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Italian Fine Wines: Pricing, Performance Profile and Herding Behavior among International Buyers

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Abstract

This paper investigates the case of Italian fine wine as an investment. Firstly, employing a hedonic approach, significant price premiums are detected for various observable wine attributes. For example, variables such as wine classification, producer, time and place of sale, and weather conditions in the year of harvest, all contribute to the determination of wine prices. Moreover, the aging of wine also affects prices and it suggests non-pecuniary benefits of wine. Secondly, 18,019 hammer prices are used to construct Italian wine indices over 1997-2018. A hedonic model as well as a repeat-sales regression estimate a real financial return of around 4% with low risk. The risk-return profile seems to outperform other art assets and the Italian equity index. Lastly, a behavioral approach based on the autocorrelation of returns and some dispersion measures is implemented to study herding behavior among international investors in Italian wine. Results discard the presence of herding and are robust when controlling for the macroeconomic situation of the Italian and US markets.

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Introduction

Nowadays, alternative assets, such as art and other collectibles, present a real opportunity for investors to generate positive returns in the expectation that they can swim against the tide of standard financial investments. Because of their aesthetic dividend and especially in the wake of the most recent financial crisis of 2008, investors are looking for new assets that do not follow the market in order to diversify their portfolios.

Among these various types of collectibles (e.g. paintings, classic cars, and diamonds), fine wine differs in a number of aspects. Firstly, unlike diamonds, wine is a tangible and consumable asset that needs to be delivered physically, stored and cared for when acquired. Moreover, the value of this type of investment to the buyer is obtained from either the utility of consumption, the so-called “user benefit”, or from the difference between the purchase and the sales price, after considering related costs. These last two characteristics of fine wine, namely its user benefit (such as the pride of cellar) and the transaction and storage costs associated with the trading and holding of the asset, provide confusion for economists about which rate of return wine should provide.

On the one hand, because of its consumption utility, wine might be thought to yield a rate of return lower than other financial assets and, at the same time, higher than those collectibles that do not involve actual physical destruction to be fully enjoyed (drinking, in this case), and which do not thus experience the same “depreciation” rates. However, significant transportation, handling, and administration expenses issue eagerness amongst investors for higher returns. Moreover, the less liquid nature of the wine market should also raise the rate of return, given that it usually takes a long time for collectors to sell their product. Indeed, after contacting the auction house[1], the transaction has to be put under contract and the wine must be sent to the auctioneer’s premises. Finally, the sales price, and consequently the wine rate of return, is made unpredictable by the relative thinness of the market: well-attended wine auctions have on average 40 sellers against around 150 buyers, who drive the auction and set the price.

Although characteristics about fine wine and its market might give collectors an idea about the rate of return to expect, academics have not yet reached a consensus toward the attractiveness of wine and it therefore remains an open issue. Even if cases of extreme high returns have been reported (Masset and Weisskopf, 2010), these examples of extraordinary performance are by no means limited to wine, and agents are not willing to invest solely on

[1] In this paper, ‘auction house’ and ‘auction company’ are used interchangeably.

the basis of a few cases. Nonetheless, wine could still produce systematic excess returns over other collectibles and/or financial instruments with similar risk profiles.

In this article we focus on Italian fine wines and we investigate (1) the determinants of wine prices, (2) their risk-return characteristics, and (3) the tendency of international investors to herd toward Italian wines. We consider the most traded Italian wines sold at major auctions held in the 1997-2018 period, and we select vintages between 1990 and 2015, accounting for 18,019 transactions and a total sales value of more than USD 26 million.

Chapter 1 applies a hedonic pricing model to study the determinants of wine prices. This research concludes that the most valued characteristics for wine collectors are objective, easy observable attributes, such as wine classification (i.e., the belonging to the Super Tuscan category), and producer. Moreover, results show a significant “quantity discount” effect that dominates the full case premium paid for complete cases of 12 bottles. The time and the place where wine is traded, in terms of both individual auction house and country of sale, seem also to be important for the determination of the final price. Wines sold in the last quarter of the year and from the largest auction companies carry indeed a relevant price increment. In addition, Asian wine collectors are willing to pay a price up to 42 times higher than US buyers and 78 times higher than European investors. Furthermore, weather conditions of the year in which the grapes were harvested, and, in particular, the temperature during the growing season that created the wines have a strong impact on the sales value. Lastly, the effect of aging is also noteworthy, and it demonstrates the non-pecuniary benefits related to wine investment. Italian fine wines, indeed, continue rising in value, even after losing their gastronomic appeal, because of the pride they provide to their owners as collectible goods. These results are robust when correcting standard errors for any bias due to the dependency of residuals across observations.

In Chapter 2, we focus on the generation of a wine price index. For the sake of completeness and robustness, this paper derives the wine price index from both a hedonic model and a repeat-sales regression. When the two indices are compared, results show that the average annual return for Italian fine wine is very similar between the two methods (4.08 and 4.16 percent, respectively). Although these regressions, despite their different properties, are considered to be accurate for the determination of a price index, they produce dissimilar results in terms of return volatility, and the RSR seems to provide a more stable index. The paper then proceeds to compare the risk-return profile of Italian wine with other art and financial investment vehicles. In spite of a rate of return lower than its French and Australian counterparts, Italian wine is demonstrated to outperform paintings, stamps, classic cars, sculptures and the Italian stock market index and it also shows strong performance in terms of Sharpe ratio. When analyzing these results, one should also bear in mind that, compared to other financial assets, the performance of collectibles could be depressed by high transaction costs, which weigh more than trading costs for the return of financial assets. Because of the general low correlation with art and stock market, wine indexes could also present some diversification benefits, although results are not statistically significant.

The variability of asset returns is often explained by the influence of the herding of investors. In the financial market, herding is defined as the tendency of individuals to influence each other when trading and it describes those behavioral patterns that are correlated among investors. Herding can be found in very different environments, from the equity market to fashion and fads, but it is hard to judge if investors are affected by the decisions of other agents because of some behavioral bias or just because of correlated news received by independently acting individuals. The last part of this paper aims therefore at investigating whether the performance of Italian wine investors is generated by this behavioral trading rule rather than by just superior information.

Chapter 3 applies a behavioral approach to study the presence of herding behavior among Italian wine investors by analyzing the instantaneous auto-covariance of the market index and its relationship with other dispersion measures. In particular, the cross-sectional dispersion of returns and the market variance are the measures of turbulent conditions, which, according to the behavioral theory, cause the suppression of personal information in case of herding patterns. Results show that investors, although slightly reacting to turbulence related to their individual extreme returns, do not follow the herd when trading Italian wine. Results are robust to the introduction of exogenous variables related to the macroeconomic situation of both the Italian and the US market, which are included to display the exposure of wine investors to the equity market.

This research paper creates vast value for existing literature in a variety of ways. By the use of hedonic and repeat-sales regressions, this study opens the door to the investigation of the Italian wine market, which, to the best of my knowledge, has never been independently examined by academics. Furthermore, Italian wines belong to the wider category of alternative instruments and collectible assets upon which the literature has not clearly pronounced yet and for which the evidence is still mixed. Moreover, this paper contributes to behavioral finance and concentrates on the price implications of herding by exploring the presence of herd behavior among Italian wine investors. The aim is to understand whether collectors affect each other when they invest in fine wines, and, consequently, to study how information is integrated into wine prices, for which the literature is still within its infancy. Along with building upon the existing literature, this research paper also holds significant ramifications for practitioners in alternative assets, specifically with regards to the analysis of Italian fine wines and the presence of herding behavior toward collectible goods.

Literature review

This section reviews the most important and signifying research studies within the context of collectible fine wines. For reasons of clarity, papers are not presented in chronological order, but they are subdivided according to their field of research and the main contributions they add to the literature. The first part presents the main findings concerning price determinants and returns of wine investments, while the second part goes over past studies on herding behavior among investors.

Pricing and performance of wine

Wine returns

The first branch of literature about the performance of wine as a speculative asset class focuses on risk and returns of the French wine market from the perspective of an US investor in the late 70s. Studies mainly concentrate on Bordeaux wines, especially the Bordeaux five first growths, and research usually compares the returns of these wines with the performance of wines from other regions (California, Australia, Italy, Rhône, and Spain). However, authors have not yet reached a consensus about the real trend in returns. Indeed, outcomes strongly depend on the period studied, the type of wine, and the benchmark assets.

That part of literature considering wine an underperforming asset starts with the work of Krasker (1979), which is the first study on the performance of fine wines. He concentrates on red Bordeaux and Californian Cabernets over the period 1973 to 1977, and he concludes that wine underperforms a riskless asset, yielding 5.9% less than the average US Treasury rate. Although wine is not a good investment instrument, Krasker finds that returns are tax-exempt and early purchase reduces real risk. Since this pioneer empirical investigation, the question of what the performance of fine wine is remains an open issue.

More recently, Weil (1993) studies the return on a wine portfolio and argues that it does not generate good returns compared to US financial assets. Later, other authors examine the performance characteristics of wine in comparison to standard investments assets. For example, Burton and Jacobsen (1999) argue that wine, and collectibles in general, has a higher variability than equities and its price trend tends to follow a typical boom-burst movement. Later, Fogarty (2006) agrees on the cyclical characteristic of wine returns, whereas Burton and Jacobsen (1999) describe that different collectibles seem to be more correlated in falling markets.

Except the ones just cited, many other studies have addressed the issue of wine pricing. Among others, Ashenfelter et al. (1995), Di Vittorio and Ginsburgh (1996), and Cardebat and Figuet (2004) use hedonic models to analyze the way wine is priced. Again, Burton and

Jacobsen (2001) equate wine to art and other collectibles with the characteristic of containing some user benefits, and they note that they behave differently from traditional financial assets. In particular, wine should carry a premium for storage costs and its less liquid nature. When comparing wine with other art and financial assets, Burton and Jacobsen (2001) discuss that because wine consumption implies destruction, it should provide higher return relative to other collectibles. However, since its value also carries an intrinsic utility, the return on wine should be lower than for stocks. Indeed, these theoretical assumptions find an empirical support when they apply a repeat-sale regression in their study. They show that post-1960 red Bordeaux performs poorly over the period 1986 to 1996, with a rate of return 5.9% lower than the Dow Jones, without considering liquidity issues, insurance and storage costs. They, however, also argue that the heterogeneity of the wine market should be considered, as vintage can remarkably affect return on wine investments. Investors can, indeed, make profits on single bottles, e.g. the vintage 1982, or by timing the market.

However, other empirical studies on the relative attractiveness of wine have demonstrated that this alternative asset class can yield high capital gains. For instance, Jaeger (1981), in response to Krasker's paper (1979), argues that his results are biased by a short period and a low number of observations. Therefore, using Krasker's methodology while extending the sample period that spans recessions and reducing storage costs, Jaeger (1981) produces more encouraging results. He demonstrates that wine, from 1969 to 1977, provides a considerable premium over the risk-free rate and, precisely, it outperforms, on average, the US Treasury bills by 16.6%.

International wines

Around the 2000s, research started encompassing non-Bordeaux wines and non-US investors. Taking Australia as an example, the paper of Oczkowski (1994) constitutes the first attempt to study the price of Australian wine through a hedonic model. In his work, the explanatory variables consist of both objective, such as region and vintage, and subjective, e.g. quality measures, measures of wine characteristics. As regards the latter subjective determinants of Australian wine prices, later works will concentrate on providing different statistical methods to deal with subjectively estimated quality ratings (Oczkowski, 2001; Schamel and Anderson, 2003). Continuing with the discovery of the Australian wine heritage, Byron and Ashenfelter (1995) ascertain that Australian premier wine, more precisely the Penfold's Grange, has produced a modest real rate of return, 4% on average, for the period covering 1966 to 1991, representing a nominal rate of return of around 12%. Similarly, Bentzen et al. (2002) focus on returns of Bordeaux wines sold at Danish auctions in the period between 1988 and 2002 and observe they yield high returns, besides not being related to the Danish stock prices.

Wine in portfolio diversification

Authors have also begun looking at fine wines from a more global investment point of view, by studying the link between wine and financial markets. Using the risk-return framework of previous works, part of the literature starts investigating potential diversification benefits of wines, when these are seen as investment class on their own. The idea is that wine can reduce a portfolio risk in case of low correlation with other financial assets. Wine is thus inserted in a more comprehensive picture, where investors do not only look at each asset separately, but within the framework of their overall portfolio.

In this regard, Fogarty (2007) decides to introduce wine in investor's portfolios already consisting of stock and bonds, and he shows that, once wine is included, the efficient frontier shifts to the left, implying a more profitable risk-return trade-off. Again, Sanning et al. (2008) examine the risk-return relation between US equity and Bordeaux wine in more detail. In order to assess the benefits of wine in terms of portfolio diversification, they use the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model and they observe high returns and low exposure to market risk factors. This represents a strong argument, as, if true, then it would mean that wine represents a hedge in a portfolio loaded on positive-beta assets, like one consisting of stock and bonds. Similarly, the scope of the previous study is also pursued by Masset and Henderson (2010), who agree on the general lack of correlation between wines and US equities, but also note that, although attractive, their performance characteristics strongly vary among Bordeaux wines. The fact that the inclusion of wine in investment portfolios is favorable in terms of diversification benefits is then extended to Australian wines (Fogarty, 2010), and to high-quality fine wines from different regions worldwide (Kourtis et al., 2012).

Furthermore, Masset and Weisskopf (2010), using Burton and Jacobsen's methodology (2001) on a longer period (1996 to 2007), find that, because of wine's low volatility compared to the US stock market, its inclusion in financial portfolios is beneficial for its risk level, improving both skewness and kurtosis. However, while individually picked portfolio including French, Italian and US wine outperforms both the Russel 3000 and the First Growth Wine Index, the latter wine index seems to behave like other financial assets and incur substantial losses during periods of financial crisis. This exposure to the market risk contradicts the hedging-effect argument of Sanning et al. (2008) and states that wine can indeed be susceptible to the financial crisis. More recently, Fogarty and Sadler (2014) also warn investors against wine true ability to improve portfolio diversification. The methods used to build price indices and to size the diversification benefits are indeed of major importance.

In conclusion, the lack of previous work on Italian fine wines and the heterogeneity of previous evidence on wine investments make it difficult to predict the performance profile of

Italian wines. On the one hand, the consumption utility included in this type of asset points towards a rate of return lower than that of standard financial assets but higher than the one yielded by other collectibles that do not involve actual physical destruction. On the other hand, high transaction costs and the illiquidity nature of the market make investors hope for higher returns.

Herding behavior

Wine is usually an emotional and hedonistic investment and, unlike standard financial assets such as stocks and bonds, it is linked to some sentimental factors, instead of merely speculative ones. From what has been discussed above, when buying fine wine, investors can combine returns and pleasure, while potentially also diversifying their portfolio. The recent growth in fine wine trading activity, together with the evolution and financialization of the wine market allow to study the behavior of fine wine investors. With the goal of understanding the way in which wine prices incorporate information, one should study to what extent investors influence each other when trading on rare wines.

Herding is usually defined as the tendency of investors to mimic the actions of others when they trade securities. Experts divide herding behavior in financial markets in two different types, i.e. the non-rational and the rational view. On the one hand, non-rational herding occurs when individuals follow one another blindly by assuming they own the relevant information. Non-rationality of herding focuses on investors' psychology, creates inequalities besides being detrimental to mutual interactions, and it can also be recognized as the cause of bubbles and crashes in financial markets. Setting aside this irrational type of herding, there also are rational reasons for profit maximizing agents to be influenced after observing others, such as imperfect information, compensation structures, and reputation concern. Following the herd can in fact be considered a rational behavior, when it allows investors to deal with uncertainty and to improve individual performance (Orléan, 1989). Rational herding literature aims at understanding why financial markets may display phenomena like waves or high fragility. The fact that some market participants recognize that their decisions are highly influenced by other agents is a clear example of herding behavior, although finding evidence that investors herd might be challenging. As outlined by Banerjee (1992), rationality is embodied in investors idea that other decision makers may own some relevant information that could be important for them as well.

Herding behavior, together with momentum trading strategies, is a model often used by researchers to explain apparently irrational markets, and this makes herd behavior an issue frequently addressed by academic literature in financial markets. The so-called cascades models, where investors, after deriving information about the actions of other agents, optimally decide to neglect their own private information by acting alike, are proposed by Scharfstein and Stein (1990). Moreover, a number of academics provide reasons of excessive trading among institutional investors (Trueman, 1988), and describe why the same agents tend to invest in the same direction by, for instance, being influenced by earnings forecasts released by other analysts (e.g., Scharfstein and Stein, 1990; Lakonishok et al., 1991; and Hirshleifer et al., 1994). Banerjee (1992) developed a simplified model to study herd behavior among investors that rules out any incentives problems connected to principal-agent relationships. The tendency of agents to show conformity in situations like fads and fashions is then described by Bikhchandani et al. (1992). Froot et al. (1992) study the behavior of short-term investors to herd on the same information, while Welch (1992) identifies in sequential issues of IPOs a potential explanation for the creation of cascades.

Henceforth, this paper will only concentrate on the potential creation of rational herding among investors of Italian fine wine, investigating its presence and its potential reasons and implications. The literature on herding aims at studying how investors collectively behave toward the market and how they make buying and selling decisions simultaneously. Herding behavior among institutional investors has been detected by Shiller and Pound (1989), who argue that these agents highly follow the advice of other professionals in volatile stocks. However, a few years later, in 1992, Lakonishok, Shleifer, and Vishny (hereafter LSV) find only weak support for herding behavior in small stocks, while they produce no evidence of such an attitude among large stocks.

When it comes to statistically examining the presence of herding behavior, the empirical evidence provides very mixed results and the literature tends to use two different strategies: the group-wide and the market-wide approach. Contrary to the group-wide herding, the market-wide approach applies the theory of cross-sectional dispersion of investment returns for studying those investors that hunt the market performance, while ignoring individual stocks attributes. Among those who choose the market-wide method, Christie and Huang (1995) study the US stock market and think that investors tend to abandon their own opinions in favor of market agreement during period of acute price fluctuations. The idea is that, when herding occurs, individual return dispersion is low, because “individual stock returns are clustered around the overall market return” (Christie and Huang, 1995). However, they find no evidence of herding behavior in the US stock market. Five years later, Chang et al. (2000) come to the same conclusion after expanding the study of Christie and Huang (1995): no herding behavior is detected in US and Hong Kong markets. However, they do detect strong evidence in Taiwan and South Korea. On the contrary, other more recent works (Chen, 2013; Khan et al., 2011; Lakshman et al., 2013) recognize herding in both the US and South Korean and they conclude that herding behavior toward the market is persistent and moves independently of any macro factors. Speaking in broader terms, most of the studies done in developed countries show indeed that herd behavior is not common among investment managers, although it is more likely to be found among those agents with a higher tendency to follow momentum investment strategies (Bikhchandani and Sharma, 2000).

In general, most of previous works concentrate on the stock market and find that herding is more likely to occur in emerging markets, rather than in developed ones. Herding in the wine industry has been studied by Aytaç et al. in 2018, who applied the methodology of Christie and Huang (1995), Chang et al. (2000), and Chiang and Zheng (2010) to the fine wine market, together with an alternative method based on "the instantaneous autocorrelation of returns". However, Aytaç et al. (2018) only provide unclear results, as coefficients are not statistically significant, and they fail to produce a definitive verdict on the issue. Therefore, this paper undertakes to expand the study about the presence of herding behavior among investors of fine wines and hopes to provide significant results to practitioners.

