0.00441)	(0.00446)	(0.00504)	(0.00774)	(0.00914)	(0.00401)	(0.00329)
_IYM_556	0.0772***	0.127***	0.124***	0.0209***	0.0557***	0.0426***	0.297***	0.310***
	(0.00322)	(0.00475)	(0.00472)	(0.00499)	(0.00758)	(0.00885)	(0.00401)	(0.00304)
_IYM_557	0.143***	0.190***	0.187***	0.0881***	0.120***	0.108***	0.300***	0.315***
	(0.00418)	(0.00552)	(0.00473)	(0.00543)	(0.00778)	(0.00854)	(0.00390)	(0.00308)
_IYM_558	0.0667***	0.109***	0.107***	0.0140***	0.0431***	0.0314***	0.362***	0.371***
	(0.00367)	(0.00463)	(0.00409)	(0.00522)	(0.00730)	(0.00826)	(0.00440)	(0.00361)
_IYM_560	0.140***	0.182***	0.180***	0.0838***	0.113***	0.101***	0.282***	0.292***
	(0.00267)	(0.00393)	(0.00394)	(0.00468)	(0.00721)	(0.00862)	(0.00458)	(0.00357)
_IYM_561	0.215***	0.256***	0.253***	0.158***	0.186***	0.175***	0.369***	0.384***
	(0.00303)	(0.00421)	(0.00411)	(0.00493)	(0.00732)	(0.00861)	(0.00385)	(0.00298)
_IYM_562	0.289***	0.330***	0.327***	0.233***	0.261***	0.249***	0.415***	0.433***
	(0.00400)	(0.00516)	(0.00433)	(0.00537)	(0.00763)	(0.00847)	(0.00392)	(0.00319)
_IYM_563	0.223***	0.267***	0.264***	0.167***	0.197***	0.185***	0.504***	0.514***
	(0.00306)	(0.00442)	(0.00423)	(0.00484)	(0.00737)	(0.00869)	(0.00421)	(0.00344)
_IYM_564	0.194***	0.245***	0.242***	0.129***	0.165***	0.152***	0.445***	0.458***
	(0.00361)	(0.00494)	(0.00451)	(0.00582)	(0.00841)	(0.00954)	(0.00379)	(0.00311)
_IYM_565	0.321***	0.371***	0.369***	0.258***	0.292***	0.280***	0.434***	0.448***
	(0.00363)	(0.00514)	(0.00466)	(0.00559)	(0.00831)	(0.00951)	(0.00500)	(0.00358)
_IYM_566	0.261***	0.308***	0.306***	0.198***	0.231***	0.219***	0.557***	0.569***
	(0.00309)	(0.00443)	(0.00434)	(0.00541)	(0.00803)	(0.00937)	(0.00439)	(0.00329)
_IYM_567	0.315***	0.363***	0.360***	0.254***	0.287***	0.275***	0.503***	0.513***
	(0.00391)	(0.00528)	(0.00457)	(0.00570)	(0.00822)	(0.00910)	(0.00447)	(0.00334)
_IYM_568	0.353***	0.402***	0.399***	0.289***	0.323***	0.311***	0.553***	0.565***

	(0.00323)	(0.00462)	(0.00444)	(0.00551)	(0.00821)	(0.00953)	(0.00451)	(0.00349)
_IYM_569	0.390***	0.439***	0.437***	0.330***	0.364***	0.352***	0.601***	0.614***
	(0.00324)	(0.00470)	(0.00444)	(0.00525)	(0.00792)	(0.00916)	(0.00457)	(0.00328)
_IYM_570	0.453***	0.505***	0.502***	0.391***	0.427***	0.414***	0.628***	0.641***
	(0.00467)	(0.00607)	(0.00520)	(0.00611)	(0.00860)	(0.00937)	(0.00450)	(0.00340)
_IYM_572	0.385***	0.429***	0.427***	0.326***	0.356***	0.344***	0.708***	0.721***
	(0.00344)	(0.00473)	(0.00417)	(0.00527)	(0.00777)	(0.00887)	(0.00496)	(0.00391)
_IYM_573	0.440***	0.487***	0.485***	0.378***	0.410***	0.399***	0.634***	0.648***
	(0.00301)	(0.00417)	(0.00420)	(0.00550)	(0.00798)	(0.00939)	(0.00433)	(0.00335)
_IYM_574	0.468***	0.514***	0.511***	0.410***	0.442***	0.430***	0.684***	0.697***
	(0.00317)	(0.00456)	(0.00413)	(0.00505)	(0.00766)	(0.00883)	(0.00481)	(0.00346)
_IYM_575	0.370***	0.414***	0.412***	0.311***	0.341***	0.330***	0.714***	0.726***
	(0.00302)	(0.00431)	(0.00402)	(0.00507)	(0.00761)	(0.00883)	(0.00434)	(0.00332)
_IYM_576	0.353***	0.406***	0.403***	0.288***	0.326***	0.314***	0.628***	0.644***
	(0.00328)	(0.00472)	(0.00463)	(0.00574)	(0.00844)	(0.00974)	(0.00433)	(0.00331)
_IYM_577	0.406***	0.457***	0.455***	0.340***	0.377***	0.365***	0.621***	0.633***
	(0.00356)	(0.00490)	(0.00472)	(0.00604)	(0.00860)	(0.00985)	(0.00514)	(0.00369)
_IYM_578	0.419***	0.471***	0.468***	0.355***	0.391***	0.379***	0.673***	0.685***
	(0.00392)	(0.00547)	(0.00484)	(0.00591)	(0.00858)	(0.00948)	(0.00493)	(0.00378)
_IYM_579	0.460***	0.510***	0.507***	0.397***	0.432***	0.420***	0.689***	0.700***
	(0.00335)	(0.00457)	(0.00433)	(0.00569)	(0.00820)	(0.00947)	(0.00474)	(0.00368)
_IYM_580	0.413***	0.463***	0.460***	0.352***	0.386***	0.374***	0.729***	0.745***