Data

Dataset

The data for this research is taken from the Wine Market Journal (WMJ) website[2]. Since 1997, the WMJ tracks wine auction trades documented by all the major houses in Europe, Asia, the US, and through the Internet. Prices, in US dollars (USD), are intended per bottle (750ml), and exclude buyer premiums and sale taxes. Each sale entry contains the wine's name, producer, vintage, color, bottle size, quantity sold, auction house, date and hammer price. Auction hammer prices are reported from several houses[3] over the period January 1997 to December 2018. The original dataset comprises 18,019 transactions, representing 151,775 standard bottles sold and a total sales value of more than USD 26 million.

Similar to Liv-ex Italy 100 index, we consider five Super Tuscan and five other leading Italian producers (Masseto, Ornellaia, Sassicaia, Solaia, and Tignanello as "Super Tuscans" and Barbaresco, Barolo Cascina Francia, Barolo Monfortino, Guado al Tasso, and Tua Rita as the other important Italian names). Supertuscans are those red wine, produced in Tuscany, that intentionally do not respect the traditional preparation rules of the regions and, therefore, cannot be classified as DOCG products (Controlled and Guaranteed Denomination of Origin). Moreover, unlike the Liv-ex Italy 100 index, which only includes the ten most recently physical

[2] https://www.winemarketjournal.com/
[3] Acker Merrall & Condit, Bloomsbury, Bonhams, Brentwood Wine Company, Christie's, Edward Roberts International, Hart Davis Hart, Heritage Auctions, K&L Wines, Leland Little, Morrell & Company, Skinner, Sotheby's, Spectrum Wine Auctions, Waddington's, Wally's Auctions, Wine Gavel, Winefield's, Zachys

vintages, our dataset also contains older wines and covers vintages from 1990 to 2015. This decision enables us to inspect around 260 wines (26 vintages of 10 different wine types). The sample, although it does not include Bordeaux wines, allows to differentiate wines based on their region of origin and their reputation. With this original dataset, this research paper strongly expands existing literature on alternative investments, since Italian wines represent the second most traded fine wines (after those produces in the Bordeaux region) and are bought worldwide through the major auction houses.

The fact that only wines produced since 1990 are included in the regression is intended to eliminate the factor of the “antique effect” that could cause prices to change. Removing those vintages not only helps taking off those wines that are considered antiques, but also discarding wines that are illiquid and traded infrequently. Other previous works (among others Krasker, 1979; Jaeger, 1981; Burton and Jacobsen, 2001; Masset and Weisskopf, 2010) implement similar restrictions, limiting their analyses to young Bordeaux and California red wines. Krasker (1979) and Jaeger (1981) argue that these wines are mostly traded for investment purposes, as they produce the highest potential capital gains because of their aging benefits, and could therefore provide high volatility. Moreover, vintages after 2015 are not part of the sample as they arrived on the market in 2018 at the earliest and, therefore, are not reliably priced.

The first step is to discard all those wines that are not traded on a regular basis, i.e. we only consider wines that have being sold at least once a year. This allows to eliminate long periods without trades, which do not produce comparable results and lead to incorrect and difficult to interpret price jumps. Hammer prices are then adjusted for the US inflation rate. Monthly wine prices are calculated as the average price for a given month, and price data are winsorised at the 99.9% level to eliminate very extreme outliers (Masset and Weisskopf, 2010).

In addition to fine wine data, control variables associated with macroeconomic situation of both the Italian and the US markets are included in Chapter 3 analysis. For the Italian market, an equity measure and a macroeconomic measure are introduced. In particular, we include data on the performance of the stock market index for the Italian national stock exchange (FTSE MIB), and the Italian GDP growth, as a proxy of the current state of the Italian economy. Similarly, for the US market, I considered the S&P 500 index, the US GDP growth, and the CBOE VIX index, which measures uncertainty and unpredictability in financial markets and accounts for the stress level of investors on the equity market. All macroeconomic variables are downloaded from Thomson Reuters.

Summary statistics

Table I presents a summary statistic of the number of transactions and the average price per bottle at each sale, divided for the different types of wines and chateaus. Panel A shows that the average hammer price, in both nominal and real value, across the over 18 thousand observations is around USD 200 per bottle, which translates in a median value of almost USD 140 because of the high standard deviation. Nominal hammer prices for Italian wines range from USD 7 to a maximum value of USD 1600, which was registered in the Hart Davis Hart Wine Co. auction house in June 2018 for a bottle of Barolo Riserva Speciale Monfortino of vintage 1990.

In Panel B, each wine type is examined separately. Super Tuscan wines account for almost 80% of the trade with an average price per bottle of around USD 200. However, non-Supertuscan wines, although representing only the remaining 20% of Italian wine transactions, are also traded at the same average price. Yet, this last category of DOCG wines seems to be the more volatile, as it contains both the lowest and the highest price per bottle registered.

Panel C provides information about the number of wine transactions and hammer price characteristics relative to each producer whose wine is analyzed in this research paper. In this respect, the Super Tuscan producers Bolgheri and Ornellaia are noteworthy. The former, with only one wine included in our analysis (Sassicaia), represents more than 4 thousand transactions and reflects almost 24 percent of total wine sales registered. Similarly, Tenuta dell'Ornellaia produces the wines Masseto and Ornellaia, which account together for 5879 thousand sales (2687 and 3192, respectively), and almost 33 percent of total transactions. On the other hand, the Piedmont wine cellar Giacomo Conterno produces the most expensive wine, i.e. Barolo Riserva Speciale Monfortino, which is sold at an average hammer price of USD 494 per bottle.

[Insert Table I about here]

Furthermore, we observe that most wines are sold in full cases of 12 bottles, which account for more than 32 percent of total wine transactions (Figure I in the Appendix). Investors could prefer buying lots with complete cases because these are thought to give some credibility about the wine's authenticity. Moreover, for this added value attached to full case sales, sellers may thus demand a premium. In addition, wine collectors often buy lots with half cases of 6 bottles, which represent the 24 percent of sales. This choice could be seen as a trade-off for those investors caring about the credibility provided by full cases, but who are not willing to pay such a high price. Figure I in the Appendix also shows that more that 12 percent of Italian wine investors decide to buy single bottles. This percentage decreases when lots consist of 2 to 5 bottles.

Figure II in the Appendix shows the distribution of wine sales across the world. North America is the biggest buyer of Italian fine wines, with US investors concluding almost 50% of wine sales. These are followed by European (17%) and, lastly, by Asian collectors (7%).

Nonetheless, it is important to note that auctions on the Internet account for almost 30% of total sales. The fact that the biggest auction houses have their largest premises in North America, while being only marginally present in Europe and Asia, makes us conclude that Internet sales should be mostly divided between these last two countries.

Finally, although the hammer price excludes buyer’s premium and sale taxes, one should take into account that transaction costs and other expenses weigh on the seller. Because of the lack of information disclosure by auction houses and the structure complexity of the seller’s commission, which depends e.g. on the number of transactions per auction period and on the number of lots in each auction, it is difficult to correct for these additional fees. For instance, Cardebat et al. (2017) reports that, in 2012, seller’s commission amounted for almost 6% for significant lots, e.g. first growth and other high-quality vintages.

Chapter 1. Determinants of Italian Wine Price

1 Methodology

This section starts with a description of the hedonic regression technique. In general, this method allows to measure the contribution of a product's attributes to its price by relating prices to their value-determining characteristics (Rosen, 1974). This approach breaks down the asset being analyzed into its attributes, and it allows to estimate the contributory value of each constituent. Hedonic pricing models are usually used in markets where assets are traded infrequently, in order to study their price formation. Examples are the real estate market (Campbell, Giglio, and Pathak, 2011) and the art market (see e.g. Renneboog and Spaenjers, 2013). Dimson et al. (2015) and Cardebat et al. (2017) have recently applied the hedonic regression technique to study the determinants of wine prices.

As regards the wine scenario, this method consists in regressing the price of wine on its characteristics and it aims at estimating the value that consumers ascribe to the quality of wine, in terms of reputation effect. For each transaction, the price of wine is collected, together with a certain number of characteristics generally thought to explain the price: date of sale, vintage, château, year of sale, quantity sold, country of the buyer and auction house. In order to determine the price impact of wine attributes on prices, a logarithmic-linear model is estimated. This is characterized by the natural logarithm of wine prices as the dependent variable and by various categorical variables as explanatory variables. In previous studies about the determinants of wine prices, a log-linear model is usually preferred over a fully linear regression, because, among other explanations, it is thought to be more suitable for dealing with the problem of heteroskedasticity, i.e. non-constant variance of error terms (de Haan and Diewert, 2013).

Formally, the baseline regression model is:

$$\log(P_{it}) = \alpha_0 + \alpha_1 Supertuscan_{it} + \alpha_2 Case12_{it} + \alpha_3 Case_{it} + \beta_1 \sum_{j=1}^{26} Vintage_{it} + \varepsilon_{it} \qquad (1)$$

The dependent variable, P_{it}, indicates the real USD hammer price of a producer-vintage combination i sold at date t. $Supertuscan_{it}$ is a dummy variable proxying wine quality and identifying those wines in the "Super Tuscan" category (Masseto, Ornellaia, Sassicaia, Solaia, and Tignanello). The binary variable $Case12_{it}$ controls for any premium paid for complete cases of twelve bottles. The idea is that lots with complete cases may provide some credibility about the wine's authenticity and, thus, demand a premium. However, even if complete cases are sold, there still might be a quantity discount for larger lots, captured by the variable $Case_{it}$, which considers the case in which cases with multiple bottles are sold (i.e., more than 6 bottles, excluding lots with 12-bottle cases). $Vintage_{it}$ denotes vintage fixed effects and it represents the year in which the grapes were harvested. Under the standard error assumptions, i.e. zero mean and constant variance, equation (1) is estimated using the Ordinary Least Squares (OLS). In our OLS regression, prices are expressed in real USD and standard errors are clustered by year of sale, in line with previous studies (e.g. Dimson et al., 2015).

In addition to this baseline regression, other specifications are then studied in order to account for a set of characteristics related to the chateaus, the date and country in which wine is sold, and the auction houses responsible for the trade. Each additional variable (γ_1 to γ_4) is included one at a time to study its own contribution to the price, and the final regression can be defined as follows:

$$\log(P_{it}) = \alpha_0 + \alpha_1 Supertuscan_{it} + \alpha_2 Case12_{it} + \alpha_3 Case_{it} + \beta_1 \sum_{j=1}^{26} Vintage_{it} \\ + \gamma_1 \sum_{j=1}^{6} Producer_i + \gamma_2 \sum_{j=1}^{4} Quarter_{it} + \gamma_3 \sum_{j=1}^{5} Country_{it} + \gamma_4 \sum_{j=1}^{7} Auction_{it} + \varepsilon_{it} \tag{2}$$

The added variables include various additional fixed effects that comprise:

i. $Producer_i$. These dummies take account of fixed effects for the château producing the wine, and they represent six Italian producers (Antinori, Bolgheri, Gaja, Giacomo Conterno, Redigaffi, and Tenuta dell'Ornellaia);

ii. $Quarter_{it}$. This is a variable that considers the time of the year, and specifically the quarter, in which the wine is sold. Auction sales are indeed characterized by seasons and most wine is sold in the last quarter of the year, especially in December (Figure III in the Appendix). Therefore, the goal is to examine whether this seasonality in sales also drives wine prices;

iii. $Country_{it}$. Wine is mainly sold in North America, Europe and Asia or online. Among these, the Asian market is worth noting: although the Chinese demand still lies behind the US and European wine market in terms of quantity purchased, it is growing rapidly and it is characterized by high offer prices during auctions;

iv. $Auction_{it}$. Auction house fixed effects are introduced. Of the 19 auction companies in the sub-sample, 7 of them account for almost 84 percent of the trade, while the largest four (in order of registered trades, Zachys, Acker Merrall Condit, Sotheby's and Christie's) represent approximately 63 percent of fine wine transactions (Figure IV in the Appendix). The idea is that the most famous auction houses, because of their renown and presence in the largest US and European cities, could carry a premium and raise therefore final hammer prices.

The third step in the hedonic pricing model is to account for the effect of aging on the price of wine. How aging affects wine prices is interesting because wines can be valuable even after losing their gastronomic worth, if they are still able to bring pride and pleasure to the owners, also called non-pecuniary benefits (Dimson et al., 2015). In order to study the impact of aging, vintage dummies are excluded because they would cause multicollinearity with age variables, and the regression is described as:

$$\log(p_{it}) = \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Age_{it}^2 + \alpha_3 Age_{it}^3 + \alpha_4 Supertuscan_{it} + \alpha_5 Case12_{it} + \alpha_6 Case_{it} + \beta_1 \sum_{j=1}^{4} Quarter_{it} + \varepsilon_{it} \quad (3)$$

Age_{it} controls for the wine's age at the date of sale and it is defined as year – vintage. Dimson et al. (2015), while studying the determinants of wine prices, analyze low-quality and high-quality wines separately, since the price of these two categories of wines develops differently with respect to age. In particular, they argue that, whereas the value of low-quality wines decreases after bottling for increasing after they become "antique", the consumption value of high-quality wines behaves in a different way. After bottling, in fact, the consumption value of the latter rises as the wine improves in quality, and it stabilizes when its maturity is reached. Eventually, prices begin growing again when high-quality wines start to be considered as collectibles rather than consumption goods. Because of similar characteristics in terms of climate, soil and other natural conditions, Italian wines examined here can be compared to the high-quality fine wines and they are therefore expected to follow the behavior described by Dimson et al. (2015) for high-quality vintages. Therefore, since we expect a non-linear trend of wine prices with respect to age, quadratic (Age_{it}^2) and cubic values (Age_{it}^3) are included in the regression.

2 Results

In this analysis, we regress the natural logarithm of the USD hammer prices on a set of characteristics of Italian wines. While the baseline regression only considers the quality, quantity and vintage of wines, equations (2) and (3) add in explanatory variables and include fixed effects that control for the chateau, time and place of sale, auction house and age (Models 1-6 of Table II). All models count 18,019 observations and cluster standard errors by the year of sale.

In order to interpret the coefficients of dummy variables in logarithmic-linear models, we follow the study of Halvorsen and Palmquist (1980), whose technique has also been implemented later by other studies on the price and return of fine wines. Therefore, the percentage effect on the wine price of dummy variables, that enter a semilogarithmic regression in dichotomous form, is equal to[4]

$$100 * g = 100 * \{\exp(\hat{\beta}) - 1\} \tag{4}$$

Results of equations described in the previous section are presented in Table II. Column 1 reports results for equation (1), the baseline regression, without any producer, quarter, country, auction house and age fixed effects. All effects included in the regression, i.e. $Supertuscan_{it}$, $Case12_{it}$, $Case_{it}$ and $Vintage_{it}$, are statistically significant at 1% level.

[Insert Table II about here]

As regards the dummy variable $Supertuscan_{it}$, coefficients show that the inclusion of wines in the "Super Tuscan" category has a positive and statistically significant effect on their price. Across all regressions, Supertuscan wines have an average impact of approximately 19%[5] on price, which is however distorted by the large positive coefficient estimated in the chateau regression (Column 2).

The full case premium, represented by the variable $Case12_{it}$, is about 32% and is statistically significant at the 1% level throughout all six variants of the hedonic model. Although quite important in terms of magnitude and significance, the quantity discount, expressed by the hedonic variable $Case_{it}$, is around 48% across all wines and auctions, and it therefore more than offsets the quantity premium. These results are not in line with the research of Cardebat et al. (2017), who find the full case premium to exceed, in absolute terms, the quantity discount. The quantity discount is also statistically significant at the 1% level in all models.

Substantial vintage effects are also noteworthy. In this case, dummy variables for those wines of vintage 2015 are omitted because of multicollinearity. In general, although coefficients seem to favor recent over past vintages, in line with Cardebat et al. (2017), vintage effects are all negative over the sample. In the case of dummy variables, coefficients must be interpreted relative to the reference group, namely the omitted vintage. From this perspective, negative estimates therefore mean that wines of the vintage 2015 have the strongest effect on final prices. For example, the first five vintages (1990 to 1994) have and average coefficient of -1.071, while the last five vintages, that cover wines from 2010 to 2014, display an average estimate of -0.616.

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[4] $g = (Y_1 - Y_0)/Y_0$, where Y_1 and Y_0 are the values of the dependent variable when the dummy variable is equal to one and zero, respectively (Halvorsen and Palmquist, 1980).

[5] This is calculated as $100 * \left\{exp\left(\frac{0.0931+0.105+0.604+0.0921+\ .0769+\ .087}{6}\right) - 1\right\} = 19.30\%$.

Columns 2 to 5 of Table II show the fixed effects of added dummy variables on the dependent variable, the logarithm of wine price. The first hedonic regression (Column 2) investigates the impact that different chateaus have on final hammer prices. While the Tuscan producer Bolgheri has been omitted for multicollinearity issues, the other chateaus all present statistically significant effects. In general, Giacomo Conterno, an historic Piedmont winery built in the mid-19th century, exhibits the highest positive impact on prices, with a statistically significant coefficient of 1.124. On the contrary, the Florentine wine company Marchesi Antinori, which played an important role in the Super Tuscan revolution of the 70s, has a negative coefficient of -0.343 that represents a negative effect of about 41% with respect to Bolgheri. Nonetheless, it is important to note that the price paid for Antinori's wines strongly varies across its three products (Guado al Tasso, Solaia, and Tignanello). Among the others, Guado al Tasso is indeed the wine sold at the lowest average price and might, therefore, be the cause of the negative coefficient of Antinori wine cellar. All other Italian producers, Ornellaia, Gaja and Redigaffi, have a positive and statistically significant effect on price.

Moreover, column 3 depicts the effect of the time of sale on the price. The universe of transaction is divided in quarters, in order to simplify the analysis and better replicate the distribution of sales. When the distribution of trades is analyzed, it can indeed be noticed that most wines are traded during the last quarter, especially in December, and in the months of September, June, May, and November (Figure I). From Table II it can be argued that the wines sold in the last quarter of the year tend to be traded at higher prices. The coefficient for the fourth quarter is indeed positive and statistically significant at the 5% level and it displays an increase of around 8% on the final price. While the third quarter is omitted, the coefficients for the first two periods are all positive but not statistically significant.

[Insert Figure I about here]

As regards the place of sale, we consider the auction companies where fine wine is traded and the country in which they are sold. As for the latter, with respect to Asia, which is excluded for multicollinearity, the other countries all present negative and strongly statistically significant coefficients. Column 4 of Table II shows that, when controlling for quality, quantity and vintage, the internet is the virtual place where fine wines are traded for the lowest price, with a coefficient of -0.653. Similarly, European and US buyers offer a price which is 78 and 42 percent lower than Asian wine collectors, respectively. In general, as also reported by Lucey and Devine (2011), prices at European auctions are below the US level, but Asia is the country where fine wines are sold for the highest price. This is an important result when considering the extraordinary growth of the Asian demand.