	(0.00332)	(0.00480)	(0.00446)	(0.00545)	(0.00817)	(0.00938)	(0.00507)	(0.00375)
_IYM_581	0.443***	0.488***	0.486***	0.377***	0.407***	0.396***	0.679***	0.690***
	(0.00411)	(0.00529)	(0.00447)	(0.00615)	(0.00861)	(0.00956)	(0.00461)	(0.00354)
_IYM_582	0.442***	0.499***	0.496***	0.380***	0.420***	0.408***	0.702***	0.714***
	(0.00671)	(0.00844)	(0.00711)	(0.00760)	(0.0100)	(0.00998)	(0.00500)	(0.00396)
_IYM_583	0.383***	0.434***	0.432***	0.321***	0.357***	0.346***	0.712***	0.722***
	(0.00648)	(0.00790)	(0.00671)	(0.00755)	(0.00965)	(0.00977)	(0.00585)	(0.00529)
_IYM_584	0.373***	0.421***	0.418***	0.310***	0.343***	0.331***	0.667***	0.681***
	(0.00363)	(0.00494)	(0.00434)	(0.00574)	(0.00830)	(0.00933)	(0.00626)	(0.00545)
_IYM_585	0.279***	0.327***	0.325***	0.211***	0.245***	0.233***	0.640***	0.656***
	(0.00343)	(0.00446)	(0.00445)	(0.00621)	(0.00871)	(0.0102)	(0.00501)	(0.00374)
_IYM_586	0.227***	0.272***	0.270***	0.163***	0.193***	0.183***	0.537***	0.551***
	(0.00326)	(0.00453)	(0.00412)	(0.00551)	(0.00816)	(0.00940)	(0.00531)	(0.00381)
_IYM_587	0.113***	0.155***	0.153***	0.0490***	0.0780***	0.0675***	0.487***	0.498***
	(0.00387)	(0.00508)	(0.00433)	(0.00581)	(0.00828)	(0.00927)	(0.00471)	(0.00353)
_IYM_588	0.149***	0.197***	0.195***	0.0795***	0.113***	0.102***	0.375***	0.386***
	(0.00393)	(0.00518)	(0.00474)	(0.00641)	(0.00895)	(0.0101)	(0.00476)	(0.00373)
_IYM_589	0.193***	0.240***	0.238***	0.125***	0.158***	0.147***	0.423***	0.432***
	(0.00457)	(0.00580)	(0.00491)	(0.00656)	(0.00895)	(0.00963)	(0.00514)	(0.00392)
_IYM_590	0.177***	0.228***	0.226***	0.109***	0.145***	0.134***	0.470***	0.484***
	(0.00339)	(0.00478)	(0.00462)	(0.00602)	(0.00874)	(0.0101)	(0.00533)	(0.00424)
_IYM_591	0.248***	0.294***	0.292***	0.182***	0.214***	0.203***	0.451***	0.461***
	(0.00383)	(0.00513)	(0.00447)	(0.00591)	(0.00843)	(0.00938)	(0.00514)	(0.00380)
_IYM_592	0.283***	0.329***	0.327***	0.216***	0.249***	0.238***	0.535***	0.546***

	(0.00356)	(0.00480)	(0.00439)	(0.00600)	(0.00851)	(0.00970)	(0.00521)	(0.00407)
_IYM_593	0.268***	0.314***	0.312***	0.200***	0.233***	0.222***	0.566***	0.577***
	(0.00378)	(0.00499)	(0.00442)	(0.00620)	(0.00869)	(0.00974)	(0.00517)	(0.00384)
_IYM_594	0.340***	0.382***	0.380***	0.286***	0.316***	0.309***	0.546***	0.560***
	(0.00536)	(0.00672)	(0.00595)	(0.00615)	(0.00809)	(0.00839)	(0.00525)	(0.00398)
_IYM_595	0.145***	0.202***	0.199***	0.0844***	0.126***	0.113***	0.623***	0.630***
	(0.00360)	(0.00442)	(0.00509)	(0.00613)	(0.00816)	(0.00974)	(0.00511)	(0.00463)
_IYM_596	0.384***	0.430***	0.428***	0.317***	0.349***	0.338***	0.451***	0.464***
	(0.00363)	(0.00487)	(0.00430)	(0.00601)	(0.00857)	(0.00967)	(0.00677)	(0.00505)
_IYM_597	0.402***	0.451***	0.449***	0.333***	0.368***	0.357***	0.664***	0.677***
	(0.00375)	(0.00504)	(0.00461)	(0.00631)	(0.00886)	(0.0100)	(0.00515)	(0.00390)
_IYM_598	0.370***	0.415***	0.413***	0.304***	0.335***	0.324***	0.676***	0.690***
	(0.00382)	(0.00510)	(0.00445)	(0.00598)	(0.00853)	(0.00958)	(0.00513)	(0.00384)
_IYM_599	0.398***	0.445***	0.443***	0.329***	0.363***	0.351***	0.659***	0.671***
	(0.00498)	(0.00614)	(0.00513)	(0.00689)	(0.00920)	(0.00988)	(0.00489)	(0.00379)
_IYM_600	0.459***	0.506***	0.504***	0.387***	0.420***	0.410***	0.675***	0.686***
	(0.00445)	(0.00572)	(0.00490)	(0.00677)	(0.00920)	(0.0100)	(0.00583)	(0.00455)
_IYM_601	0.371***	0.419***	0.416***	0.302***	0.336***	0.325***	0.770***	0.780***
	(0.00436)	(0.00567)	(0.00485)	(0.00651)	(0.00896)	(0.00975)	(0.00571)	(0.00436)
_IYM_602	0.381***	0.431***	0.428***	0.314***	0.348***	0.337***	0.689***	0.699***
	(0.00426)	(0.00576)	(0.00496)	(0.00624)	(0.00887)	(0.00961)	(0.00539)	(0.00414)
_IYM_603	0.418***	0.469***	0.467***	0.352***	0.388***	0.376***	0.698***	0.709***
	(0.00471)	(0.00625)	(0.00533)	(0.00645)	(0.00899)	(0.00964)	(0.00537)	(0.00427)
_IYM_604	0.469***	0.520***	0.517***	0.400***	0.436***	0.425***	0.730***	0.740***
	(0.00366)	(0.00513)	(0.00465)	(0.00609)	(0.00880)	(0.00988)	(0.00552)	(0.00448)
_IYM_605	0.315***	0.362***	0.360***	0.248***	0.281***	0.270***	0.780***	0.791***
	(0.00390)	(0.00531)	(0.00465)	(0.00608)	(0.00865)	(0.00956)	(0.00535)	(0.00400)
_IYM_606	0.434***	0.486***	0.484***	0.366***	0.403***	0.392***	0.633***	0.640***
	(0.00542)	(0.00696)	(0.00590)	(0.00688)	(0.00936)	(0.00971)	(0.00504)	(0.00398)
_IYM_607	0.413***	0.463***	0.461***	0.344***	0.380***	0.369***	0.737***	0.742***
	(0.00776)	(0.00927)	(0.00786)	(0.00851)	(0.0106)	(0.0102)	(0.00574)	(0.00484)
_IYM_608	0.486***	0.535***	0.533***	0.418***	0.451***	0.441***	0.707***	0.719***
	(0.00386)	(0.00542)	(0.00474)	(0.00599)	(0.00879)	(0.00972)	(0.00719)	(0.00694)
_IYM_609	0.542***	0.587***	0.585***	0.477***	0.508***	0.498***	0.803***	0.813***
	(0.00408)	(0.00537)	(0.00461)	(0.00610)	(0.00858)	(0.00940)	(0.00518)	(0.00411)
_IYM_610	0.511***	0.558***	0.556***	0.445***	0.477***	0.467***	0.852***	0.858***
	(0.00376)	(0.00524)	(0.00461)	(0.00588)	(0.00853)	(0.00938)	(0.00534)	(0.00420)
_IYM_611	0.526***	0.573***	0.571***	0.459***	0.492***	0.481***	0.829***	0.836***
	(0.00414)	(0.00553)	(0.00478)	(0.00619)	(0.00874)	(0.00958)	(0.00498)	(0.00397)
_IYM_612	0.595***	0.648***	0.646***	0.528***	0.566***	0.555***	0.848***	0.855***
	(0.00464)	(0.00631)	(0.00543)	(0.00651)	(0.00910)	(0.00963)	(0.00516)	(0.00408)
_IYM_613	0.479***	0.531***	0.529***	0.411***	0.448***	0.437***	0.923***	0.928***
	(0.00387)	(0.00540)	(0.00500)	(0.00626)	(0.00892)	(0.0100)	(0.00567)	(0.00451)
_IYM_614	0.588***	0.637***	0.635***	0.521***	0.556***	0.546***	0.824***	0.831***
	(0.00475)	(0.00630)	(0.00539)	(0.00656)	(0.00906)	(0.00958)	(0.00525)	(0.00404)
_IYM_615	0.585***	0.636***	0.634***	0.518***	0.553***	0.542***	0.924***	0.932***

	(0.00378)	(0.00538)	(0.00483)	(0.00604)	(0.00876)	(0.00966)	(0.00554)	(0.00454)
_IYM_616	0.566***	0.618***	0.616***	0.497***	0.534***	0.523***	0.924***	0.933***
	(0.00385)	(0.00551)	(0.00493)	(0.00614)	(0.00895)	(0.00985)	(0.00536)	(0.00409)
_IYM_617	0.498***	0.549***	0.547***	0.430***	0.466***	0.455***	0.908***	0.916***
	(0.00416)	(0.00584)	(0.00512)	(0.00617)	(0.00891)	(0.00962)	(0.00541)	(0.00417)
_IYM_618	0.590***	0.644***	0.642***	0.526***	0.565***	0.554***	0.841***	0.849***
	(0.00736)	(0.00906)	(0.00781)	(0.00829)	(0.0106)	(0.0105)	(0.00532)	(0.00432)
_IYM_619	0.532***	0.587***	0.584***	0.467***	0.506***	0.495***	0.923***	0.927***
	(0.00712)	(0.00875)	(0.00742)	(0.00804)	(0.0102)	(0.0100)	(0.00700)	(0.00619)
_IYM_620	0.569***	0.617***	0.615***	0.502***	0.535***	0.525***	0.871***	0.877***
	(0.00416)	(0.00567)	(0.00491)	(0.00623)	(0.00884)	(0.00964)	(0.00669)	(0.00583)
_IYM_621	0.517***	0.567***	0.565***	0.447***	0.482***	0.472***	0.909***	0.916***
	(0.00394)	(0.00544)	(0.00481)	(0.00629)	(0.00898)	(0.00988)	(0.00541)	(0.00434)
_IYM_622	0.518***	0.566***	0.565***	0.447***	0.481***	0.471***	0.858***	0.866***
	(0.00376)	(0.00533)	(0.00473)	(0.00613)	(0.00891)	(0.00977)	(0.00532)	(0.00416)
_IYM_623	0.451***	0.498***	0.497***	0.381***	0.414***	0.404***	0.851***	0.860***
	(0.00395)	(0.00535)	(0.00471)	(0.00627)	(0.00887)	(0.00977)	(0.00527)	(0.00409)
_IYM_624	0.463***	0.514***	0.512***	0.393***	0.430***	0.419***	0.791***	0.799***
	(0.00541)	(0.00695)	(0.00592)	(0.00719)	(0.00962)	(0.0100)	(0.00528)	(0.00411)
_IYM_625	0.407***	0.462***	0.460***	0.334***	0.373***	0.363***	0.819***	0.824***
	(0.00425)	(0.00605)	(0.00539)	(0.00661)	(0.00943)	(0.0102)	(0.00613)	(0.00490)
_IYM_626	0.423***	0.475***	0.473***	0.352***	0.389***	0.379***	0.777***	0.783***
	(0.00378)	(0.00535)	(0.00498)	(0.00635)	(0.00910)	(0.0101)	(0.00555)	(0.00429)