Column 5 includes fixed effects for auction houses where wines are sold. Table II only displays the largest auction companies, which account for more than 80 percent of the trade in collectible wine. Except for the Spectrum Wine Auctions company, all other coefficients are positive and statistically significant at the 1% level and, on average, they increase the final price by about 36%. When all the 19 auction houses are included in the analysis, results do not change (Table I in the Appendix). However, the inclusion of the whole sample of auction companies reveals strong price premiums related to smaller houses like Bloomsbury and Leland Little (with statistically significant coefficients of 0.820 and 0.747, respectively).

The last column of Table II introduces the age fixed effect and displays results for equation (3). In order to study the impact of aging, vintage dummies are excluded because they would cause multicollinearity with age variables. In general, results show that the value of wines increases as they get older and their price grows by about 10% every year. The coefficients for the quadratic and cubic effect of age are both statistically significant at the 10% level. Although quite small in statistical terms, their economic magnitude is strong, since they confirm the presence of non-linear relationship between age and price. The significance of the three age coefficients indicates that there is a curvature in the relationship between wine price and age, and the signs of the linear and cubic terms, both positive, suggest that the aging effect can be depicted as in Figure II. In order to plot the aging effect on wine prices, we present the following expression which is constituted by the constant, α_0, and the three age coefficients, representing the linear, quadratic and cubic effects displayed in Table II:

$$y = 4.332601 + 0.1034813Age_{it} - 0.0051332Age_{it}^2 + 0.0000995Age_{it}^3 \qquad (5)$$

A significant cubic coefficient indicates that the way in which aging affects wine prices is characterized by two inflection points. In other words, prices of Italian wines rise for the first ten years and then stabilize over the following decade and a half. Eventually, after age 25, their value starts soaring again and it rockets when wines reach their thirtieth year (Figure II).

[Insert Figure II about here]

These findings suggest that different characteristics of wines contribute to the creation of their prices. In particular, the quality, quantity and the vintage of wines are the main elements when examining this relationship. However, when other measures are added to the analysis, i.e. details regarding the producer, period of sale, country of buyers and auction house, the R^2 of the models increases. Moreover, it is important to note that wines are not only valuable for their gastronomic appeal, but also for the enjoyment that they provide to their owners. Indeed, the price of wines increases even after they reach their maturity. This non-linear relationship is described by the cubic effect of age and it will be discussed in more details in Section 3.2 below.

3 Discussion

Wine production is a complex technology, the result of which depends on many different inputs that cannot always be controlled. Examples are favorable weather conditions and other initial endowments that cannot be modified (e.g. soil) and that take several years before yielding good quality products.

In the following session two of the main price drivers are examined, i.e. the weather, captured by the set of dummy variables $Vintage_{it}$ in equation (1), and the aging of wine, described by the linear, quadratic and cubic variables (Age_{it}, Age_{it}^2, and Age_{it}^3) included in regression (3) in Section 1. The following reasonings should be supported by Table II.

3.1. Weather

The sample wide results reveal that wines of different vintages carry diverse loads on final prices. In essence, estimated coefficients seem to favor recent over past wines but old vintages also show some strong positive effects on prices sometimes. These findings are in contrast with some previous studies (Di Vittorio and Ginsburgh, 1996; Ashenfelter, 2008) which agree that older wines tend to result in higher prices. The year in which the grapes were harvested, represented by the dummy variable $Vintage_{it}$ in hedonic regression (1), does also constitutes a measure of wine quality. Indeed, referring to red Bordeaux wines, the quality of the analyzed vintage can be predicted by the temperature and the weather conditions during the growing season that created the wines (Ashenfelter et al., 1995). Similarly, Ashenfelter (2008) also explains that the variability in the price and quality of wine vintages can be forecasted by the weather that ripened the grapes. Therefore, when interpreting results of the vintage coefficients displayed in Table II, the weather conditions that characterized those years need to be included in the evaluation.

The majority of previous studies focus on red Bordeaux wines but, because of the strong similarity in soil and weather between the Bordeaux region and the Italian regions included in the sample (i.e. Tuscany and Piedmont), those reasonings can be applied to this research.

Generally speaking, weather conditions for red wines are only critical between April and September, as those grapes are dormant from November to March. Especially for Piedmont wines, where winters can be relatively cold, frost and hail in April may still be a problem because vines come into bud in this period. Moreover, rainy weather is helpful between April and May, but the main determinants for high quality vintage are sunshine, heat and dry weather during the summer. In particular, high temperatures are beneficial for the quality of wines in June, August and September, when grapes complete their ripening. Poor weather conditions determine delayed harvesting (after September 15) and lead to poor vintages (Ginsburgh et al., 2013).

Referring to results reported in Table II in Section 2, the vintage 2015, which is omitted for multicollinearity, seems to be the most productive vintage in the sample, since all other coefficients have a negative sign. With regard to the weather conditions that characterized that year, regions in the central North of Italy experienced an extraordinary summer, which led to an outstanding grape harvest in terms of quality as well as quantity. Because of the favorable weather conditions, in 2015 Tuscany wine export grew by 25.8%[6].

Although vintages before 2015 all have negative coefficients, some of them present only a small disparity from 2015 and are therefore signs of high-quality vintages. When comparing the estimated coefficients in Table II with description of weather conditions reported in wine magazines, it can be concluded that those vintages with smaller coefficients in absolute terms are the same characterized by favorable temperatures.

In particular, starting from 2015 and going back in time, it can be noticed that the first vintage with a coefficient smaller than 0.5 in absolute terms is 2010. Because effects of dummy variables must be interpreted in relation to the group reference (in this case vintage 2015), a vintage with an estimated coefficient smaller than 0.5 stands for high-quality, since it means that than specific year is similar to 2015 in terms of wine quality and price impact. Indeed, in harmony with the estimated results, while vintages between 2011 and 2014 were all characterized by rainy summers and a checkered climate, 2010 is reported to have experienced high summer temperatures. Similarly, vintage 2006 is also noteworthy. Its coefficient, -0.327, indicates indeed a high-quality vintage resembling 2015, which is characterized by high sales price. International wine newspapers (*Food & Wine* and *Decanter* among others) describe the grape harvest in central northern Italy in 2006 as overall excellent. Other vintages that are worth mentioning in terms of weather are 2004, 2001 and 1997, and they all in fact correspond to small coefficients in absolute terms. These years are all characterized by hot Augusts and dry summers, with good night temperature excursions. All these conditions signed some excellent vintages, described as similar to year 2015 by some wine experts. Among the oldest vintages, 1990 stands out from the others for its majestic red wines, characterized by its grand structure, balance and consistency, elegant, perfume, warm and generous taste, fine and harmonious tannins. These results are consistent with the findings of Di Vittorio and Ginsburgh (1996), who analyzed wine vintages connected to weather conditions between 1989 and 1994.

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[6] Data are taken from the webpage of Assoenologi – Associazione Enologi Enotecnici Italiani. Assoenologi is the most influential Italian interbranch organization of wine specialists. https://www.assoenologi.it/

3.2. Aging

Age coefficients in Table II reveal that the price of fine wines increases with age by around 10% each year, and that aging has a non-linear relationship with wine value, as depicted in Figure II in Section 2 above. This section aims at discussing and interpreting results from equation (3), relating and comparing these findings to previous studies.

In 2015, Dimson et al. studied the effect of aging on wine prices by distinguishing low-quality from high-quality wines on the basis of their vintage. In particular, they argue that wines can still provide pleasure and satisfaction to their owners even after having crossed the threshold of their gastronomic appeal. The authors therefore assume that fine wines not only yield pure financial returns, but they also provide non-pecuniary benefits associated with holding wines for longer than gastronomically due.

In their research, Dimson et al. (2015) develop a model that produces different predictions for the price trend of low-quality and high-quality vintages. Specifically, the price of low-quality wines decreases rapidly after bottling, caused by a decline in the consumption value. The price fall persists until the value that wines hold as collectible goods exceeds the value of consumption. After this, prices start increasing with age. On the other hand, the price trend of high-quality vintages behaves differently. Indeed, these wines grow in quality after bottling and their price continues rising until they reach maturity, at which point it stabilizes. Eventually, when the collectible value of these wines exceeds their consumption value, prices advance again.

The sample-wide results calculated as in equation (3), and displayed in Table II and, graphically, in Figure II, demonstrate that the Italian fine wines studied in this research can be linked to high-quality vintages presented in Dimson et al. (2015). In particular, from this analysis it follows that prices of Italian wines rise for about the first ten years and then they stay steady until age twenty-five, when their value starts soaring again.

Unlike wines studied in the previously mentioned research, Italian wines stand out for the age in which they reach maturity. Indeed, while high-quality vintages of red Bordeaux wines improve in drinkability for 40 years and can be classified as antique after 80 years, the age ranges for Italian wines are much shorter. In particular, medium-bodied red wines, for instance Chianti, Solaia and Tignanello, start maturing at year 5 until age 10-15, while more imposing wines (Barbaresco, Barolo and Masseto among others) reach their maturity at age 10 but they can improve until year 20. These assumptions are in line with what depicted in Figure II: analyzed wines grow in drinkability for around 12 years and do not vary in consumption value thereafter. After maturity, which is on average reached at age 12.5, wine prices increase gradually with wealth until the collectible value takes over, around age 25, after which the price rockets.

To summarize, the fact that wines which are significantly beyond their optimal consumption level, i.e. red wines approaching the thirtieth year, keep increasing in price is consistent with the hypothesis of a rising non-financial benefit to owning such rare wines. A potential non-financial utility was indeed defined as "user benefit" (Burton and Jacobsen, 2001) and observed in other not merely monetary markets, such as socially responsible mutual funds (Renneboog et al., 2011), and art (Stein, 1977; Mandel, 2009). However, it is difficult to say how much is this non-pecuniary payoff and if it exceeds the capital gains, also considering other risks and costs related, for example, to the wine storing process.

3.2.1. Robustness check: Aging effect for high-quality vintage

Finally, as robustness check, similarly to the study of Dimson et al. (2015), I run the same regression as equation (3) but only considering high-quality vintages. In this paper, in order for a specific wine to be defined as high-quality vintage, it needs to meet two conditions. In particular, high-quality vintages are here defined as, firstly, those years characterized by favorable weather conditions reported in wine magazines, as described in the previous section, and, secondly, those vintages represented in Table II by a coefficient lower than 0.5 in absolute terms[7]. Results are reported in the Appendix, Table II. In this case, coefficients for the age effects are similar to the ones of the baseline regression reported in Section 2. When the new linear, quadratic and cubic effects, together with the constant, are inserted in an expression similar to equation (5) and then plotted, it can then be seen that the trend of the wine price with respect to age is consistent to previous findings (Appendix, Figure V). The consumption value for Italian high-quality wines indeed grows until around age 10, and then stabilizes. In the end, when wines reach the twenty-five year and start being regarded as collectibles, prices advance again. However, the price development of high-quality vintages seems to follow a more stable trend. While the price in the baseline model that considers the whole wine sample exhibits an average increase of 1.5% between age 0 and age 50, with a boost of around 2.5% after age 25, high-quality vintages show an average growth of only 0.8% from year 0 to year 50. Moreover, the price boost given by the collectible value makes the wine price rise of only 0.9% from age 25 to age 50 (against the 2.5% increase in the baseline model).

[7] High-quality vintages are 1990, 1997, 2001, 2002, 2004, 2005, 2006, 2010 and 2015.

Chapter 2. Index Construction

1 Methodology

A variety of yearly indices are computed using different techniques. Wine return indices are here estimated first using a traditional hedonic regression, similar to equation (3), and then through repeat-sales coefficients.

1.1. Hedonic method

The hedonic regression has been used by several authors for the construction of return indices. Di Vittorio and Ginsburgh (1996), for instance, apply this methodology for studying the price of wines produced in the Médoc region and sold by Christie's London. More recently, Ma et al. (2019) used the same method to estimate the return index of differently colored non-figurative paintings. In line with these works, I adapt equation (3) to obtain yearly coefficients, considering a year fixed effect instead of quarter dummy variables. In order to calculate yearly return indices, the hedonic regression is therefore designed as follows:

$$\log(p_{it}) = \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Age_{it}^2 + \alpha_3 Age_{it}^3 + \alpha_4 Supertuscan_{it} + \alpha_5 Case12_{it} + \alpha_6 Case_{it} + \beta_1 \sum_{j=1}^{22} Year_{it} + \varepsilon_{it} \tag{6}$$

This estimating regression for a log-linear model is generally mentioned as the "time dummy variable hedonic model" (de Haan and Diewert, 2013). Similarly to equation (3), vintage fixed effects are excluded in order to avoid problems of multicollinearity. The yearly dummy variables ($Year_{it}$) contained in this regression are captured by binary variables indicating the year of sale. The analysis considers wines traded between January 1997 and December 2018 and, therefore, 22 dummies are included in the regression. To avoid perfect collinearity, the time dummy variable indicating the base period, in this case year 1997, is left out. Moreover, to deal with observations being correlated within the same year, standard errors are clustered by year of sale.

The hedonic price wine index follows directly from the estimated time dummy regression in equation (6). Here, the year dummy variables measure the effect of "time" on the logarithm of wine price, and their coefficients, which therefore indicate a time-inflation effect, are then translated into return indexes. Since the hedonic regression controls for any event other than time, the index represents the price for wines with constant characteristics in terms of age, quality and quantity. This means that, by exponentiating the coefficients of the time dummies, we can control for variations in the hedonic characteristics of wine and provide a quality-adjusted change in the price between the base year 1997 and each comparison year t. In other words, the wine price index going from the base period to year t is calculated as

$$I_t = \exp(\widehat{\beta_{1,t}}) \tag{7}$$

Where $\widehat{\beta_{1,t}}$ defines the estimated coefficients of year dummy variables from equation (6).

Moreover, in order to determine the returns of the Italian wines considered in the study, we take the first difference of the coefficients of year fixed effects as in Burton and Jacobsen (2001).

$$R_{I,t_1,t_2} = \widehat{\beta_{1,t_2}} - \widehat{\beta_{1,t_1}} \tag{8}$$

Where R_{I,t_1,t_2}describes the return of the wine index I calculated for the period t_2. Similarly, $\widehat{\beta_{1,t_1}}$ and $\widehat{\beta_{1,t_2}}$ are the estimated yearly time coefficients from the hedonic regression as in equation (6).

1.2. Repeat-sales regression (RSR) method

The repeat-sale regression (RSR) method, after being first presented by Bailey et. al (1963) in the real estate market, has been since employed to other infrequently traded assets (e.g. wine and art).

The model can be illustrated for any repeat sale as follows:

$$R_{n,y_1,y_2} = \frac{I_{y_2}}{I_{y_1}} * U_{n,y_1,y_2} \tag{9}$$

I_y are the unknown price indices that we aim to estimate. U_{n,y_1,y_2} is an idiosyncratic error term, and the period of repeat sales considered is expressed in years as $y = 0, \dots, Y$, with $y_1 < y_2$, and where $y_1 = 0, 1, \dots, Y-1$ and $y_2 = 1, 2, \dots, Y$ (Lucey and Devine, 2011). R_{n,y_1,y_2} represents the return of wine n in year y_2, and it is described as the ratio of the final sales price over the initial sales price $\left(R_{n,y_1,t_2} = P_{n,y_2}/P_{n,y_1}\right)$. The wine return is therefore equal to the ratio between the true but unknown price indices for years y_1 and y_2 (i.e., I_{y_1} and I_{y_2}) multiplied by a wine-specific error term for the same periods. In general, the repeat-sales regression considers both the overall wine market behavior, as it considers the wine price indices, and the unique factor of each individual wine, i.e. the idiosyncratic error term.

In order for the equation to be more easily implemented, the regression is translated in a more straightforward form by calculating the natural logarithm of equation (9) as

$$\ln\left(R_{n,y_1,y_2}\right) = -\ln\left(I_{y_1}\right) + \ln\left(I_{y_2}\right) + \ln(U_{n,y_1,y_2}) \tag{10}$$

If lower case letters are used to denote natural logarithms, then the repeat-sales model can be written as:

$$r_{n,y_1,y_2} = -i_{y_1} + i_{y_2} + u_{n,y_1,y_2} \tag{11}$$

According to Bailey et al. (1963), the error term in log form is assumed to have zero means, constant variance and to be uncorrelated with any i_y.

In order to estimate the index values (I_y), it is necessary to determine the range of i_y by creating a set of dummy variables, x_y, with $y = 0, \dots, Y$, that take value 1 at the time of sale, -1 at the time of purchase, and 0 otherwise:

$$x_y = \begin{cases} -1, if\ y = y_1 \\ +1, if\ y = y_2 \\ 0, otherwise \end{cases}$$

To summarize, a repeat sale occurs each time the same bottle of wine, in terms of equivalent vineyard, producer and vintage, is sold on two different points in time. For each pair of trades, I calculate the log-price relative by subtracting the natural logarithm of the price on the first sale from the logarithm of the price on the second date. These log-price ratios are then regressed on Y independent dummy variables. At this point, the model can be stated as:

$$r_{n,y_1,y_2} = \sum_{y=1}^{Y} i_y x_{n,y} + u_{n,y_1,y_2} \tag{12}$$

The repeat-sales regression is estimated using the ordinary least squares (OLS) method. Following the work of Bailey et al. (1963), the intercept coefficient is set to zero in order not to distort the regression estimates. The regression coefficients represent the estimates $\widehat{i_y}$, which are the natural logarithms of the estimates of the sought wine index $\hat{I}$. Because of the nature of the repeat-sales regression, which only measures the price change of identical wines, there is no need for any quality adjustments between various wines. Therefore, as described in equation (7), the wine index is calculated taking the inverse function of the regression coefficients, with the base price index value $\widehat{I_0}$ set to 100.

Additionally, the nominal rate of return of wine between two consecutive periods, in this case an annual yield for wine, is estimated by first-differencing the coefficients, as described in Section 1.1 by equation (8).

1.3. Comparison between hedonic and RSR methods

Both the hedonic regression and the repeat-sales regression model present some benefits and some downsides. However, since the dataset is quite accurate and comprehensive, and the sample is sufficiently large, we expect to get similar results.

On the one hand, the hedonic method allows to calculate the extent to which each factor influence the price of wine. Moreover, as the model relies on actual market data, the hedonic method is considered to be straightforward in valuing wine prices. Furthermore, when running the hedonic regression, since non-environmental characteristics are controlled for and held steady, any remaining difference in price expresses variations in the wine's external surroundings.

On the other hand, the hedonic method also suffers from some drawbacks. Since this approach requires generating variables for each characteristic that may affect wine prices, the model presents some challenges. Indeed, as wine sales prices can be influenced by a multitude of quality differentials, it is almost impossible to capture all these different inter-product characteristics, and, although these variables could be identified, they would have been difficult to estimate. For instance, even if numerical scores are assigned to specific wine vintages by wine critics, these are subjective and can be sensitive to conflicts of interest. Therefore, in order to overcome these problems, a repeat-sales regression method is also used to construct the wine price index, and the two return series will then be compared.

The RSR model was first developed by Bailey et al. (1963) to study real estate prices and it has then been applied to art (Goetzmann, 1993), wine (for instance, Burton and Jacobsen, 2001; Sanning et al., 2007; Masset and Weisskopf, 2010; Lucey and Devine, 2011), and other infrequently traded assets. Unlike returns of stocks and bonds, which are easy to calculate because of their high tradability, infrequently traded assets (e.g. real estate and wine) are not sold several times per year, and therefore the evaluation of their price index is much more challenging.

The repeat-sales regression method consists in calculating the price index by analyzing repeat sales of the same wine. Thus, the model involves considering wines of the same type, in terms of name, producer and vintage, which are traded at different times. Since identical products are only examined, the method allows to eliminate any differences in quality that may distort results in hedonic regressions. Hence, the use of identical goods means that quality-adjusted price indices are calculated. Moreover, as wine is produced in multiple-bottle batches, implying many occurrences of repeat sales of equivalent assets, wine return indices so calculated are therefore supposed to be accurate. Goetzmann (1992) demonstrates that the model is a reliable representation of the overall trend of wine prices over the index time period, especially when large datasets are studied. Large datasets are defined as those where the number of observations is considerably higher than the number of time periods included in the index. The idea of the repeat-sales regression method is that the price movement that results when the same wine is traded reflects the general trend of the market. When considering the entire subsample, the method allows to generate a unique price index for all wines analyzed. Also, the RSR method maximizes the information incorporated in intermediate sales and it therefore allows to produce estimates for each period, by simply using two endpoints.

Although the repeat-sales regression seems to fit properly to the wine market, it also presents some disadvantages. First, even if a certain wine is usually produced in multiples and, hence, it is traded more than once, the method can still suffer from sample reduction. This can particularly be the case when less frequently traded wines are analyzed, which are only sold in small numbers at any auction, and this can bias results as outliers are created. However, we can state that our research does not suffer from this problem, as only the most traded Italian wines are here considered. Indeed, each wine studied in this paper has been sold on average 1,800 times, with some products, e.g. Ornellaia and Sassicaia, being traded almost four thousand times over the sample period.

Another problem is the so-called non-random sample selection and it refers to fact the dataset resulting from the repeat-sales regression could potentially be non-random. In the context of real estate market, Gatzlaff and Haurin (1997) argue that the chance of observing a property in an auction strongly depends on its price appreciation, and the same reasoning can be applied to the case of wine. Indeed, it should be remembered that the value of wine is deduced either from sale income or from the benefits that users get from its consumption (Burton and Jacobsen, 2001). This particular nature of fine wine implies that, if consumption benefits are high or if the value of wine does not increase as expected, the investor may conclude that the utility of drinking the wine exceeds the potential return from sale. In this case, the asset price cannot be captured by the model since the repeat sale has not occurred. For this reason, wine indices are said to be biased toward wines with higher investment performance.

Finally, some authors argue that heteroscedasticity and multicollinearity could be present when using the RSR method. The first issue arises when random variables have non-constant standard errors and different variances. If this is true, one of the key assumptions of the method, i.e. the error term has constant variance, is invalidated. As regards multicollinearity, happening when independent variables are intercorrelated, it would imply that small changes in the data may have important effects on regression estimates (Lucey and Devine, 2011). However, both econometric problems are thought to be solved when dealing with sufficiently large datasets, as in our case.

2 Results

This section of the study reports the wine price indices constructed using the hedonic regression expressed in equation (6), and the repeat-sales regression defined by equation (12). Price indices and returns from the two methods are then compared in Table III.

3.3. Hedonic method

Equation (6) uses a traditional hedonic regression in order to estimate yearly return indices for Italian fine wines included in the sample. Unlike the hedonic model presented in Chapter 1, and described by equations (1) to (3), this regression does not focus on the impact of wine attributes on the final price, but rather on how time dummy variables can be translated into price index. With this aim, the hedonic regression controls for any event other than time by including constant characteristics in terms of age, quality and quantity. As regards the time coefficients, it is important to note that the first year of sale considered in this analysis, i.e. year 1997, is left out to prevent perfect collinearity. Results are reported in Table III.

[Insert Table III about here]

Column 1 of Table III displays results for equation (6) and reports hedonic coefficients. The estimates of the quality characteristics of Italian wines appear to stay fairly robust with the findings calculated from equation (3) and summarized in Table II, column 6. Since equation (6) is also a log-linear hedonic regression, the relative effects of dummy variables on the dependent variable are interpreted following the methodology of Halvorsen and Palmquist (1980), i.e. subtracting 1 to the exponential of the coefficients (look at equation (4) in Section 2, Chapter 1).

In particular, results show that those wines described as Super Tuscan are sold with a price increment of 11% and, although smaller, the quantity discount, of almost 27%, is large enough to compensate the increase in price due to the full case premium, which is estimated to be around 15%. Again, similarly to results reported in table II, aging seems to have a non-linear relationship with wine prices. The coefficients of the linear, quadratic and cubic age effects are indeed all statistically significant at the 5% level and they describe a trend of wine price similar to the one depicted in Figure II.

However, Table III focuses attention on time dummy variables. From year 2002, all estimates are strongly statistically significant, with the one exception of the 1998 coefficient which is statistically significant at the 10%. In general, year coefficients follow an increasing trend and they seem to favor wines that are sold more recently. For example, the time coefficient grows from -0.018 in 1998 to 0.857 for year 2018.

The wine price index calculated as in equation (7) is described in column 2 of Table III and illustrated in Figure III. Year 1997, which is omitted to avoid multicollinearity, is set as the base year and it is associated to an index value of 100. The index, in line with the trend of time coefficients, has an increasing evolution and it reaches a growth of 136% in 2018. In particular, after a slight decline in 1998 and 1999, the value of Italian fine wines starts to constantly rise up to 2006, with an upper peak in 2007. Following a small fall in conjunction with the economic recession in 2008, which nevertheless maintains the index above the 2006 level, wine prices continue to increase continuously for the next five years thereafter, until they experience a negligible decline up to 2016, when the index starts its ascent again.

[Insert Figure III about here]

Column 3 of Table III reports the returns of Italian fine wines calculated by taking the first difference of yearly coefficients. Returns, as estimated from the hedonic regression, have a positive arithmetic mean of 4.08% and a standard deviation of 7.49%. Extreme returns are observed in 2007 and 2008, with yields of around 25 and -11.5 percent, respectively. A negative outlier is then registered in 2014 (-9.93%), followed by a positive peak in 2017 of almost 14%.

3.3.1. Robustness check: clustered standard errors

This section of the paper is designed to describe the methodology and outline results of a number of robustness checks that have been implemented in order to deal with potential biases in the standard errors reported in Table III and described in the hedonic regression (6).

It is well known that, when residuals are independent and identically distributed, OLS standard errors are unbiased. However, and in particular in panel data sets, you might suspect residuals to be correlated across observations. In this case, OLS regressions provide biased standard errors, which may either under or overestimate the variability of estimated betas. In general, financial literature most commonly faces two forms of dependence, which are usually described as time effect and firm effect. The former case, which is also called cross-sectional dependence, is the subject of regression (6) and the basis of the abovementioned analysis, and it considers the case when residuals on different firms are correlated within the same year. On the contrary, the firm effect deals with the fact that residuals of a given firm may be correlated across years (time-series dependence). When these concepts are applied to our case and adapted to the data set studied, the time effect is expressed by the year of sale, while the different types of wine represent the id variable in the panel data.

Besides these two within-cluster correlations, this section also investigates the presence of dependence within other dimensions, i.e. assuming correlation across auction houses and producers as well. In order to examine the impact of clustering on standard errors, the following analysis reports the hedonic regression without adjusted standard errors as baseline model, which is then modified in order to allow for clustering on different dimensions. Results are presented in Table IV.

[Insert Table IV about here]

Considering a fixed time effect means that, although the regression is still as the one presented by regression (6), the assumption of independent errors has been relaxed and both the error term (ε_{it}) and the independent variables (X_{it}) are specified as

$$\varepsilon_{it} = \delta_t + \eta_{it} \tag{13}$$

$$X_{it} = \zeta_t + \upsilon_{it} \tag{14}$$

Similarly to what studied by Petersen (2009), equation (13) shows the residuals consisting of a time-specific components (δ_t), and an idiosyncratic component which is specific to each observation (η_{it}). In the same way, the independent variables (X_{it}) are also assumed to have a time-specific component (ζ_t), and a term particular to each observation (υ_{it}). In order for the estimates to be consistent, the components of both ε_{it} and X_{it} are independent of each other, have zero mean, and finite variance. In other words, both the residuals and the independent variables are correlated across observations within the same year but are independent across years of sale.

Indeed, Column 2 of Table IV shows that, when data are clustered by year of sale, resulted standard errors are on average twice the size of the White standard errors (compare Column 1 and 2). It is important to note that all specifications (Columns 1-7) include year dummies and, therefore, they already control for constant time effects. The fact that clustering by the year of sale provides higher standard errors means that there is still a significant nonconstant time effect besides the constant year effect already explained by time dummies. In particular, a nonconstant time effect could be illustrated by saying that a trade happening in a certain year has a larger impact on wine A rather than on wine B. Indeed, if the time effect impacted each wine in a given year by the same amount, the year dummies would suppress the impact and clustering by year of sale would not change standard errors. For example, we might want to investigate how a wine sale happening in the early nineties would affect Supertuscan wines' returns differently. In this case, a nonconstant time effect could be present since Super Tuscans are more recent wines compared to the ancient wine history of Tuscany, and they thus represent only a small proportion of 90s' sales. In other words, nonconstant year effects imply that residuals of wines in the same category, in this case Supertuscan wines, are correlated (within the year) with each other, but less correlated with non-Supertuscan wines, e.g. Barbaresco and Barolo.

The story is very similar when data are clustered by wine. Both residuals and independent variables are correlated across years, but independent across wines. Similarly to the fixed time effect, both residuals (ε_{it}) and independent variables (X_{it}) consist of a wine-specific component (γ_i and μ_i, respectively) and an observation-unique component (η_{it} and υ_{it}) as follows.

$$\varepsilon_{it} = \gamma_i + \eta_{it} \tag{15}$$

$$X_{it} = \mu_i + \upsilon_{it} \tag{16}$$

In case of wine fixed effects, Peterson (2009) argues that estimated standard errors are very close to the true values when they are calculated by clustering, i.e. considering the potential correlation within a cluster to adjust the White standard errors. Previous literature about autocorrelation in data analysis and precise estimates also agrees that clustered standard errors, also called Rogers standard errors in financial studies, are robust variance estimators and are unbiased for cluster-correlated data (Liang and Zeger, 1986; Moulton, 1986; Arellano, 1987; Andrews, 1991; Williams, 2000). In fact, these clustered estimates seem to be more precise, i.e. closer to the true standard errors, when the fraction of variability coming from the wine effect ($\rho_\varepsilon = \sigma_\gamma^2/\sigma_\varepsilon^2$ and $\rho_X = \sigma_\mu^2/\sigma_X^2$) rises.

In our case, Column 3 of Table IV shows that clustering by wine has a strong effect on standard errors, which experience a sharp increase compared to the baseline model without adjustments. Rogers standard errors are indeed more than two times larger than White standard errors, with the exception of the standard error associated with the Supertuscan dummy variable which is over 30 times larger than the base case and makes indeed the estimated coefficient non statistically significant.

In Column 4 and 5, standard errors are clustered by the producer and the auction house, respectively. As regards the former, Column 4 discovers a strong producer effect characterizing the Italian wine market. In particular, a fixed producer effect means that the return on every wine from the same producer is increased by the same amount at each sale. This might be connected to the reputation of certain wine cellars and the role they play in influencing the price and the perceived quality of the product even before sale. However, if clustering by producer provides significant effects in increasing standard errors, observations within the same auction house are less correlated. Although the baseline regression underestimated the standard errors, the clustered ones are indeed only slightly higher than in the unadjusted hedonic model.

The last part of Table IV reports standard errors clustered by two dimensions to deal with the fact that residuals might also be correlated across clusters. For example, Column 6 assumes the presence of both cross-sectional and time-series dependence and, therefore, it clusters by year of sale and wine simultaneously. One way to treat two sources of correlation could be to parametrically control for one of the dimensions, i.e. absorbing one of the two effects, by including dummy variables for that dimension and then clustering by the other. However, this parametric approach only produces unbiased results when the time effect is fixed, and, as we showed in Column 2, the dataset is here characterized by nonconstant year effect. Therefore, in order to estimate unbiased standard errors, a less parametric approach is preferred, and standard errors are thus clustered on the two dimensions at the same time. In line with the works of Cameron, Gelbach, and Miller (2011), and Thompson (2011), standard errors are clustered as described by the following variance-covariance matrix:

$$V_{Time\&Wine} = V_{Time} + V_{Wine} - V_{White} \tag{17}$$

The first term on the right-hand side of equation (17) describes the standard errors clustered by year of sale and expresses the unspecified correlation among observations on different wines in the same time, i.e. dependence between ε_{it} and ε_{kt}. Similarly, the second term absorbs the unspecified correlation between ε_{it} and ε_{is}, meaning between observations on the same wine in different times. The third term, representing the White variance-covariance matrix, is subtracted off since both the year- and wine-clustered matrix already contain the diagonal of the variance-covariance matrix. In the two-way clustering, the dataset is assumed to be structured as follows

$$\varepsilon_{it} = \delta_t + \gamma_i + \eta_{it} \tag{18}$$

$$X_{it} = \zeta_t + \mu_i + v_{it} \tag{19}$$

Where the variability of both residuals and independent variables is caused, simultaneously, by year and wine effects. If the dataset presents this type of double correlation, standard errors adjusted for only one dimension will be biased downward.

Column 6 of Table IV shows indeed that standard errors clustered by time and wine simultaneously are almost three times larger than White standard errors, and bigger than the ones adjusted for cross-sectional and time-series dependence individually.

Likewise, Column 7 reports standard errors clustered by both time and auction house. With respect to these two dimensions, the baseline hedonic regression provides less underestimated standard errors. Yet, the two-way clustering produces on average larger standard errors, even if the main source of correlation is due to the time effect. Indeed, as illustrated in Column 5, since the auction house effect is only small, the two-way clustered standard errors are essentially identical to the ones clustered by year of sale alone (compare Column 2 and 7 in Table IV). This implies that residuals and independent variables are correlated across observation within the same year and, to a lesser extent, within the same auction house.

In general, although clustering by different dimensions provides more precise and larger standard errors, almost all the estimated coefficients remain statistically significant across the different specifications. The one-way and two-way clustering can therefore be used as a robustness check for the soundness of the explanatory variables in the hedonic regression (6), in Section 1.1, Chapter 2.

3.4. Repeat-sales regression (RSR) method

This part of the study reports results of the repeat-sales regression described by equation (12) in Section 1.2. Running an RSR for the whole sample of Italian fine wines provides the estimated coefficients reported in the second set of columns in Table III. Table III indicates each time period's result, with its standard error in parenthesis. As the table shows, most of the coefficients are statistically significant at a high level of confidence, while the adjusted R^2 for the RSR OLS index is however only 0.0349.

[Insert Table III about here]

Results derived from the repeat-sales regression method are, generally speaking, quite similar to those described in the previous section, and calculated with the hedonic model. As regards the time coefficients, these present a general increasing trend, starting from 0.013 in 1998 and arriving at 0.873 in 2018. As before, the dummy variable corresponding to the year 1997 has been omitted to prevent multicollinearity and it is therefore associated to a null coefficient (column 4 Table III).

Following the methodology described in Section 1.2, we use the coefficients generated by the RSR to create a quality-adjusted price index over the period 1997 to 2018. The wine price index is presented in Column 5 of Table III. The index allows to show in a more direct way the behavior of wine prices over the studied period. Similarly to the yearly coefficients, Figure III shows that the wine index exhibits a stable increment over the entire period, and it does not display any specific year when the Italian wine market experienced important downfalls. Despite some slight price declines, it seems indeed that the market has always been bullish over the analyzed period, until reaching a price index level of 239 in 2018.

In addition, first-differencing the time coefficients results in quality-invariant real annual rates of return. Returns of Italian wines are displayed in the sixth column of Table III. The real rate of return between 1998 and 2018 is characterized by an average value of 4.16% and a standard deviation of 4.17%. Such a low standard deviation, compared to the 7.49% in the previous section, means that time coefficients derived from the repeat-sales regression present a lower variability than the ones resulting from the hedonic analysis.

A comparison between the hedonic and the RSR method will be more closely discussed in Section 3.1.

3.4.1. Robustness check: RSR and quarterly wine index

This section is designed to check the robustness of the annual index series and wine returns calculated in Section 2.2 with a repeat-sales regression.

In this part of the research, we use the same model described by equation (12) but substituting year dummy variables with a set of quarterly dummies. The aim of this robustness check is to derive quarterly rates of returns of Italian wines over the period 1997-2018, and compare them with yearly results displayed in Table III. The model can be stated as:

$$r_{n,q_1,q_2} = \sum_{q=1}^{Q} i_q x_{n,q} + u_{n,q_1,q_2} \tag{20}$$

In this case, the period of repeat sales is expressed in quarters as $q = 0, \dots, Q$, with $q_1 < q_2$, and where $q_1 = 0, 1, \dots, Q-1$ and $q_2 = 1, 2, \dots, Q$. Again, r_{n,q_1,q_2} is the log-return calculated as $r_{n,q_1,q_2} = \ln(P_{n,q_2}) - \ln(P_{n,q_1})$, for the period between the purchase (q_1) and sale (q_2) of wine. i_q is the value of the natural logarithm of the index at time q; and $x_{n,q}$ is a quarterly dummy variable taking the value 1 in the quarter in which the wine was sold, -1 at the quarter of purchase, and 0 otherwise. u_{n,q_1,q_2} is the logarithm of the idiosyncratic error term.

The repeat-sales regression is estimated using the ordinary least squares (OLS) method. In the same way as before, the intercept coefficient for the last quarter of 1997 is set to zero in order not to distort the regression estimates. Regression coefficients represent the estimates $\widehat{\iota_y}$, which are the natural logarithms of the estimates of the sought wine index $\hat{I}$. Quarterly wine indices and returns are calculated from estimated coefficients as described in Section 1.

Results of regression (20) are reported in Table III in the Appendix. Unlike the annual RSR, the adjusted R^2 for the annual model is improved (8.1% in contrast to 4.4%), although quarterly coefficients only become significant from 2007. In terms of wine index, results show an increasing trend starting from 100, in the last quarter of year 1997, and ending at almost 230 at the end of 2018 (Figure VI, Appendix).

In addition, first-differencing the time coefficients results in quality-invariant real annual rates of return. Returns of Italian wines are displayed in Column 4 of Table III (Appendix). These quarterly rates of return have a positive arithmetic average of 0.99%. While rates of return, being calculated on a quarterly basis, are in line with annual wine returns reported in the previous section, wine prices appear, in this case, to be much more volatile. This quarter-based study estimates, indeed, a standard deviation of 8.36%, compared to 4.17% calculated in the annual baseline repeat-sales regression. This high variation, however, is caused by the quarterly nature of the study: when you zoom in and more data points are revealed, you can expect to capture higher dispersion compared to single annual data. Alike stock prices, wine prices also tend to fluctuate day by day.

In summary, despite the higher standard deviation, the repeat-sales regression based to quarterly dummy variable provide a solid robustness check both in terms of the index trend and in respect of the average rate of returns.