_IYM_627	0.493***	0.543***	0.541***	0.423***	0.458***	0.448***	0.784***	0.790***
	(0.00458)	(0.00624)	(0.00541)	(0.00661)	(0.00926)	(0.00989)	(0.00542)	(0.00415)
_IYM_628	0.418***	0.467***	0.465***	0.347***	0.382***	0.372***	0.854***	0.861***
	(0.00417)	(0.00572)	(0.00504)	(0.00646)	(0.00911)	(0.00987)	(0.00571)	(0.00459)
_IYM_629	0.375***	0.424***	0.422***	0.303***	0.337***	0.327***	0.786***	0.794***
	(0.00393)	(0.00555)	(0.00495)	(0.00633)	(0.00910)	(0.00997)	(0.00538)	(0.00425)
_IYM_630	0.420***	0.472***	0.470***	0.348***	0.385***	0.375***	0.734***	0.743***
	(0.00647)	(0.00812)	(0.00701)	(0.00794)	(0.0103)	(0.0104)	(0.00526)	(0.00424)
_IYM_631	0.332***	0.383***	0.381***	0.257***	0.294***	0.284***	0.771***	0.777***
	(0.00585)	(0.00749)	(0.00648)	(0.00768)	(0.0101)	(0.0104)	(0.00691)	(0.00562)
_IYM_632	0.453***	0.500***	0.498***	0.381***	0.414***	0.404***	0.698***	0.704***
	(0.00415)	(0.00566)	(0.00497)	(0.00648)	(0.00919)	(0.0101)	(0.00642)	(0.00519)
_IYM_633	0.446***	0.492***	0.490***	0.374***	0.406***	0.396***	0.813***	0.822***
	(0.00433)	(0.00586)	(0.00510)	(0.00650)	(0.00919)	(0.0100)	(0.00528)	(0.00431)
_IYM_634	0.437***	0.486***	0.484***	0.363***	0.397***	0.387***	0.800***	0.806***
	(0.00394)	(0.00546)	(0.00490)	(0.00656)	(0.00934)	(0.0104)	(0.00536)	(0.00450)
_IYM_635	0.455***	0.502***	0.500***	0.383***	0.415***	0.405***	0.790***	0.801***
	(0.00414)	(0.00561)	(0.00493)	(0.00654)	(0.00924)	(0.0102)	(0.00536)	(0.00420)
_IYM_636	0.454***	0.507***	0.505***	0.383***	0.421***	0.410***	0.807***	0.815***
	(0.00445)	(0.00594)	(0.00527)	(0.00694)	(0.00944)	(0.0103)	(0.00531)	(0.00432)
_IYM_637	0.416***	0.465***	0.464***	0.340***	0.376***	0.366***	0.840***	0.845***
	(0.00465)	(0.00639)	(0.00562)	(0.00692)	(0.00968)	(0.0104)	(0.00613)	(0.00466)
_IYM_638	0.442***	0.490***	0.488***	0.366***	0.401***	0.391***	0.799***	0.807***

	(0.00403)	(0.00526)	(0.00487)	(0.00698)	(0.00952)	(0.0106)	(0.00561)	(0.00455)
_IYM_639	0.456***	0.506***	0.504***	0.383***	0.418***	0.408***	0.818***	0.824***
	(0.00529)	(0.00698)	(0.00602)	(0.00718)	(0.00981)	(0.0103)	(0.00590)	(0.00451)
_IYM_640	0.446***	0.493***	0.491***	0.367***	0.401***	0.391***	0.834***	0.840***
	(0.00508)	(0.00672)	(0.00582)	(0.00731)	(0.0100)	(0.0106)	(0.00589)	(0.00495)
_IYM_641	0.434***	0.479***	0.477***	0.355***	0.387***	0.377***	0.818***	0.824***
	(0.00465)	(0.00606)	(0.00525)	(0.00718)	(0.00980)	(0.0107)	(0.00586)	(0.00486)
_IYM_642	0.380***	0.429***	0.427***	0.306***	0.340***	0.331***	0.808***	0.815***
	(0.00493)	(0.00663)	(0.00581)	(0.00701)	(0.00973)	(0.0104)	(0.00583)	(0.00469)
_IYM_643	0.432***	0.484***	0.482***	0.359***	0.396***	0.386***	0.763***	0.771***
	(0.00583)	(0.00752)	(0.00646)	(0.00765)	(0.0102)	(0.0105)	(0.00585)	(0.00478)
_IYM_644	0.470***	0.515***	0.514***	0.392***	0.423***	0.413***	0.816***	0.822***
	(0.00442)	(0.00588)	(0.00514)	(0.00698)	(0.00972)	(0.0107)	(0.00660)	(0.00548)
_IYM_645	0.492***	0.539***	0.537***	0.416***	0.448***	0.439***	0.836***	0.844***
	(0.00483)	(0.00644)	(0.00559)	(0.00708)	(0.00978)	(0.0105)	(0.00566)	(0.00461)
_IYM_646	0.478***	0.525***	0.524***	0.401***	0.435***	0.425***	0.872***	0.879***
	(0.00419)	(0.00575)	(0.00509)	(0.00675)	(0.00951)	(0.0105)	(0.00565)	(0.00465)
_IYM_647	0.427***	0.473***	0.472***	0.349***	0.382***	0.372***	0.849***	0.857***
	(0.00464)	(0.00619)	(0.00539)	(0.00704)	(0.00979)	(0.0106)	(0.00564)	(0.00451)
_IYM_648	0.451***	0.501***	0.499***	0.378***	0.413***	0.404***	0.805***	0.810***
	(0.00426)	(0.00569)	(0.00527)	(0.00695)	(0.00954)	(0.0106)	(0.00555)	(0.00463)
_IYM_649	0.469***	0.518***	0.516***	0.392***	0.427***	0.417***	0.857***	0.863***
	(0.00608)	(0.00782)	(0.00673)	(0.00788)	(0.0105)	(0.0108)	(0.00592)	(0.00467)
_IYM_650	0.395***	0.443***	0.441***	0.314***	0.348***	0.338***	0.864***	0.870***
	(0.00480)	(0.00652)	(0.00573)	(0.00734)	(0.0101)	(0.0107)	(0.00644)	(0.00545)
_IYM_651	0.457***	0.505***	0.503***	0.378***	0.412***	0.402***	0.795***	0.799***
	(0.00588)	(0.00749)	(0.00648)	(0.00801)	(0.0106)	(0.0112)	(0.00579)	(0.00479)
_IYM_652	0.481***	0.529***	0.527***	0.403***	0.437***	0.427***	0.836***	0.841***
	(0.00415)	(0.00555)	(0.00503)	(0.00704)	(0.00969)	(0.0107)	(0.00641)	(0.00534)
_IYM_653	0.378***	0.426***	0.425***	0.299***	0.333***	0.323***	0.876***	0.883***
	(0.00504)	(0.00684)	(0.00598)	(0.00729)	(0.0100)	(0.0105)	(0.00592)	(0.00467)
_IYM_654	0.400***	0.449***	0.447***	0.322***	0.357***	0.347***	0.783***	0.790***
	(0.00647)	(0.00818)	(0.00709)	(0.00826)	(0.0108)	(0.0109)	(0.00576)	(0.00497)
_IYM_655	0.404***	0.452***	0.450***	0.330***	0.365***	0.354***	0.792***	0.799***
	(0.00797)	(0.00963)	(0.00835)	(0.00903)	(0.0114)	(0.0112)	(0.00710)	(0.00596)
_IYM_656	0.415***	0.463***	0.461***	0.337***	0.370***	0.361***	0.802***	0.811***
	(0.00458)	(0.00627)	(0.00553)	(0.00703)	(0.00975)	(0.0104)	(0.00754)	(0.00682)
_IYM_657	0.409***	0.456***	0.454***	0.333***	0.366***	0.356***	0.818***	0.827***
	(0.00555)	(0.00720)	(0.00620)	(0.00749)	(0.0101)	(0.0105)	(0.00569)	(0.00474)
_IYM_658	0.412***	0.457***	0.455***	0.333***	0.365***	0.355***	0.812***	0.820***
	(0.00475)	(0.00633)	(0.00551)	(0.00718)	(0.00985)	(0.0105)	(0.00630)	(0.00537)
_IYM_659	0.355***	0.402***	0.400***	0.277***	0.311***	0.301***	0.810***	0.817***
	(0.00451)	(0.00611)	(0.00541)	(0.00703)	(0.00976)	(0.0106)	(0.00573)	(0.00486)
_IYM_660	0.414***	0.463***	0.461***	0.337***	0.373***	0.363***	0.757***	0.767***
	(0.00565)	(0.00743)	(0.00644)	(0.00771)	(0.0103)	(0.0106)	(0.00563)	(0.00466)
_IYM_661	0.390***	0.440***	0.438***	0.315***	0.352***	0.342***	0.847***	0.855***

	(0.00453)	(0.00603)	(0.00549)	(0.00717)	(0.00970)	(0.0106)	(0.00660)	(0.00534)
_IYM_662	0.358***	0.405***	0.403***	0.279***	0.312***	0.303***	0.821***	0.829***
	(0.00501)	(0.00674)	(0.00587)	(0.00740)	(0.0100)	(0.0106)	(0.00602)	(0.00484)
_IYM_663	0.354***	0.404***	0.402***	0.275***	0.311***	0.301***	0.779***	0.786***
	(0.00526)	(0.00707)	(0.00616)	(0.00753)	(0.0102)	(0.0107)	(0.00599)	(0.00503)
_IYM_664	0.391***	0.439***	0.437***	0.313***	0.347***	0.338***	0.776***	0.784***
	(0.00477)	(0.00643)	(0.00567)	(0.00723)	(0.00989)	(0.0106)	(0.00611)	(0.00513)
_IYM_665	0.333***	0.380***	0.379***	0.252***	0.286***	0.277***	0.811***	0.819***
	(0.00529)	(0.00715)	(0.00626)	(0.00757)	(0.0103)	(0.0107)	(0.00582)	(0.00480)
_IYM_666	0.336***	0.385***	0.383***	0.259***	0.294***	0.285***	0.754***	0.763***
	(0.00681)	(0.00893)	(0.00789)	(0.00832)	(0.0110)	(0.0111)	(0.00591)	(0.00496)
_IYM_667	0.313***	0.365***	0.363***	0.233***	0.270***	0.261***	0.767***	0.775***
	(0.00768)	(0.00977)	(0.00859)	(0.00915)	(0.0118)	(0.0115)	(0.00662)	(0.00570)
_IYM_668	0.333***	0.380***	0.379***	0.255***	0.289***	0.280***	0.737***	0.748***
	(0.00446)	(0.00601)	(0.00538)	(0.00713)	(0.00977)	(0.0106)	(0.00770)	(0.00675)
_IYM_669	0.366***	0.411***	0.410***	0.285***	0.318***	0.308***	0.757***	0.766***
	(0.00486)	(0.00650)	(0.00567)	(0.00739)	(0.0100)	(0.0106)	(0.00579)	(0.00474)
_IYM_670	0.306***	0.353***	0.351***	0.226***	0.259***	0.250***	0.782***	0.790***
	(0.00498)	(0.00675)	(0.00592)	(0.00744)	(0.0101)	(0.0107)	(0.00596)	(0.00493)
_IYM_671	0.305***	0.350***	0.348***	0.225***	0.257***	0.248***	0.726***	0.734***
	(0.00475)	(0.00641)	(0.00568)	(0.00723)	(0.00989)	(0.0105)	(0.00605)	(0.00500)
_IYM_672	0.300***	0.347***	0.345***	0.220***	0.254***	0.244***	0.729***	0.737***
	(0.00580)	(0.00769)	(0.00665)	(0.00790)	(0.0105)	(0.0107)	(0.00571)	(0.00487)
_IYM_673	0.309***	0.354***	0.352***	0.226***	0.259***	0.249***	0.744***	0.753***
	(0.00599)	(0.00793)	(0.00688)	(0.00806)	(0.0107)	(0.0108)	(0.00650)	(0.00552)