3 Discussion

This section of the research paper is designed to discuss the results presented in Section 2 of Chapter 2. This allows the study to, firstly, deduce concise findings about the difference between the hedonic regression and repeat-sales regression method and, secondly, to compare the performance characteristics of Italian fine wines with other art and financial assets.

3.1. Comparison between hedonic and RSR methods

Results reported in Section 2 refer to two different approaches used in the literature about collectible goods to construct price indices. These two methods, while providing similar results, also present some differences related to both their structure and their outputs.

First, while both models produce estimates with a low R^2, the adjusted R-squared of the repeat-sales regression is only 3.49%, compared to the 15.74% of the hedonic method. There can be several reasons for a low R^2. Firstly, the difference in the precision level between the two regressions can be explained by the different number of observations considered. Indeed, while the hedonic method works with the whole sample, the RSR regression is only interested in couples of same wines and this requirement cuts the dataset by almost 88%.

However, when referring to collectible goods, as illustrated in Burton and Jacobsen (2001), a relatively low R^2 usually indicates, at least in part, the significant "noise" that constitutes auction prices. In fact, other return-to-art studies based on auction data have experienced similar results and they all have discarded a low R^2. Indeed, although a low R-squared generally indicates a lack of precision of the model, in the art market, it can be justified if it is caused by characteristics of the goods being analyzed. For example, in his research about the modern print market, Pesando (1993) approves an R-squared of 0.239 by arguing that "prices of identical prints that are sold within relatively narrow windows often vary substantially". Similarly, when analyzing the wine market, it can be noted that wine prices generally differ consistently, depending on several factors such as the wine's provenance. In this regard, as found by Ashenfelter (1989), and additionally discussed by Ginsburgh (1998), the price of fine wines usually decreases when they are sold late in the day, mainly because of the overall thinness of the wine market, an event referred as "declining price anomaly". Therefore, the high stochasticity of wine prices can be justified when considering the rather subjective nature of the determinants of wine quality.

Another difference between the hedonic method and the repeat-sales regression is the variability of the returns calculated from the estimated coefficients. As illustrated in Table III, the coefficients generated by the two approaches are used to estimate a quality-adjusted price index and to calculate real rates of return. However, while the hedonic and the RSR methods both generate an average return of around 4% (specifically, of 4.08 and 4.16 percent, respectively), its standard deviation varies greatly between the two models. In particular, the standard deviation of annual rates of return from the hedonic regression is almost 7.5 percent, against 4.17 of the RSR. Such a high standard deviation identifying the pricing model implies that the mean only provides a poor measure of central tendency, and that the distribution is asymmetrical and characterized by more outliers. Indeed, as depicted in Figure III, the trend of wine returns calculated from the RSR presents a smoother, increasing flow. Finally, since the two datasets have approximately the same mean, the standard deviation can be useful to compare their spread. Rates of return estimated from the RSR have a narrower spread of measurements around the mean and, therefore, have comparatively fewer high or low values.

In summary, the comparison between the hedonic model and the repeat-sales regression posits that these approaches, while providing similar results in terms of average price index, also differ when it comes to the model's precision and the variability of returns. In general, the rate of return on fine wine seems to be quite volatile, as significant positive returns are frequently followed by considerable negative returns. Generally speaking, the RSR method provides a less volatile wine price index, while being based on a lower number of observations. To conclude, it could be argued that the estimated wine returns are specific to the period and wine type that is being considered. Indeed, Jaeger (1981) demonstrates that, as fine wine has a fairly elastic demand, its rate of return can be relatively sensitive to the time period that is being studied. However, our results can be considered consistent with past studies, as similar performance characteristics are found by previous academics (for example, Burton and Jacobsen, 2001; Lucey and Devine, 2011). Again, Spurrier (1997) outlines that the return on wine, although studied during the so called "auction fever", was still subpar.

3.2. Comparison with other art and financial assets

The aim of this section is to place the wine return characteristics in context. In particular, Table V provides summary information on the return of red Italian fine wines, and it compares their investment performance and correlations with other wine, art, and financial assets. Besides details on Italian wines, which are the focus of the paper, Panel A also shows real returns and investment characteristics of other wines, i.e. red French wines (from the Bordeaux and Rhone regions), red Australian wines, and the Liv-ex Fine Wine 100 Index as proxy of the wine industry benchmark. Moreover, wines are compared to a series of art investment vehicles, namely an art index, paintings, stamps, classic cars, sculptures, and white diamonds. Finally, two financial indices are used as representatives of the financial market, i.e. the S&P 500 and the FTSE MIB equity index.

Details about the art index and sculptures returns (in the 1998-2018) are downloaded from the Artprice (2019) website. Similarly, real returns of the Liv-ex Fine Wine 100 Index, S&P 500 and FTSE MIB are retrieved from Thomson Reuters database. Additionally, information on wine and art investment assets is derived from published articles. In particular, the study of Lucey and Devine (2011) is used to calculate red French wines returns in the 1996-2006 period; Australian wines returns are estimated from Fogarty (2010) for the 1990-2000 period; returns on paintings (in the 1958-2016 period) are calculated from Ma (2019); the article of Dimson and Spaenjers (2011) is used to get information on Stamps returns for the 1900-2008 period; classic cars returns are derived from Laurs and Renneboog (2019) in the 1999-2017 period, while the paper of Renneboog and Spaenjers (2012) is used to calculate white diamonds returns for the 2000-2010 period.

[Insert Table V about here]

In Panel A, for each investment asset, the first two entries report the arithmetic average of real returns and their standard deviation, as proxy for total risk, respectively. As regards Italian fine wines, details about their return and volatility are derived from the repeat-sale regression as outlined in Table III. From the first two rows, it can be argued that higher returns are not always associated with higher risk, and paintings, stamps, and sculptures are only some examples of this behavior. When comparing average returns on fine wines with other financial assets, it is noteworthy to say that the relative performance of collectibles could be depressed by high transaction costs, which weigh more than trading costs for the return of financial assets. For example, Cardebat et al. (2017) report that the buyer's premium at Christie's London and Christie's New York in 2012 was 17.5 and 22.5 percent, respectively, and the same premia were paid at Sotheby's. However, the commission paid by the seller, in the same year, was less than 6% for prestigious lots, meaning that the seller received only about 76.5% (at Christie's London) and 71.5% (at Christie's New York). Moreover, final costs also need to include any transportation, handling, and administration expenses that purchasers and sellers can incur.

Furthermore, Italian, French, and Australian wines have all outperformed paintings, stamps, classic cars, sculptures and the Italian stock market index. This high financial return of wines might be caused by the fact that traded wines are relatively young and high-quality, when compared to, for example, art collectibles. In addition, as argued by Dimson et al. (2015), the attractiveness of wine, more than that of art or stamps, is strongly determined by its age, and this makes fine wine an investment asset "with higher capital gains but a lower nonfinancial dividend yield".

In order to compare the risk-adjusted performance of different asset classes, the third entry shows the Sharpe ratio, which is a measure of excess portfolio return per unit of risk. The Sharpe ratio is therefore calculated as the asset return minus the risk-free rate relative to the asset standard deviation. Here, the 90-day Treasury bill rate is taken as a proxy for the risk-free rate, which is retrieved from the website of the Federal Reserve Bank of St. Louis. Since the Sharpe ratio measures the risk-adjusted return of an investment vehicle, a portfolio with a higher ratio is preferred to its peers. In this regard, Panel A demonstrates that, generally speaking, the wine index shows greater performance (Sharpe ratio of 0.37) relative to both the art and the equity indices (Sharpe ratios of -0.01, 0.30, and -0.01 for the art index, S&P 500, and FTSE MIB, respectively). In particular, although characterized by relatively lower mean returns, Italian fine wine is the asset class with the highest Sharpe ratio (0.51). It is noteworthy to say that such a high Sharpe ratio for Italian wines may be caused by the use of RSR results. Indeed, as discussed in the previous section and shown in Table III, when returns are derived from a hedonic model, they show higher standard deviation. However, by including hedonic mean and variability estimates (4.08 and 7.49 percent, respectively), the Sharpe ratio, even if falling to 0.27, remains higher that the Sharpe ratio for both art assets and Italian equity. Among art collectibles, white diamonds are associated with great risk-adjusted return (0.35), whereas sculptures present extremely high volatility compared to their return (Sharpe ratio of -0.07).

The fourth entry in Panel A reports the three-factor alphas. Alphas are calculated by regressing the expected excess return of each asset, at time t, on the excess return of the market portfolio, the size premium and the valued premium, following the Fama French model. The market, small-minus-big and high-minus-low factors are downloaded from the K. French's website. Three-factor alpha is a helpful indicator to determine the risk-return profile of an investment and it represents the excess return of a particular asset over a benchmark index, besides considering other risk-adjusted components in its estimation. In this regard, Italian wines show a statistically significant alpha of 0.2%, while the alpha estimated for the Liv-ex

Wine 100 index is about 0.5%. This could imply that Italian wines, and the wine index in general, tend only slightly to outperform the benchmark and to yield returns in excess of the assumed risk. Similarly, the art index and most other collectibles, such as paintings, stamps, classic cars and sculptures, display alphas statistically close to zero, meaning that they earn a return adequate to the expected risk. The constant parameter for both the equity indices, S&P 500 and FTSE MIB, has a negative value of 0.02%, despite differing in statistically significance: alpha for the S&P 500 is statistically significant at the 1% level, while the one of the Italian equity benchmark is statistically undistinguishable from zero.

Panel B of Table V reports the pairwise correlation of Italian wines with the other art and financial assets. Red Italian fine wines, which are the subject of this research, are, as expected, strongly correlated with the Liv-ex Fine Wine Index (0.40), and only slightly correlated with white diamonds (0.09). Moreover, the correlation coefficients of Italian wines returns are close to zero when they are compared with sculptures (-0.02) and paintings (0.01). In terms of potential diversification gains, Italian wines seem to be negatively correlated with other wine and art collectibles, as well as with equity indices, although coefficients are not statistically significant.

Chapter 3. Herding Behavior among Investors

1 Methodology

The aim of the following section is to study investors' behavior in the wine market and to determine whether or not investors influence each other when they trade collectible wines. In particular, this analysis is critical to understand how information, intended as the observation of state variables related to market uncertainty and risk, is included into wine prices. In line with Orléan (1989), who studied herding in financial markets, my analysis focuses on the collective behavior of all investors in buying and selling wine at the same time.

Previous literature on herding behavior is split between the study of a group-wide and a market-wide type of herding. While the first refers to the behavior of market participants and investigates their tendency to trade together, the latter examines the collective attitudes of all traders toward the market view and, hence, their decision to buy and sell a particular asset at the same time. In other words, as described by Henker et al. (2006) in their study about herding on Australian equities, market-wide herding happens when investors track the market performance without considering the individual properties of stocks. In this research we investigate the presence of a market-wide herding behavior among traders of Italian fine wines.

In general, previous empirical studies of herding in financial markets have demonstrated that the occurrence of herding causes the dispersion of individual returns to be relatively low, leading returns on single assets to cluster around the overall market return (Christie and Huang, 1995). When studying the US stock market, they argue that this behavior happens because, during periods of market turbulence and sever price fluctuations, people tend to abandon their own opinions for the market consensus, which results in herding.

Most empirical analyses on herding behavior, which focus on the stock market, try to capture the cross-sectional dispersion of stock returns, and its relationship with market returns, with the aim of identifying herding behavior. Applying this concept to the wine market means analyzing the instantaneous auto-covariance of the market index (C_t), and its relationship with other dispersion measures. The regression follows the methodology developed by Aytaç et al. (2018), and can be written as follows:

$$C_t = \alpha + \beta_1 CSSD_{t-1} + \beta_2 mvar_t + \varepsilon_t \qquad (21)$$

The dependent variable, C_t, represents the suppression of individual beliefs and personal information during turbulent markets, and it is defined as the average "instantaneous covariance" between past market returns and actual returns of assets.

Unlike Aytaç et al. (2018), who assume zero mean for returns, the formula for the instantaneous covariance has here been modified in order to allow returns to have an average different from zero. Indeed, the assumption of a zero mean for returns can only be valid when short-time horizons, i.e. one to ten days, are considered. However, since this research is based on quarterly data, a standard covariance formula is applied.

$$C_t = \frac{1}{N-1}\sum_{i=1}^{N}(R_{m,t-1} - \mu_{m,t-1})(R_{i,t} - \mu_{i,t}) = \frac{1}{N-1}\sum_{i=1}^{N}(R_{m,t-1} - \mu_{m,t-1})(R_{m,t} - \mu_{m,t}) \quad (22)$$

$R_{m,t}$ and $R_{m,t-1}$ represent the time-t and time-*t-1* market returns, respectively, while $\mu_{m,t}$ and $\mu_{m,t-1}$ describe their expected values. Market returns are the ones derived from the quarterly repeat-sales regression (20) in Section 2.2.1, Chapter 2. Since the goal of this chapter is to investigate the behavior of investors in volatile market situations, the quarterly repeat-sales regression is preferred over both the annual RSR and the annual hedonic model. Indeed, as previously discussed, a quarterly analysis allows to have more rates of returns on which to base the study of herding behavior, and it therefore represents the perfect candidate for the research. Coefficients of repeat-sales dummy variables, quarterly indexes and wine returns are reported in Table III in the Appendix. Finally, $R_{i,t}$ is the one-period time-t return of the i^{th} asset, i.e. the return between time $t-1$ and t, and $\mu_{i,t}$ is its mean.

The rationale behind this model is that herding can be described as a three-phase behavior among investors. In the first phase, wine investors observe a specific behavior among their peers, together with other macroeconomic variables, and, in a later stage, agents can choose to replicate that behavior (second phase). Rational reasons to copy others are mostly associated with imperfect information, as herding can be viewed as an instrument that allows investors to deal with uncertainty and to improve individual performance by generating future profits. The third phase of the investment decision depicts how this behavior will affect the prices of the related assets. This process has been described in empirical articles about herding behavior on financial markets, which investigate the presence of herding patterns among institutional investors (Lakonishok et al., 1992; Grinblatt et al., 1995).

As a consequence, the instantaneous covariance is designed to study the first two phases of the herding process: investors acknowledge the market return at time $t-1$, and then they decide to invest accordingly at time t. The core idea is that if the performance of the market is positive (respectively negative) at time $t-1$, then herding implies that agents will buy (respectively sell) wines at time t, so that the covariance between market returns and assets' returns is positive. Since we are interested in the market-wide form of herding behavior, this translates in a positive instantaneous auto-covariance, i.e. between the market and itself at pairs of time points.

By plotting market returns and their lagged values (Figure IV), it can be seen that their relationship is slightly negative with a correlation coefficient of -0.003. Therefore, from a covariance study only, we can already say that investors, after having observed the market movement at time $t-1$, tend not to invest in the same direction. If herding behavior describes the tendency of investors to influence each other and copy their peers, such a small correlation coefficient makes us discard the assumption of herding.

[Insert Figure IV about here]

The right-hand side of regression (21) displays two different measures of turbulent conditions in the market, which, according to the behavioral theory, cause the suppression of personal information in case of herding patterns.

The first reason for instability is the market variance, which is here depicted as the exponentially weighted moving average of past quadratic market returns, $mvar$. This variable can be described as follows:

$$mvar_t = \sum_{s=1}^{\tau} \theta^{s-1} R_{m,t-s}^2 \tag{23}$$

Here, the squared market returns, $R_{m,t-s}^2$, are used as a proxy for the market volatility, and θ is a memory parameter weighing the market turbulence. This weight divides investors in two categories, short-memory and long-memory traders, depending on the values it takes. Specifically, θ takes the value of either 0.4, to indicate investors with less memory, or 0.8, for those investors who react more slowly to market instability (long-memory investors). In this analysis, short memory refers to those investors who elaborate and use information in a period of maximum one month, while long-memory investors remember stress events happening until one year ago. Since θ is raised to a power that increases going back in time, and since it only takes values between 0 and 1, the further investors move away from the market turbulence, the smaller the parameter becomes. The assumption behind the memory parameter is that investors are more likely to remember stress events that happened more recently, and, therefore, if we consider $t = 0$ as the further point in time, θ will be, at that point, the lowest possible.

Secondly, $CSSD$ is the cross-sectional standard deviation and aims at measuring the individual variance. $CSSD$ is calculated following the study of Christie and Huang (1995).

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N_t - 1}} \tag{24}$$

This investor-level dispersion measure is introduced because, unlike financial markets, aggregate wine indices tend to be still quite confidential and they do not have a large media coverage as the equity market. Consequently, collectors might be biased toward particular wines and might not consider the market as a whole. As a consequence, individual squared returns ($R_{i.t}^2$) are used to capture individual dispersions that usually drive investors' appreciation of turbulence. Again, since the aggregate level is analyzed, the cross-sectional standard deviation ($CSSD$) is used. Regression (21), however, includes the lagged cross-sectional standard deviation, i.e. $CSSD_{t-1}$, in order to deal with the fact that investors are not expected to react immediately when the market becomes volatile. Indeed, time-t cross-sectional standard deviation should, at least, impact the time- $t+1$ auto-covariance.

To summarize, regression (21) aims at investigating the existence of herding behavior by analyzing the effect of any return turbulence, both on a market level and on an individual level, on the suppression of individual beliefs and personal information, captured by the average instantaneous covariance, C_t. Positive βs are therefore signals of herding behavior among wine investors, since they represent the increase of market autocorrelation due to uncertainty in the financial environment.

2 Results

2.1. Baseline approach

This section of the paper presents results for the study on herding behavior among wine investors as outlined in Section 1. Results are expressed in Table VI.

[Insert Table VI about here]

Table VI introduces the two choices of the memory parameter θ, and reports results for short-memory and long-memory investors separately. This allows to detect any difference in the time wine collectors need to elaborate market turbulence.

In general, coefficients, although small in size, are all strongly significant at the 1% level, and this represents a notable difference with the work of by Aytaç et al. (2018), which did not report any statistically significant results. As regards the economic magnitude, however, coefficients for the market variance and the cross-sectional standard deviation point in different directions. Indeed, for both short-memory and long-memory investors, the negative and statistically significant coefficients of the market uncertainty, as depicted by the variable $mvar$, point toward the absence of herding behavior among wine investors. However, the coefficients for the cross-sectional standard deviation, $CSSD$, are positive in both models. This means that investors react to any turbulence related to their individual extreme returns by suppressing their personal information. Nonetheless, this behavior is not strong enough to cause herding among agents, since its effect is small compared to the negative coefficients of the market variance measure. However, even if the negative coefficients of quadratic market returns, $mvar$, are higher in size than the positive effect of the CSSD, all coefficients are quite small in statistical terms.

Finally, short-memory and long-memory investors seem to behave slightly differently. Firstly, short-memory wine collectors respond to a lesser extent to the turbulence caused by their individual variance (the coefficient associated to $\theta = 0.4$ is 0.000137 for the $CSSD$, against 0.0000146 for long-memory investors). Secondly, when it comes to market volatility, represented by the variable $mvar$, although both types of investors show negative coefficients, short-memory buyers display a much higher estimates in absolute terms (-0.00277 for $\theta = 0.4$, and -0.00135 for $\theta = 0.8$).