_IYM_674	0.280***	0.326***	0.324***	0.199***	0.232***	0.223***	0.741***	0.749***
	(0.00506)	(0.00687)	(0.00603)	(0.00752)	(0.0101)	(0.0105)	(0.00637)	(0.00559)
_IYM_675	0.310***	0.354***	0.352***	0.231***	0.263***	0.254***	0.724***	0.732***
	(0.00498)	(0.00654)	(0.00574)	(0.00746)	(0.00994)	(0.0105)	(0.00601)	(0.00510)
_IYM_676	0.345***	0.387***	0.385***	0.270***	0.300***	0.290***	0.756***	0.763***
	(0.00531)	(0.00692)	(0.00598)	(0.00737)	(0.00980)	(0.0102)	(0.00604)	(0.00505)
_IYM_677	0.306***	0.351***	0.349***	0.226***	0.259***	0.249***	0.785***	0.793***
	(0.00509)	(0.00685)	(0.00598)	(0.00747)	(0.0101)	(0.0105)	(0.00622)	(0.00544)
_IYM_678	0.283***	0.323***	0.321***	0.210***	0.238***	0.230***	0.745***	0.753***
	(0.00713)	(0.00886)	(0.00789)	(0.00838)	(0.0107)	(0.0108)	(0.00596)	(0.00505)
_IYM_679	0.309***	0.357***	0.355***	0.233***	0.268***	0.259***	0.719***	0.728***
	(0.00814)	(0.0103)	(0.00914)	(0.00919)	(0.0118)	(0.0116)	(0.00759)	(0.00696)
_IYM_680	0.322***	0.364***	0.362***	0.243***	0.273***	0.264***	0.766***	0.776***
	(0.00462)	(0.00621)	(0.00547)	(0.00717)	(0.00962)	(0.0102)	(0.00698)	(0.00647)
_IYM_681	0.343***	0.388***	0.387***	0.263***	0.296***	0.287***	0.758***	0.766***
	(0.00542)	(0.00724)	(0.00633)	(0.00773)	(0.0103)	(0.0107)	(0.00596)	(0.00514)
_IYM_682	0.336***	0.379***	0.377***	0.257***	0.288***	0.278***	0.782***	0.791***
	(0.00498)	(0.00662)	(0.00575)	(0.00740)	(0.00989)	(0.0104)	(0.00605)	(0.00501)
_IYM_683	0.319***	0.363***	0.362***	0.239***	0.272***	0.262***	0.773***	0.781***
	(0.00501)	(0.00670)	(0.00587)	(0.00746)	(0.00997)	(0.0105)	(0.00595)	(0.00513)
_IYM_684	0.325***	0.368***	0.366***	0.249***	0.280***	0.270***	0.758***	0.767***

	(0.00631)	(0.00819)	(0.00704)	(0.00806)	(0.0106)	(0.0107)	(0.00585)	(0.00494)
_IYM_685	0.312***	0.357***	0.355***	0.232***	0.265***	0.255***	0.782***	0.788***
	(0.00584)	(0.00771)	(0.00662)	(0.00799)	(0.0105)	(0.0107)	(0.00647)	(0.00566)
_IYM_686	0.315***	0.360***	0.358***	0.235***	0.269***	0.258***	0.777***	0.785***
	(0.00531)	(0.00712)	(0.00620)	(0.00766)	(0.0102)	(0.0106)	(0.00616)	(0.00536)
_IYM_687	0.367***	0.411***	0.409***	0.288***	0.320***	0.310***	0.775***	0.782***
	(0.00497)	(0.00647)	(0.00570)	(0.00769)	(0.0101)	(0.0107)	(0.00588)	(0.00509)
_IYM_688	0.380***	0.425***	0.423***	0.304***	0.336***	0.326***	0.825***	0.830***
	(0.00511)	(0.00678)	(0.00594)	(0.00744)	(0.00995)	(0.0105)	(0.00598)	(0.00500)
_IYM_689	0.359***	0.401***	0.399***	0.277***	0.307***	0.298***	0.841***	0.846***
	(0.00500)	(0.00668)	(0.00585)	(0.00761)	(0.0101)	(0.0106)	(0.00574)	(0.00503)
_IYM_690	0.265***	0.310***	0.308***	0.190***	0.223***	0.213***	0.816***	0.823***
	(0.00834)	(0.0105)	(0.00928)	(0.00938)	(0.0118)	(0.0115)	(0.00578)	(0.00506)
_IYM_691	0.341***	0.383***	0.381***	0.261***	0.291***	0.281***	0.731***	0.737***
	(0.00827)	(0.0104)	(0.00910)	(0.00951)	(0.0120)	(0.0116)	(0.00751)	(0.00709)
_IYM_692	0.428***	0.469***	0.467***	0.349***	0.379***	0.370***	0.799***	0.808***
	(0.00488)	(0.00645)	(0.00563)	(0.00742)	(0.00976)	(0.0103)	(0.00757)	(0.00713)
_IYM_693	0.407***	0.449***	0.448***	0.326***	0.356***	0.347***	0.885***	0.891***
	(0.00535)	(0.00703)	(0.00607)	(0.00780)	(0.0103)	(0.0106)	(0.00584)	(0.00509)
_IYM_694	0.462***	0.505***	0.503***	0.379***	0.411***	0.401***	0.864***	0.871***
	(0.00534)	(0.00717)	(0.00622)	(0.00773)	(0.0102)	(0.0105)	(0.00619)	(0.00536)
_IYM_695	0.435***	0.476***	0.475***	0.355***	0.385***	0.376***	0.916***	0.921***
	(0.00482)	(0.00635)	(0.00560)	(0.00741)	(0.00983)	(0.0105)	(0.00592)	(0.00530)
_IYM_696	0.472***	0.515***	0.512***	0.395***	0.426***	0.416***	0.890***	0.895***
	(0.00616)	(0.00804)	(0.00689)	(0.00809)	(0.0106)	(0.0107)	(0.00576)	(0.00505)
_IYM_697	0.434***	0.474***	0.472***	0.351***	0.381***	0.371***	0.942***	0.945***
	(0.00550)	(0.00731)	(0.00630)	(0.00797)	(0.0104)	(0.0107)	(0.00656)	(0.00584)
_IYM_698	0.499***	0.539***	0.537***	0.413***	0.444***	0.433***	0.913***	0.918***
	(0.00509)	(0.00677)	(0.00591)	(0.00791)	(0.0102)	(0.0107)	(0.00605)	(0.00532)
_IYM_699	0.483***	0.522***	0.520***	0.401***	0.430***	0.420***	0.973***	0.978***
	(0.00515)	(0.00680)	(0.00595)	(0.00778)	(0.0101)	(0.0106)	(0.00606)	(0.00518)
_IYM_700	0.501***	0.541***	0.539***	0.422***	0.451***	0.441***	0.959***	0.965***
	(0.00540)	(0.00699)	(0.00603)	(0.00791)	(0.0102)	(0.0108)	(0.00593)	(0.00519)
_IYM_701	0.471***	0.511***	0.509***	0.390***	0.419***	0.409***	0.981***	0.988***
	(0.00534)	(0.00711)	(0.00614)	(0.00779)	(0.0102)	(0.0106)	(0.00618)	(0.00528)
_IYM_702	0.425***	0.464***	0.462***	0.345***	0.374***	0.364***	0.945***	0.949***
	(0.00610)	(0.00809)	(0.00697)	(0.00803)	(0.0105)	(0.0106)	(0.00617)	(0.00546)
_IYM_703	0.394***	0.431***	0.430***	0.311***	0.338***	0.328***	0.901***	0.908***
	(0.00707)	(0.00895)	(0.00771)	(0.00887)	(0.0113)	(0.0114)	(0.00647)	(0.00584)
_IYM_704	0.521***	0.561***	0.559***	0.443***	0.472***	0.462***	0.865***	0.873***
	(0.00504)	(0.00648)	(0.00570)	(0.00766)	(0.00996)	(0.0107)	(0.00711)	(0.00643)
_IYM_705	0.440***	0.479***	0.477***	0.361***	0.389***	0.379***	0.998***	1.004***
	(0.00560)	(0.00740)	(0.00635)	(0.00774)	(0.0102)	(0.0106)	(0.00605)	(0.00520)
_IYM_706	0.482***	0.520***	0.518***	0.399***	0.427***	0.417***	0.910***	0.916***
	(0.00582)	(0.00763)	(0.00661)	(0.00808)	(0.0106)	(0.0110)	(0.00624)	(0.00567)
_IYM_707	0.483***	0.521***	0.519***	0.400***	0.427***	0.417***	0.955***	0.963***

	(0.00511)	(0.00662)	(0.00578)	(0.00784)	(0.0102)	(0.0108)	(0.00638)	(0.00571)
_IYM_708	0.442***	0.479***	0.476***	0.362***	0.389***	0.378***	0.956***	0.962***
	(0.00542)	(0.00701)	(0.00606)	(0.00801)	(0.0102)	(0.0108)	(0.00605)	(0.00527)
_IYM_709	0.409***	0.446***	0.444***	0.329***	0.356***	0.345***	0.941***	0.946***
	(0.00574)	(0.00760)	(0.00647)	(0.00800)	(0.0104)	(0.0107)	(0.00629)	(0.00537)
_IYM_710	0.445***	0.481***	0.478***	0.362***	0.388***	0.377***	0.914***	0.920***
	(0.00541)	(0.00707)	(0.00612)	(0.00798)	(0.0103)	(0.0108)	(0.00628)	(0.00563)
_IYM_711	0.458***	0.495***	0.493***	0.377***	0.405***	0.393***	0.941***	0.948***
	(0.00520)	(0.00656)	(0.00580)	(0.00797)	(0.0101)	(0.0109)	(0.00598)	(0.00538)
_IYM_712	0.408***	0.446***	0.443***	0.330***	0.357***	0.346***	0.958***	0.965***
	(0.00543)	(0.00701)	(0.00607)	(0.00787)	(0.0102)	(0.0108)	(0.00624)	(0.00531)
_IYM_713	0.375***	0.410***	0.408***	0.290***	0.316***	0.305***	0.910***	0.916***
	(0.00566)	(0.00745)	(0.00633)	(0.00820)	(0.0105)	(0.0109)	(0.00612)	(0.00537)
_IYM_714	0.371***	0.409***	0.407***	0.294***	0.322***	0.311***	0.872***	0.879***
	(0.00655)	(0.00855)	(0.00732)	(0.00824)	(0.0108)	(0.0110)	(0.00626)	(0.00557)
_IYM_715	0.284***	0.321***	0.318***	0.199***	0.227***	0.216***	0.879***	0.885***
	(0.00761)	(0.00986)	(0.00837)	(0.00923)	(0.0116)	(0.0113)	(0.00657)	(0.00594)
_IYM_716	0.392***	0.428***	0.426***	0.309***	0.336***	0.325***	0.786***	0.794***
	(0.00549)	(0.00707)	(0.00612)	(0.00808)	(0.0103)	(0.0109)	(0.00710)	(0.00659)
_IYM_717	0.395***	0.431***	0.429***	0.315***	0.341***	0.330***	0.887***	0.893***
	(0.00559)	(0.00727)	(0.00621)	(0.00805)	(0.0104)	(0.0109)	(0.00610)	(0.00544)
_IYM_718	0.374***	0.410***	0.408***	0.293***	0.319***	0.308***	0.894***	0.900***
	(0.00571)	(0.00748)	(0.00635)	(0.00799)	(0.0104)	(0.0107)	(0.00621)	(0.00554)
_IYM_719	0.402***	0.437***	0.434***	0.318***	0.343***	0.332***	0.876***	0.882***
	(0.00532)	(0.00693)	(0.00596)	(0.00804)	(0.0103)	(0.0108)	(0.00630)	(0.00573)
_IYM_720	0.375***	0.407***	0.405***	0.298***	0.322***	0.310***	0.896***	0.902***