2.2. Robustness check: Impact of Italian and US markets

This section of the results outlines the robustness check related to the assumption of herding behavior that has been implemented in the study. This check has been designed to test the validity of the results that have been produced in the main findings of the research.

In particular, the aim of this section is to verify whether results derived from regression (21) are robust to the introduction of some exogenous variables. To do that, control variables related to the macroeconomic situation are included in the regression. The reason to control for these variables is that wine collectors are wealthy individuals who are also exposed to the equity market. Their investment in wines can therefore be linked to the performance of their equity portfolio.

Exogenous variables for both the Italian and the US market are included. The reason to study the Italian macroeconomic situation is that only Italian wines are studied, and, therefore, collectors' behavior might be influenced by the environment in which wines are produced. However, since Italian wines represent the second most collected fine wines, they are generally sold to worldwide investors. Moreover, since US data are very often the source of international economic movements, US control variables are also included in the regression.

As regards the Italian market, the new variables included in the regression control for the equity and the macroeconomic situation. In particular, the equity measure is represented by the stock market index of the Italian national stock exchange (FTSE MIB), while the growth of the Italian GDP is introduced as a proxy of the current state of the Italian economy. When these variables are included, regression (21) can be rewritten as

$$C_t = \alpha + \beta_1 CSSD_{t-1} + \beta_2 mvar_t + \beta_3 FTSEMIB_t + \beta_4 GDPgrowth_t^{IT} + \varepsilon_t \qquad (25)$$

Similarly, for the US market, the S&P 500 index was included to proxy the current state of the US economy. Moreover, the model also controls for the CBOE VIX index, which is a forward-looking measure of uncertainty in financial markets that accounts for the stress level of investors on the equity market. Lastly, the US GDP growth wants to measure the macroeconomic situation. The regression for the US market is therefore defined as

$$C_t = \alpha + \beta_1 CSSD_{t-1} + \beta_2 mvar_t + \beta_3 S\&P500_t + \beta_4 GDPgrowth_t^{US} + \beta_5 VIX_t^{US} + \varepsilon_t \quad (26)$$

Table VII collects the findings of the regressions in which the benchmark case, i.e. regression (21), has been augmented with the macroeconomic variables.

[Insert Table VII about here]

In particular, Panel A displays the estimates for regression (25) and investigates the presence of herding behavior controlling for the Italian market. Both control variables, for each type of investor, are statistically sound, and the R-squared is improved in this case, compared to Table VI. As regards the coefficients of the variables indicating the market turbulence, both $CSSD$ and $mvar$ remain statistically significant at the 1% level, and they keep their original economic magnitude in terms of both sign and size. Finally, the lack of herding behavior is registered among all investors, i.e. short and long-memory collectors, although these two types of wine collectors tend to respond to individual and market turbulence differently.

Similarly, Panel B considers the impact of the US market on herding behavior. The estimates for the effects of the S&P 500 index and the US GDP are both strongly statistically significant and similar in size compared to the equity and macroeconomic measures describing the Italian market and illustrated in Panel A. However, the volatility index, expressed by the variable VIX in regression (26) seems to have no explanatory power on the tendency of wine investors to herd. Since the Volatility Index (CBOE VIX) describes the implied volatility of S&P 500 index options that the stock market expects, a null coefficient implies that wine investors, when making their investment decisions, are not influenced by the expectation of the market volatility. This is an important result since herding behavior is generally though to be driven by the market instability.

When examining the US market, the βs for the $mvar$ and the $CSSD$ are still statistically significant at the 1% and they preserve they sign. After controlling for the macroeconomic US situation, however, turbulence related to the market variance and the individual extreme returns have a lower impact on herding patterns among wine investors, as the economic magnitude of all coefficients decreases with respect to Table VI. In general, for both short-memory and long-memory collectors, the negative effect of market uncertainty, as described by $mvar$, exceeds the impact of the cross-sectional standard deviation of their individual returns, i.e. $CSSD$, on suppressing personal informational, and thus, herding. When including the effect of the US market, the precision of the model grows and the R^2 reaches 34.4 percent for the short-term investors.

In summary, the introduction of macroeconomic variables provides a solid robustness check for the study of herding behavior among international wine investors. Variables measuring turbulent conditions in the market ($CSSD$ and $mvar$) keep indeed their statistical significance and their economic meaning. However, the slight change in results after controlling for the US economic situation makes us conclude that those wine collectors exposed to the US equity market display an even lower tendency to herd.

3 Discussion

The sample wide results reveal that, in general, wine investors do not follow the herd while choosing the type of fine wine to collect. These findings are valid for both short-memory and long-memory investors. Since no previous studies, to the best of my knowledge, have reached significant results about herding behavior in the wine market, we will discuss the findings depicted in Table VI, Section 2.1, on the basis of the main empirical tests about herding in financial markets.

After having investigated the drivers of wine prices (Chapter 1), and their risk-return characteristics (Chapter 2), this last chapter aims at understanding the way in which wine prices incorporate information. In order to understand the meaning and the implications of our results, this section starts with describing herding behavior and the environment in which it is more likely to rise, according to past literature. Christie and Huang, in 1995, described herding behavior in a market setting as the tendency of individuals to "suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions." The fact that investors are attracted by the consensus of the market results in individual returns to stay close to the market return.

Herding behavior is a model often used by researchers to explain apparently irrational markets. However it still represents a cause of division among scholars, who split between those considering it a non-rational behavior (e.g., Trueman, 1988; Grinblatt et al., 1995), and those supporting a rational view of herding (for instance, Orléan, 1989; Devenow and Welch, 1996). The notion of rational herding is here examined, which deals with externalities and lack of perfect information. Academics indeed acknowledge some rational reasons for profit maximizing agents to be influenced after observing others, if they want for example to deal with uncertainty and improve individual performance. In this setting, herding is usually described as a rational behavior employed by agents in response to situations like imperfect information, reputational concern and compensation structures. However, among these circumstances, since the wine market is inspected here, this study mainly explores the case in which investors have private, although imperfect, information when dealing with similar investment decisions. In this framework, herding behavior may arise.

Generally speaking, the model presented in Section 1 investigates whether a group of investors in Italian fine wines tend to buy, or sell, specific bottles at the same time, with respect to what could be expected if they traded independently. As described in Lakonishok, Shleifer and Vishny in 1992, the method studies a particular group of investors and their correlation in trading patterns. The basic assumption is that herding behavior generates correlated trading, although the reverse does not have to be true.

However, results, as reported in Table VI, do not show any sign of herding behavior, as the negative impact of the $mvar$ coefficient exceeds the weak positive effect of the individual dispersion ($CSSD$) on the suppression of personal beliefs. In general, different implications could be derived from these findings.

First, the lack of herding behavior connected to a lack of perfect information could mean that the wine market is, in general, quite transparent. In fact, the market has strongly improved in both liquidity and transparency in the past twenty years, resulting also in an increased attractiveness for worldwide investors. Because of the growth in popularity, wine funds, e.g. the Ascot Wine Management Fine Wine Fund and the Orange Wine Fund, and indices, like Idealwine in France and Liv-Ex in the UK, have indeed emerged to meet this new strong demand from collectors all over the world, boosting the transparency of the market. However, it also noteworthy to underline that, although transparency makes wine prices more closely track fundamentals, it does not necessary mean that it diminishes price volatility (Bikhchandani and Sharma, 2000).

Moreover, according to Bikhchandani and Sharma (2000), an information cascade, which defines the tendency of investors to follow their predecessors, does not start in those markets where the price, after every investment decision, adjusts to consider the information disclosed by that decision. In other words, herding behavior does not emerge in informationally efficient markets, where the price takes into account available information, reflects fundamentals, and, thus, there is no mispricing. Therefore, a lack of herding behavior means that the wine market is only subject to uncertainty about the underlying investment, and not about the accuracy of the information possessed by wine collectors.

Furthermore, as observed by Bikhchandani and Sharma (2000), individual investors are not likely to observe their peers' holdings soon enough to adjust their own portfolios. This would explain why no intentional herding is detected at the level of individual wines. Additionally, Table VI indicates that wine investors with a longer memory show, if any, a greater tendency to herd, as their negative $mvar$ coefficient decreases in magnitude. This means that, although collectors are more likely to remember stress events that happened more recently, short-memory investors are not able to get reliable information in a one-month period, namely soon enough to herd. If we analyze the coefficients reported in Table VI, they show that short-memory collectors, while having a small positive estimate for the cross-sectional standard deviation ($CSSD$), present a much higher negative $mvar$ coefficient compared to long-memory investors. This means that, after short-term wine investors observe a specific behavior in the market, together with other macroeconomic variables, they decide not to invest in the same direction. In other words, faced with turbulence conditions in the market, short-memory investors maintain their individual beliefs and personal information to a greater extent than long-memory collectors.

Lastly, coefficients about herding are difficult to interpret without precise details about the demand elasticity of Italian wines. Indeed, as discussed by LSV (1992), even small estimates could result in large price impacts, and, therefore, the possibility of herding behavior cannot be ruled out. This means that, although very small in size, the coefficient related to the cross-sectional standard deviation in regression (21) may have an economically significant effect on the instantaneous autocovariance of market returns. Since the wine market is generally thought to be fairly demand elastic (Burton and Jacobsen, 2001), even mild herding behavior, caused by individual turbulent conditions, i.e. $CSSD$, might indeed have large price effects.

In conclusion, the results obtained for this behavioral model are in line with expectations. Firstly, the increasing liquidity and transparency of the market make wine collectors more and more aware of their investments. Also, previous studies discarded the presence of herding behavior in developed countries among investment managers. Finally, one should think that fine wine, besides potentially providing a financial return, is an emotional investment that could make investors be biased toward picking those wines they mostly like instead of what perform highly. Consequently, the characteristics of the wine market, the economic context in which the study is done, and the nature of wine as financial asset are all signs that point toward the absence of herding behavior.

Limitations and conclusion

This section of the research paper summarizes and implicates the findings presented in this study, discusses the limitations that were present throughout the process of conducting the research, while finally bringing the paper to a conclusion.

Limitations

While this study uncovers a variety of findings pertaining to the pricing, performance and investors' behavior in the Italian fine wine market, a number of limitations have been encountered throughout the course of the study.

With regards to the sample universe used in this study, a vast analysis of the market of red collectible Italian wines is carried out. Despite this, the nature and the vastness of the wine industry imply that our dataset presents availability and data mining concerns. In the first place, the hedonic price equation developed in Chapter 1 is driven by data availability. Besides the objective drivers included in the hedonic regression, wine prices are indeed known to be driven by other subjective characteristics of wine which cannot be estimated and for which data do not exist. Therefore, for wine pricing models, the starting question is usually what data are available instead of what attributes are likely to be more important. Moreover, data mining concerns arise due to the fact that the paper only focuses on the ten most traded Italian wines. Although they represent the most significant and indicative class in the Italian wine industry in terms of quality and traded quantity, many other Italian wines are left out.

With final regards to the limitations presented by the dataset, the study of herding behavior in Chapter 3 suffers some data availability biases. Indeed, because of the nature of wine trading, it is not possible to distinguish between individual buyers and wine funds when inspecting transactions and this has implications on the analysis of the presence of herd behavior. Different studies agree that the tendency of agents to follow the herd seems indeed to be more pronounced among institutions than individuals. First, since institutions have higher chances of obtaining information from each others' trades, herding behaviors are more likely to occur (Shiller and Pound, 1989; Banerjee, 1992; and Bikhchandani et al., 1992). Second, as argued by Scharfstein and Stein (1990), institutional investors have higher incentives to hold the same stocks as their peers, in order to avoid falling behind the other money managers. Lastly, institutional agents tend all to respond to the same signals, but, since signals at the institutional level are usually more correlated than the ones arriving at individuals, institutions might herd to a greater extent (Lakonishok, Shleifer, and Vishny, 1992). Therefore, not separating individuals from institutional investors may lead to underestimating the presence of herding behavior. In this direction, Lakonishok, Shleifer, and Vishny (1992) argue that "herding can only be detected within subsets of investors", and thus, when the whole market is considered, herding is more difficult to occur. However, despite the herding measure is here calculated without distinction between individual and institutional investors, this fact is not supposed to influence the results to a great extent. Indeed, although the sample is broad enough to provide solid results, it is not representative of the whole trading and it leaves room to the potential creation of herding. Moreover, even if the wine market is developing rapidly, wine funds only represents a small fraction of trading and they are not thought to follow the same rules as other institutional investors in financial markets with regard to herd behavior.

Another limitation that was encountered in the study relates to the methodology used to investigate the presence of herding behavior, but it refers again to the nature of the wine market. To be more precise, besides considering the universe of wine buyers homogeneous, another potential reason why the magnitude of herding behavior might be understated lies in the amount of trading. In particular, as Grinblatt, Titman, and Wermers (1995) point out, when the herding measure is aggregated even across those periods characterized by low trading, the estimated results can then be undervalued. However, evidence shows that the extent of herding behavior among wine buyers does not significantly increase even if the attention is limited only to those periods with high trading. In fact, the problem is related to the characteristic of fine wine to be an infrequently traded asset, with a still rather illiquid market.

Conclusion

In times of market turbulence and economic downturn, when diversification is most needed, correlation among financial assets seems instead to increase, and standard investment vehicles are deemed indeed to become less effective in terms of portfolio benefits. This leads investors to the detection of alternative assets with favorable performance profiles and diversification characteristics. In this regard, fine wines, in general, are known to offer a valid alternative because of their attractive risk-return properties and low correlation with other financial assets. In particular, this research paper explores the topic of Italian wine as collectible investment, by analyzing its main price determinants, the risk-return profile, and the creation of potential herding behavior around it.

In this study, we use data regarding 18,019 transactions and about 152 thousand bottles of the ten most traded Italian wine types that are sold over the period 1997-2018. After conducting a pricing analysis through a hedonic method, we find that quality and quantity attributes are among the most important determinants of wine prices. In particular, we demonstrate that, for example, the inclusion in the Super Tuscan category, the wine vintage, and the chateau are all valuable quality indicators for wine investors. Also, prices of Italian wines seem to be negatively related to the quantity sold in each lot, signifying a ‘quantity discount’ effect. Price determinants are robust when correcting standard errors for any bias due to the dependency of residuals across observations. Furthermore, weather conditions in the year in which the grapes were harvested are here used as a proxy for quality and play a fundamental role in the price determination. Similarly, aging of wine is also significant. The paper shows indeed a non-financial benefit connected to holding fine wines even beyond their drinkability threshold that can be explained by the non-linear relationship between age and price.

By performing both a hedonic and a repeat-sales regression to the price pairs, we are then able to build and compare the two derived indices. While the arithmetic average annual return from both methods is strongly similar (4.08% for hedonic and 4.16% for RSR), wine volatility is instead rather different (7.49% and 4.17%, respectively). However, when compared to other art and financial assets, such as paintings, stamps, classic cars, sculptures, and the Italian stock market index, Italian wine investments tend to outperform in terms of both real return and Sharpe ratio. In a portfolio context, wine indices seem to exhibit, on average, low correlation with analyzed art and stock markets, implying potential beneficial diversification effects, even if results are not always statistically significant.

Although Italian fine wine looks like an attractive investment, a number of caveats come together. Firstly, risk-return characteristics and the performance of Italian wine are not absolute, but they are instead proved to change with the period and the wine type analyzed. This point thus opens the door for further inspection of Italian wines as collectible investment assets in broader timeframe and wine variety. In addition, the comparison between wine and other financial assets should be conducted with the knowledge that the relative performance of collectibles could be depressed by high transaction costs, which are present in only smaller amount for financial assets. Similarly, transportation, handling, and administration expenses also weigh on the return of fine wines, and art investments in general. In summary, we can conclude that the heterogeneity of the wine market should be considered when discussing the performance of wine investments, as vintage can remarkably affect their return. Information is therefore an issue of considerable importance, implying that sophisticated investors can hence make profits on single bottles, e.g. the vintage 2015 for most Italian wines.

The last part of this paper investigates the presence of market-wide herding behavior in the Italian wine market, where herding is defined as the tendency of agents to imitate others by suppressing their private information. We show that international investors do not herd when trading Italian wine, and, if any, they are only slightly influenced by turbulence related to their individual extreme returns, instead of by their peer's actions. Results are robust to the introduction of other macroeconomic variables related to both the Italian and the US market, which is here used as a proxy for the international economic situation. Although no previous study has ever examined herding in the Italian wine market, our results are in line with past literature that discards the occurrence of herd behavior in developed countries and quite illiquid markets, as is the one studied.

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Tables

Table I. Summary Statistics of Hammer Prices

This table presents the number of sales and details on hammer prices that are recorded for each wine type and for each wine producer. For each variable, the table reports the number of observations (N), mean (Mean) and median (Median) values, standard deviation (S.D.) and min (Min) and max (Max) values. Panel A reports a descriptive statistic of hammer prices, in both nominal and real values. Panel B analyzes hammer prices, in nominal terms, of the different wine types. The wines included in the dataset are, in alphabetical order, Barbaresco, Barolo Cascina Francia, Barolo Riserva Speciale Monfortino, Guado al Tasso, Masseto, Ornellaia, Sassicaia, Solaia, Tignanello, Tua Rita. For each wine, the first column specifies whether the wine is included in the Super Tuscan category. Panel C shows a summary statistic of nominal hammer prices paid to wines produced by different chateaus. For each chateau, the first column specifies the wine type produced by that specific wine cellar. Reported producers are Antinori, Bolgheri, Gaja, Giacomo Conterno, Redigaffi, Tenuta dell'Ornellaia.

Panel A: Summary statistic of hammer prices

Hammer Price	N	Mean	Median	S.D.	Min	Max
Nominal	18,019	203	142	172	7	1,600
Real	18,019	199	140	169	6	1,555

Panel B: Summary statistic of hammer prices divided by wine type

Wine	Super Tuscan	N	%	Mean	S.D.	Min	Max
Barbaresco	No	982	5.45%	130	41	32	313
Barolo Cascina Francia	No	611	3.39%	142	91	14	800
Barolo Riserva Speciale Monfortino	No	864	4.79%	494	242	93	1,600
Guado al Tasso	No	815	4.52%	62	20	7	144
Masseto	Yes	2,687	14.91%	466	195	54	1,527
Ornellaia	Yes	3,192	17.71%	137	48	21	415
Sassicaia	Yes	4,191	23.26%	154	55	38	506
Solaia	Yes	2,138	11.87%	169	67	44	496
Tignanello	Yes	2,153	11.95%	87	33	23	320
Tua Rita	No	386	2.14%	208	112	50	583
Total		18,019	100%				

Panel C: Summary statistic of hammer prices divided by producer

Producer	Wine	N	%	Mean	S.D.	Min	Max
Antinori	Guado al Tasso Solaia Tignanello	5,106	28.34%	117	66	7	496
Bolgheri	Sassicaia	4,191	23.26%	154	55	38	506
Gaja	Barbaresco	982	5.45%	130	41	32	313
Giacomo Conterno	Barolo Cascina Francia Barolo Riserva Monfortino	1,475	8.19%	348	260	14	1,600
Redigaffi	Tua Rita	386	2.14%	208	112	50	583
Tenuta dell'Ornellaia	Masseto Ornellaia	5,879	32.63%	288	213	21	1,527
Total		18,019	100%				

Table II. Price Determinants and Hedonic Regressions

This table presents estimates from the hedonic regressions. All regressions are estimated using OLS. The dependent variable is the natural log of deflated wine hammer prices in US dollars. Column 1 reports results for regression (1) described in Section 1, Chapter 1. Column 2-5 report results for regression (2). Column 6 reports results for regression (3). The variable *supertuscan* is a dummy variable identifying those wines included in the Super Tuscan category. *case12* is a dummy variable controlling for complete cases premium; and *case* controls for quantity discount. Vintage variables denote any vintage fixed effect and represents the year in which the grapes were harvested. *age*, *agesq*, and *agecu* denote the linear, quadratic, and cubic effect of wine aging, respectively. *quarter1*, *quarter2*, *quarter3*, and *quarter4* variables considers the quarter in which the wine is sold. The producer fixed effect is considered by the six chateau dummy variables *Antinori*, *Bolgheri*, *Gaja*, *Conterno*, *Redigaffi*, and *Ornellaia*. *Asia*, *UE*, *NorthAmerica*, *Internet*, and *World* are dummy variables taking the value 1 if the wine is sold in Asia, Europe, US, on the Internet, or in the rest of the world, respectively. The last set of dummy variables considers the auction house fixed effects and includes, in particular, the seven largest auction companies: Acker Merrall & Condit, Christie's, Hart Davis Hart, K&L Wines, Sotheby's, Spectrum Wine Auctions, and Zachys. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year of sale level and reported in parentheses beneath the coefficients.