	(0.00648)	(0.00847)	(0.00710)	(0.00836)	(0.0108)	(0.0110)	(0.00619)	(0.00542)
_IYM_721	0.359***	0.392***	0.390***	0.275***	0.300***	0.288***	0.901***	0.908***
	(0.00630)	(0.00833)	(0.00699)	(0.00853)	(0.0108)	(0.0110)	(0.00653)	(0.00583)
_IYM_722	0.392***	0.424***	0.421***	0.310***	0.334***	0.322***	0.886***	0.895***
	(0.00559)	(0.00723)	(0.00617)	(0.00816)	(0.0103)	(0.0109)	(0.00660)	(0.00584)
_IYM_723	0.379***	0.412***	0.409***	0.298***	0.323***	0.310***	0.919***	0.926***
	(0.00563)	(0.00735)	(0.00629)	(0.00802)	(0.0103)	(0.0108)	(0.00639)	(0.00551)
_IYM_724	0.396***	0.429***	0.426***	0.319***	0.343***	0.330***	0.905***	0.911***
	(0.00676)	(0.00868)	(0.00718)	(0.00848)	(0.0109)	(0.0109)	(0.00621)	(0.00561)
_IYM_725	0.400***	0.430***	0.428***	0.317***	0.340***	0.327***	0.911***	0.920***
	(0.00564)	(0.00735)	(0.00616)	(0.00818)	(0.0103)	(0.0108)	(0.00657)	(0.00600)
_IYM_726	0.426***	0.459***	0.457***	0.350***	0.374***	0.362***	0.918***	0.926***
	(0.00564)	(0.00729)	(0.00620)	(0.00801)	(0.0102)	(0.0108)	(0.00642)	(0.00569)
_IYM_727	0.387***	0.420***	0.417***	0.307***	0.331***	0.319***	0.950***	0.955***
	(0.00746)	(0.00976)	(0.00818)	(0.00900)	(0.0115)	(0.0112)	(0.00640)	(0.00554)
_IYM_728	0.426***	0.461***	0.458***	0.348***	0.373***	0.360***	0.919***	0.927***
	(0.00592)	(0.00774)	(0.00645)	(0.00809)	(0.0104)	(0.0107)	(0.00691)	(0.00628)
_IYM_729	0.456***	0.490***	0.487***	0.374***	0.399***	0.387***	0.947***	0.955***
	(0.00565)	(0.00727)	(0.00621)	(0.00819)	(0.0103)	(0.0109)	(0.00655)	(0.00601)
_IYM_730	0.420***	0.454***	0.451***	0.339***	0.364***	0.352***	0.978***	0.983***

	(0.00599)	(0.00789)	(0.00657)	(0.00819)	(0.0105)	(0.0108)	(0.00625)	(0.00561)
_IYM_731	0.507***	0.539***	0.536***	0.425***	0.449***	0.437***	0.939***	0.947***
	(0.00566)	(0.00735)	(0.00621)	(0.00818)	(0.0103)	(0.0108)	(0.00648)	(0.00587)
_IVintage_1991							-0.403***	1.034***
							(0.0141)	(0.00557)
_IVintage_1992							-0.692***	-0.394***
							(0.0110)	(0.0153)
_IVintage_1993							-0.524***	-0.675***
							(0.00887)	(0.0109)
_IVintage_1994							-0.651***	-0.515***
							(0.00767)	(0.00875)
_IVintage_1995							-0.460***	-0.648***
							(0.00598)	(0.00808)
_IVintage_1996							-0.467***	-0.467***
							(0.00727)	(0.00607)
_IVintage_1997							-0.686***	-0.470***
							(0.00945)	(0.00696)
_IVintage_1998							-0.499***	-0.667***
							(0.00721)	(0.00906)
_IVintage_1999							-0.535***	-0.508***
							(0.00940)	(0.00745)
_IVintage_2000							-0.284***	-0.536***
							(0.00641)	(0.00921)
_IVintage_2001							-0.580***	-0.290***
							(0.00934)	(0.00561)
_IVintage_2002							-0.613***	-0.575***
							(0.00858)	(0.00854)
_IVintage_2003							-0.552***	-0.606***
							(0.00579)	(0.00779)
_IVintage_2004							-0.698***	-0.547***
							(0.00834)	(0.00557)
_IVintage_2005							-0.468***	-0.697***
							(0.0107)	(0.00769)
_IVintage_2006							-0.725***	-0.469***
							(0.00721)	(0.00993)
_IVintage_2007							-0.641***	-0.727***
							(0.00773)	(0.00693)
_IVintage_2008							-0.762***	-0.636***
							(0.00737)	(0.00754)
_IVintage_2009							-0.626***	-0.774***
							(0.0115)	(0.00724)
_IVintage_2010							-0.659***	-0.624***
							(0.0131)	(0.0110)
_IVintage_2011							-0.699***	-0.663***
							(0.0108)	(0.0120)
_IVintage_2012							-0.783***	-0.703***

							(0.00953)	(0.0107)
_IVintage_2013							-0.691***	-0.791***
							(0.0155)	(0.00953)
_IVintage_2014							-0.807***	-0.688***
							(0.0118)	(0.0153)
_IVintage_2015							-0.652***	-0.824***
Constant	-3.720***	-4.026***	-4.013***	-3.975***	-3.838***	-0.632***	1.028***	(0.0118)
	(0.100)	(0.103)	(0.116)	(0.0846)	(0.0824)	(0.0164)	(0.00628)	
Observations	103,755	103,755	103,755	103,755	103,755	103,755	100,447	99,616
R-squared	0.926	0.927	0.927	0.928	0.928	0.928	0.940	0.940