Variables	(1) **Benchmark** log(p)	(2) **Château** log(p)	(3) **Quarter** log(p)	(4) **Country** log(p)	(5) **Auction** log(p)	(6) **Aging** log(p)
supertuscan	0.0931***	0.604***	0.0921***	0.0769**	0.0878***	0.105***
	(0.0236)	(0.0230)	(0.0237)	(0.0277)	(0.0255)	(0.0192)
case12	0.299***	0.252***	0.299***	0.355***	0.179**	0.289***
	(0.0699)	(0.0595)	(0.0702)	(0.0653)	(0.0765)	(0.0818)
case	-0.474***	-0.429***	-0.476***	-0.646***	-0.407***	-0.461***
	(0.0711)	(0.0592)	(0.0713)	(0.0856)	(0.0738)	(0.0871)
vintage1990	-0.393***	-0.269***	-0.387***	-0.253***	-0.272***	
	(0.0407)	(0.0470)	(0.0424)	(0.0362)	(0.0275)	
vintage1991	-1.369***	-1.178***	-1.362***	-1.145***	-1.181***	
	(0.0824)	(0.0858)	(0.0836)	(0.0966)	(0.0690)	
vintage1992	-1.200***	-1.237***	-1.195***	-0.985***	-1.027***	
	(0.0879)	(0.103)	(0.0892)	(0.0901)	(0.0792)	
vintage1993	-1.163***	-1.167***	-1.155***	-0.977***	-1.016***	
	(0.0716)	(0.0733)	(0.0713)	(0.0777)	(0.0629)	
vintage1994	-1.229***	-1.125***	-1.221***	-1.007***	-1.066***	
	(0.0804)	(0.0912)	(0.0807)	(0.0908)	(0.0752)	
vintage1995	-0.964***	-0.854***	-0.958***	-0.785***	-0.843***	
	(0.0617)	(0.0667)	(0.0622)	(0.0671)	(0.0552)	
vintage1996	-0.869***	-0.772***	-0.863***	-0.687***	-0.731***	
	(0.0724)	(0.0673)	(0.0743)	(0.0740)	(0.0628)	
vintage1997	-0.483***	-0.281***	-0.477***	-0.346***	-0.383***	
	(0.0426)	(0.0522)	(0.0444)	(0.0421)	(0.0377)	
vintage1998	-0.741***	-0.670***	-0.735***	-0.572***	-0.633***	
	(0.0572)	(0.0557)	(0.0591)	(0.0599)	(0.0509)	
vintage1999	-0.717***	-0.603***	-0.713***	-0.541***	-0.619***	
	(0.0634)	(0.0627)	(0.0636)	(0.0676)	(0.0559)	
vintage2000	-0.765***	-0.666***	-0.760***	-0.587***	-0.665***	
	(0.0494)	(0.0632)	(0.0492)	(0.0536)	(0.0485)	
vintage2001	-0.389***	-0.348***	-0.384***	-0.248***	-0.307***	
	(0.0584)	(0.0604)	(0.0565)	(0.0575)	(0.0505)	
vintage2002	-0.467***	-0.601***	-0.462***	-0.324***	-0.371***	
	(0.117)	(0.101)	(0.117)	(0.105)	(0.105)	
vintage2003	-0.844***	-0.801***	-0.837***	-0.676***	-0.762***	
	(0.0441)	(0.0582)	(0.0428)	(0.0467)	(0.0389)	

Variables	(1) **Benchmark** log(p)	(2) **Château** log(p)	(3) **Quarter** log(p)	(4) **Country** log(p)	(5) **Auction** log(p)	(6) **Aging** log(p)
vintage2004	-0.461***	-0.458***	-0.456***	-0.310***	-0.375***	
	(0.0572)	(0.0507)	(0.0578)	(0.0584)	(0.0455)	
vintage2005	-0.482***	-0.517***	-0.476***	-0.335***	-0.393***	
	(0.0835)	(0.0733)	(0.0864)	(0.0754)	(0.0714)	
vintage2006	-0.327***	-0.349***	-0.319***	-0.197***	-0.256***	
	(0.0689)	(0.0615)	(0.0720)	(0.0607)	(0.0606)	
vintage2007	-0.628***	-0.477***	-0.619***	-0.482***	-0.533***	
	(0.0621)	(0.0693)	(0.0645)	(0.0547)	(0.0496)	
vintage2008	-0.507***	-0.459***	-0.502***	-0.357***	-0.417***	
	(0.0919)	(0.0656)	(0.0948)	(0.0889)	(0.0897)	
vintage2009	-0.652***	-0.584***	-0.646***	-0.483***	-0.570***	
	(0.0581)	(0.0444)	(0.0585)	(0.0461)	(0.0559)	
vintage2010	-0.413***	-0.340***	-0.410***	-0.277***	-0.343***	
	(0.0529)	(0.0514)	(0.0516)	(0.0567)	(0.0487)	
vintage2011	-0.716***	-0.575***	-0.712***	-0.553***	-0.649***	
	(0.0768)	(0.0566)	(0.0760)	(0.0617)	(0.0714)	
vintage2012	-0.585***	-0.525***	-0.580***	-0.406***	-0.519***	
	(0.0272)	(0.0407)	(0.0277)	(0.0258)	(0.0237)	
vintage2013	-0.651***	-0.562***	-0.650***	-0.494***	-0.590***	
	(0.0431)	(0.0672)	(0.0424)	(0.0436)	(0.0356)	
vintage2014	-0.717***	-0.905***	-0.713***	-0.528***	-0.545***	
	(0.0147)	(0.0168)	(0.0154)	(0.0302)	(0.0263)	
vintage2015	-	-	-	-	-	
age						0.103***
						(0.0351)
agesq						-0.00513*
						(0.00263)
agecu						0.0000995*
						(0.0000)
quarter1			0.0205			0.0461
			(0.0295)			(0.0369)
quarter2			0.0320			0.0276
			(0.0271)			(0.0322)
quarter3			-			-
quarter4			0.0550*			0.0784**
			(0.0294)			(0.0309)
Antinori		-0.343***				
		(0.0121)				
Bolgheri		-				
Gaja		0.419***				
		(0.0318)				
Conterno		1.124***				
		(0.0721)				
Redigaffi		0.752***				
		(0.0776)				
Ornellaia		0.388***				
		(0.0532)				
Asia				-		
EU				-0.578***		
				(0.0530)		
NorthAmerica				-0.350***		
				(0.0712)		

Variables	(1) **Benchmark** log(p)	(2) **Château** log(p)	(3) **Quarter** log(p)	(4) **Country** log(p)	(5) **Auction** log(p)	(6) **Aging** log(p)
Internet				-0.653***		
				(0.0529)		
World				-0.804***		
				(0.0534)		
AckerMerrall					0.250***	
					(0.0398)	
Christies					0.183**	
					(0.0722)	
HartDavisHart					0.441***	
					(0.0549)	
KLwines					0.257***	
					(0.0441)	
Sothebys					0.323***	
					(0.0615)	
SpectrumWine					0.0732	
					(0.0538)	
Zachys					0.381***	
					(0.0479)	
Constant	5.668***	5.013***	5.632***	6.019***	5.353***	4.333***
	(0.0236)	(0.0448)	(0.0248)	(0.0450)	(0.0447)	(0.123)
Observations	18,019	18,019	18,019	18,019	18,019	18,019
R-squared	0.149	0.435	0.150	0.215	0.192	0.072

Table III. Annual Wine Indexes Based on Hedonic and RSR Method

This table presents the wine price indices and real returns derived from both the hedonic regression and the repeat-sales regression methods. Column 1 reports the estimated coefficients of the hedonic regression (6) presented in Section 1.1, Chapter 2, and the standard errors, which are clustered by year of sale and reported in parentheses. Column 4 reports the coefficient estimates as derived from the RSR (12) in Section 1.2, Chapter 2, and the standard errors in parentheses. For each year, Columns 2 and 3 (for the hedonic model), and 5 and 6 (for the RSR model) report the wine price index and the real return, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variables	(1) **Hedonic** log(p)	(2) **Index**	(3) **Return**	(4) **RSR** $\log(p_2/p_1)$	(5) **Index**	(6) **Return**
age	0.0817**					
	(0.0338)					
agesq	-0.00511**					
	(0.00236)					
agecu	0.000107**					
	(0.0000)					
supertuscan	0.104***					
	(0.0198)					
case12	0.141*					
	(0.0735)					
case	-0.268***					
	(0.0683)					
1997	-	100		-	100	
1998	-0.0181*	98	-1.81%	0.0132	101	1.32%
	(0.00900)			(0.0765)		
1999	-0.0176	98	0.05%	0.00829	101	-0.49%
	(0.0125)			(0.0915)		
2000	0.0113	101	2.89%	0.0448	105	3.65%
	(0.0136)			(0.0985)		
2001	0.00358	100	-0.77%	0.185*	120	14.04%
	(0.0157)			(0.104)		
2002	0.0888***	109	8.53%	0.261**	130	7.60%
	(0.0175)			(0.110)		
2003	0.116***	112	2.72%	0.253**	129	-0.78%
	(0.0209)			(0.114)		
2004	0.181***	120	6.50%	0.278**	132	2.42%
	(0.0288)			(0.117)		
2005	0.204***	123	2.25%	0.378***	146	10.04%
	(0.0352)			(0.119)		
2006	0.277***	132	7.33%	0.449***	157	7.13%
	(0.0374)			(0.121)		
2007	0.527***	169	25.02%	0.534***	171	8.44%
	(0.0395)			(0.124)		
2008	0.412***	151	-11.51%	0.523***	169	-1.10%
	(0.0402)			(0.125)		
2009	0.475***	161	6.27%	0.590***	180	6.73%
	(0.0383)			(0.126)		
2010	0.502***	165	2.69%	0.651***	192	6.12%
	(0.0357)			(0.128)		
2011	0.564***	176	6.21%	0.653***	192	0.21%
	(0.0360)			(0.129)		
2012	0.634***	189	7.05%	0.711***	204	5.74%
	(0.0363)			(0.130)		
2013	0.685***	198	5.11%	0.735***	209	2.42%

Variables	(1) Hedonic log(p)	(2) Index	(3) Return	(4) RSR $\log(p_2/p_1)$	(5) Index	(6) Return
	(0.0345)			(0.131)		
2014	0.586***	180	-9.93%	0.803***	223	6.84%
	(0.0344)			(0.132)		
2015	0.657***	193	7.08%	0.776***	217	-2.70%
	(0.0324)			(0.133)		
2016	0.674***	196	1.77%	0.822***	228	4.59%
	(0.0320)			(0.135)		
2017	0.811***	225	13.68%	0.844***	232	2.15%
	(0.0327)			(0.136)		
2018	0.857***	236	4.56%	0.873***	239	2.93%
	(0.0334)			(0.138)		
Constant	4.032***					
	(0.110)					
Arithmetic mean			**4.08%**			**4.16%**
Geometric mean			**4.16%**			**4.24%**
St.dev.			**7.49%**			**4.17%**
Observations	18,019			2,145		
R-squared	0.157			0.035		

Table IV. Wine Return with Clustered Standard Errors

The table contains coefficient and standard error estimates of the hedonic regression (6) described in Section 1.1, Chapter 2, and modified according to clustering discussion in Section 2.1.1. The estimated coefficients in columns 1-7 are OLS coefficients and all the regressions include year dummies to control for fixed time effect. Standard errors are reported in parentheses. White standard errors are reported in Column 1, Column 2 reports standard errors clustered by year of sale and displays the same coefficient and standard error estimates as Column 1 of Table III. Columns 3-5 show standard errors clustered by wine type, producer and auction house, respectively. Standard errors clustered by both year of sale and wine type are reported in column 6, while column 7 displays standard errors adjusted for time and wine. Statistical significance at the 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	log(p)	log(p)	log(p)	log(p)	log(p)	log(p)	log(p)
age	0.0817***	0.0817**	0.0817**	0.0817**	0.0817***	0.0817**	0.0817***
	(0.0130)	(0.0338)	(0.0333)	(0.0316)	(0.0196)	(0.0392)	(0.0301)
agesq	-0.00511***	-0.00511**	-0.00511*	-0.00511*	-0.00511***	-0.00511*	-0.00511**
	(0.000978)	(0.00236)	(0.00236)	(0.00224)	(0.00147)	(0.00272)	(0.00211)
agecu	0.000107***	0.000107**	0.000107*	0.000107*	0.000107***	0.000107*	0.000107**
	(0.0000224)	(0.0000497)	(0.0000524)	(0.00005)	(0.0000339)	(0.0000577)	(0.0000454)
supertuscan	0.104***	0.104***	0.104	0.104	0.104**	0.104	0.104***
	(0.0117)	(0.0198)	(0.384)	(0.273)	(0.0419)	(0.347)	(0.0368)
case12	0.141***	0.141*	0.141*	0.141	0.141*	0.141*	0.141*
	(0.0392)	(0.0735)	(0.0685)	(0.0785)	(0.0710)	(0.0806)	(0.0772)
case	-0.268***	-0.268***	-0.268**	-0.268**	-0.268***	-0.268***	-0.268***
	(0.0386)	(0.0683)	(0.0952)	(0.103)	(0.0715)	(0.0969)	(0.0772)
Constant	4.032***	4.032***	4.032***	4.032***	4.032***	4.889***	4.889***
	(0.169)	(0.110)	(0.360)	0.305	0.084	0.247	0.127
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	**White**	**Year**	**Wine**	**Producer**	**Auction House**	**Year + Wine**	**Year + House**
Observations	18,019	18,019	18,019	18,019	18,019	18,019	18,019
R-squared	0.157	0.157	0.157	0.157	0.157	0.157	0.157

Table V. Comparison of Investment Performance and Correlation with Other Art and Financial Assets

Panel A shows the comparison of red Italian fine wine investment performance with other art and financial assets. The arithmetic average of real return, the return volatility, Sharp ratio and the three-factor Alpha are reported. The Sharpe ratio is calculated as the excess real returns divided by their standard deviations. T-bill rates are used as a proxy for the risk-free rate and are downloaded from the website of the Federal Reserve Bank of St. Louis. MKT, SMB, and HML factors are downloaded from the K. French's website. Panel B presents the pairwise correlation coefficients between Italian wines and other art and financial assets. In Panel A and B, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Red French Wines returns (in the 1996-2006 period) are calculated from Lucey and Devine (2011); Red Australian Wines returns (in the 1990-2000 period) are calculated from Fogarty (2010); the Liv-ex Fine Wine 100 index (in the 2001-2018 period) is downloaded and calculated from Thomson Reuters; Art index (in the 1998-2018 period) is downloaded and calculated from Artprice (2019). Paintings returns (in the 1958-2016 period) are calculated from Ma (2019); Stamps returns (in the 1900-2008 period) are calculated from Dimson and Spaenjers (2011); Classic Cars returns (in the 1999-2017 period) are calculated from Laurs and Renneboog (2019); Sculpture returns (in the 1998-2018 period) are calculated from Artprice (2019). White Diamonds returns (in the 2000-2010 period) are calculated from Renneboog and Spaenjers (2012). Real returns of S&P 500 and FTSE MIB are downloaded and calculated from Thomson Reuters.

PANEL A: Comparison of investment performance with other art and financial assets

Asset Class	**IT Wines**	**FR Wines**	**AUS Wines**	**Liv-ex Wine 100**	**Art Index**	**Paintings**	**Stamps**	**Classic Cars**	**Sculpture**	**White Diamond**	**S&P 500**	**FTSE MIB**
Period	**1997-2018**	**1996-2006**	**1990-2000**	**2001-2018**	**1998-2018**	**1958-2016**	**1900-2008**	**1999-2017**	**1998-2018**	**2000-2010**	**1997-2018**	**1998-2018**
Real Return	4.16%	5.15%	8.47%	8.35%	1.75%	2.49%	3.57%	3.37%	1.11%	6.84%	7.29%	1.64%
Volatility	4.17%	9.12%	8.99%	18.65%	12.59%	16.21%	12.50%	10.03%	10.68%	12.44%	17.70%	21.99%
Sharpe Ratio	0.51	0.16	0.39	0.37	-0.01	-0.13	-0.03	0.16	-0.07	0.35	0.30	-0.01
Alpha	0.002***	0.001	0.002***	0.005**	0.00	-0.001***	0.001	0.001***	-0.001	0.005***	-0.002***	-0.002

PANEL B: Pairwise correlation of wine and other art and financial assets

	IT Wines	FR Wines	AUS Wines	Liv-ex Wine 100	Art Index	Paintings	Stamps	Classic Cars	Sculpture	White Diamond	S&P 500	FTSE MIB
IT Wines	1.00											
FR Wines	-0.35	1.00										
AUS Wines	-0.86	0.87*	1.00									
Liv-ex Wine 100	0.40	0.67	-	1.00								
Art Index	-0.14	0.39	0.87	0.07	1.00							
Paintings	0.01	-0.06	0.03	0.46*	0.76***	1.00						
Stamps	-0.50	-0.42	0.03	-0.54	-0.05	-0.02	1.00					
Classic Cars	-0.16	0.18	1.00***	-0.09	0.20	0.19	0.21	1.00				
Sculptures	-0.02	0.75**	0.54	0.37	0.74***	0.85***	-0.35	0.31	1.00			
White Diamonds	0.09	0.55	1.00***	0.49	0.32	0.57*	-0.13	0.48	0.54*	1.00		
S&P 500	-0.12	0.73**	0.77***	0.25	0.13	-0.10	-0.18	-0.06	0.17	0.16	1.00	
FTSE MIB	-0.14	0.49	-0.14	0.17	-0.08	0.00	-0.56*	0.24	0.07	0.08	0.70***	1.00

Table VI. Herding Behavior among Investors of Italian Wine

The table presents results from regression (21) described in Section 1.1, Chapter 3. The table reports results for the two levels taken by the memory parameter θ. $\theta = 0.4$ denotes wine investors characterized by a short-memory; while $\theta = 0.8$ marks long-memory investors. The regression is estimated using OLS. The dependent variable is the instantaneous auto-covariance of the wine market index, denoted by (C_t) in regression (21). $CSSD$ is the cross-sectional standard deviation that measures individual variance. $mvar$ is the market turbulence measured by the exponentially weighted moving average of past quadratic market returns, where $\tau = 4$. Standard errors are reported in parentheses beneath the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively. The number of observations and the R^2 are also reported.

θ	CSSD	mvar	Constant	Observations	R-squared
0.4	0.000137***	-0.00277***	-0.0000345***	18,426	0.231
	(0.000)	(0.000)	(0.000)		
0.8	0.000146***	-0.00135***	-0.0000217***	18,426	0.187
	(0.000)	(0.000)	(0.000)		

Table VII. Robustness Check for Herding Behavior

The table studies the effect of the Italian and the US macroeconomic situation on the herding behavior presented in Table III. Panel A presents results for regression (25), while Panel B reports results for regression (26), both described in Section 1.2, Chapter 3. The table reports results for the two levels taken by the memory parameter θ. $\theta = 0.4$ denotes wine investors characterized by a short-memory; while $\theta = 0.8$ marks long-memory investors. All regressions are estimated using OLS. The dependent variable is the instantaneous auto-covariance of the wine market index, denoted by (C_t) in regressions (25) and (26). $CSSD$ is the cross-sectional standard deviation that measures individual variance. $mvar$ is the market turbulence measured by the exponentially weighted moving average of past quadratic market returns, where $\tau = 4$. In Panel A, $FTSE\ MIB$ represents the stock market index of the Italian national stock exchange (FTSE MIB), and $GDPgrowth^{IT}$ represents the growth of the Italian GDP. Panel B reports the S&P 500 index, the growth of the US GDP, and the CBOE Volatility Index using the variables $S\&P500$, $GDPgrowth^{US}$, and VIX^{US}, respectively. Standard errors are reported in parentheses beneath the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

PANEL A: $C_t = \alpha + \beta_1 CSSD_{t-1} + \beta_2 mvar_t + \beta_3 FTSEMIB_t + \beta_4 GDPgrowth_t^{IT} + \varepsilon_t$

θ	CSSD	mvar	FTSEMIB	$\mathrm{GDPgrowth^{IT}}$		Constant	Observations	R-squared
0.4	0.000113***	-0.00272***	0.000253***	-0.00280***		-0.0000268***	18,426	0.268
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)		
0.8	0.000132***	-0.00125***	0.000165***	-0.00228***		-0.0000198***	18,426	0.205
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)		

PANEL B: $C_t = \alpha + \beta_1 CSSD_{t-1} + \beta_2 mvar_t + \beta_3 S\&P500_t + \beta_4 GDPgrowth_t^{US} + \beta_5 VIX_t^{US} + \varepsilon_t$

θ	CSSD	mvar	S&P500	$\mathrm{GDPgrowth^{US}}$	VIX	Constant	Observations	R-squared
0.4	0.0000515***	-0.00303***	0.000510***	-0.00264***	0.000	0.00000462	18,426	0.344
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
0.8	0.0000868***	-0.00130***	0.000375***	-0.00221***	-0.000	0.00000741*	18,426	0.251
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		

Figures

Figure I. Number of Transactions by Month

This figure reports the number of Italian fine wine transactions over time. In the graph, transactions refer to auction house sales registered between January 1997 and December 2018.

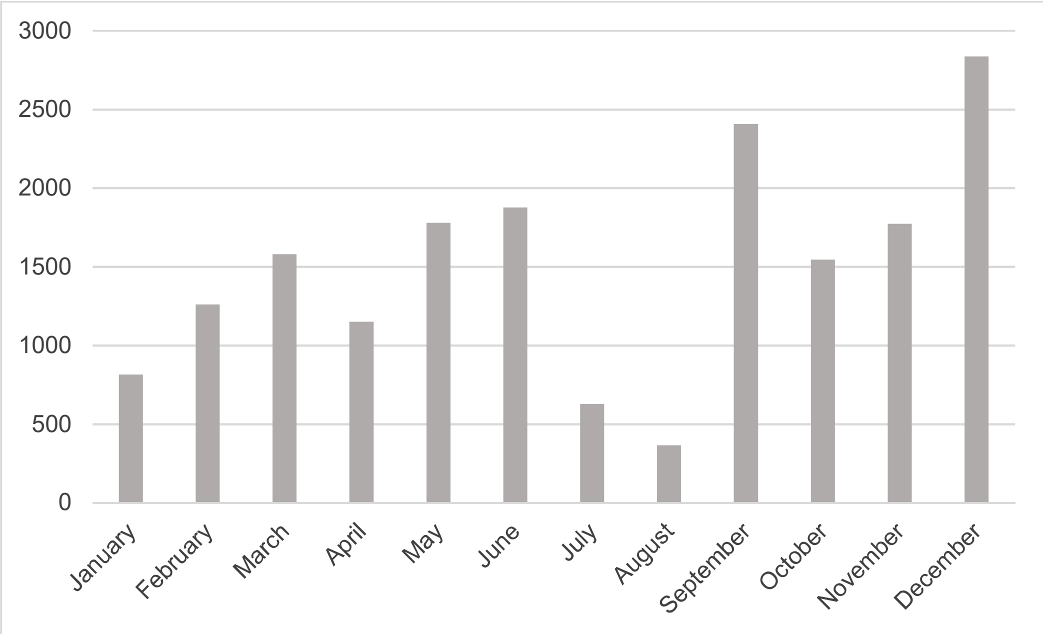


Figure II. Aging and Wine Price

This figure shows the predicted life-cycle price pattern of the Italian fine wines as implied by the coefficients of the model described by equation (5) in Section 2, Chapter 1. Age is expressed in years.

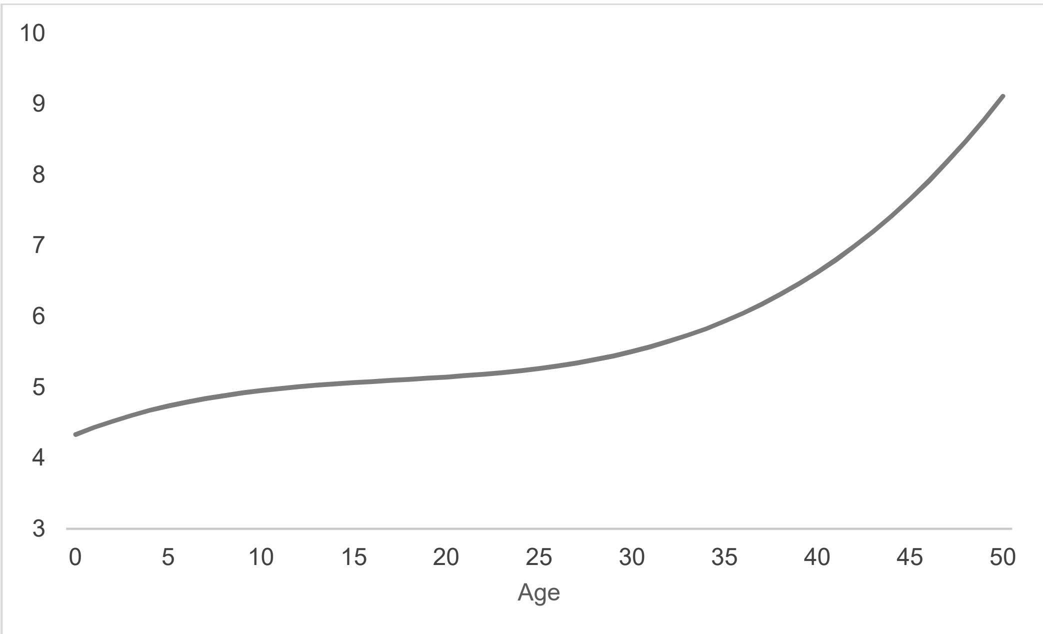


Figure III. Wine Price Index with the Hedonic and the RSR Methods

The figure presents the baseline Italian wine price indices from 1997 to 2018 detailed in Table III. The initial index values are set to 100 in year 1997 for both the hedonic regression and the RSR methods.

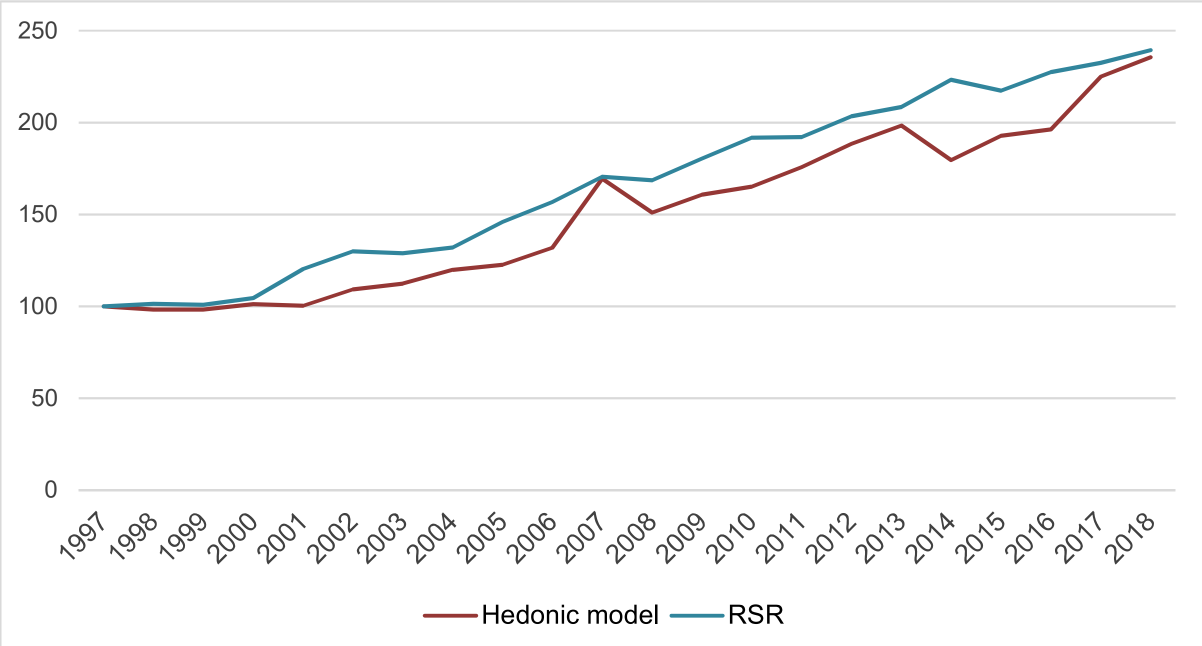
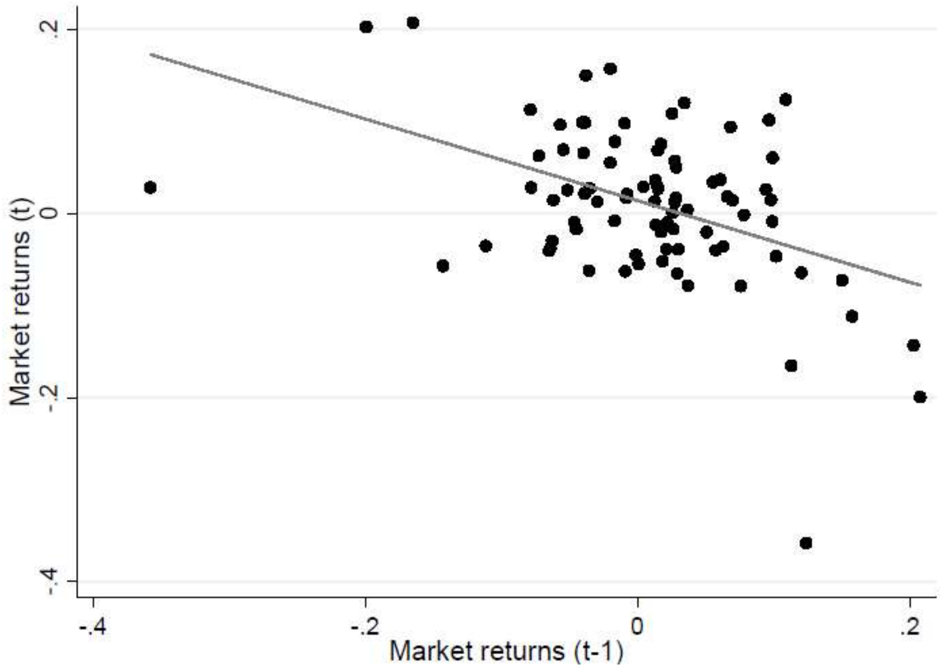


Figure IV. Market Returns and Lagged Market Returns Correlation.

This figure presents the correlation between the market returns and their lagged values. The covariance study shows a correlation coefficient of -0.003.



Appendix

Figure I. Number of Transactions by Case size

This figure reports the number of auction sales by number of bottles presented in the lot sold. The variable 'Others' includes cases with 13-23, 25-35, and 37-510 bottles.

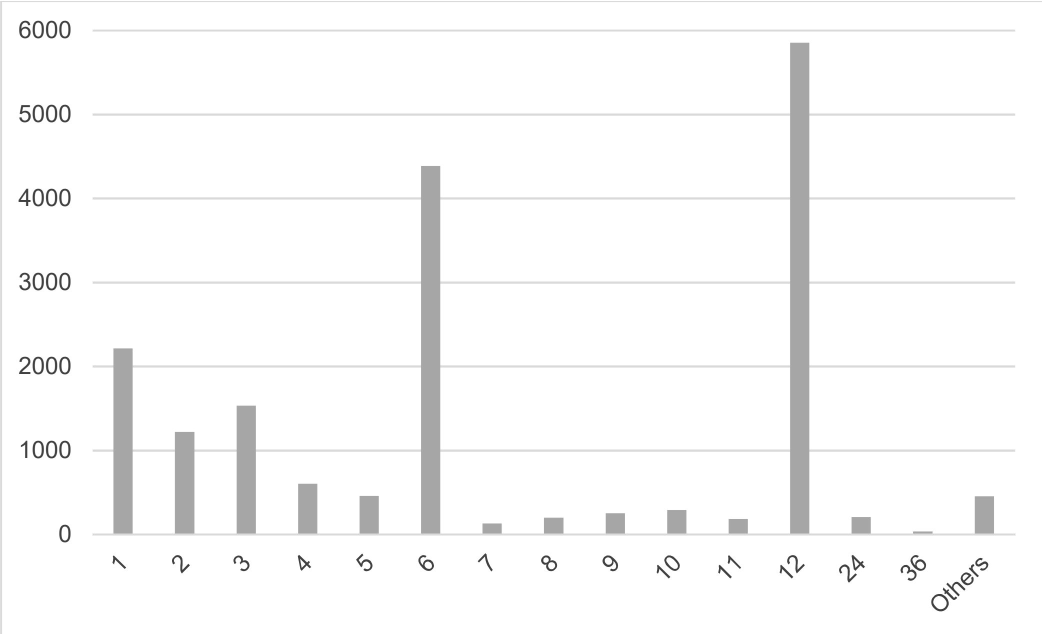


Figure II. Number of Transactions by Continent

This figure shows the number of auction sales about Italian fine wines by continent in which the auction house is located. The variable Internet represents all those sales managed by auction houses on the Internet and sold, potentially, all over the world.

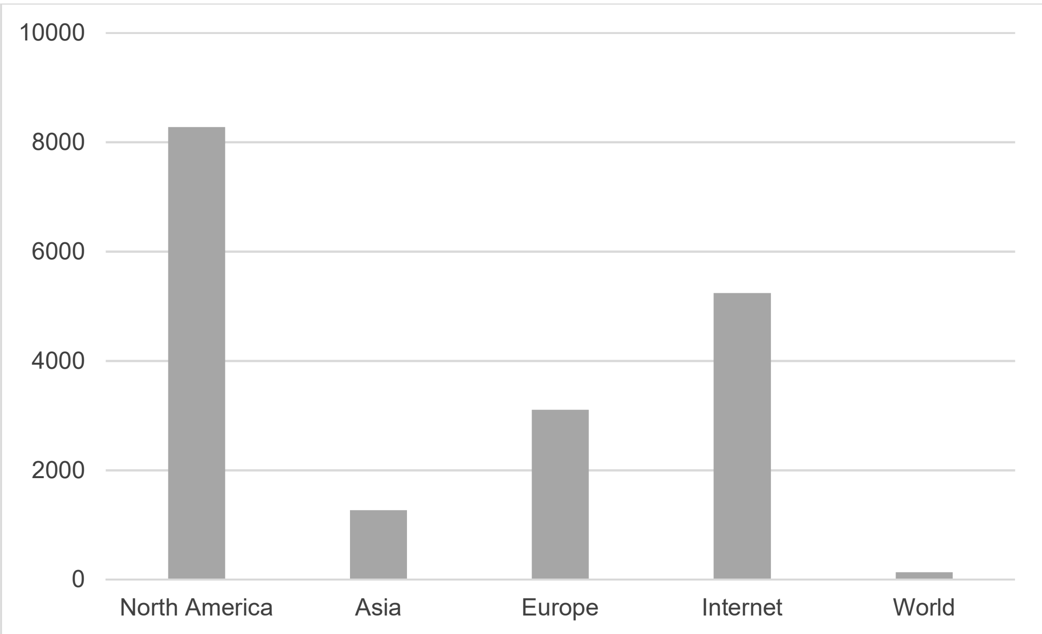


Figure III: Number of Transactions by Quarter

This figure reports the number of auction sales by time of sale, and, in particular, by the quarter in which the transaction takes place.

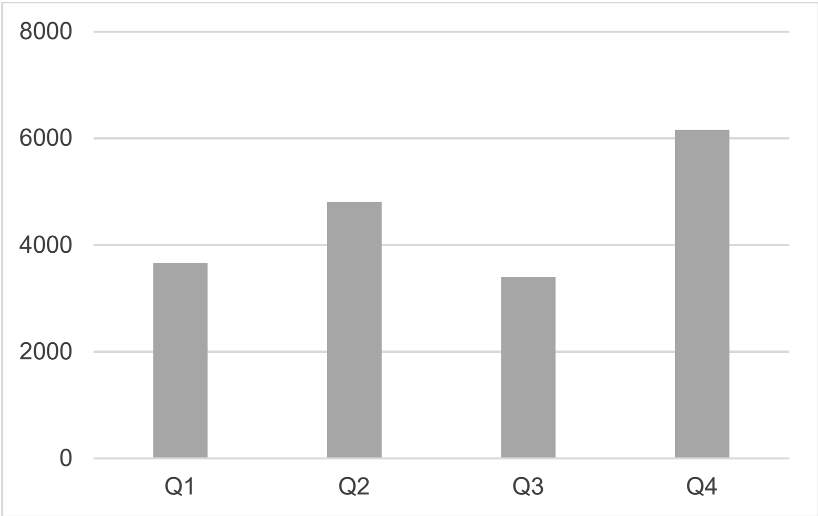


Figure IV: Number of Transactions by Auction House

This figure reports the number of auction sales by the auction house in which the transactions happens.

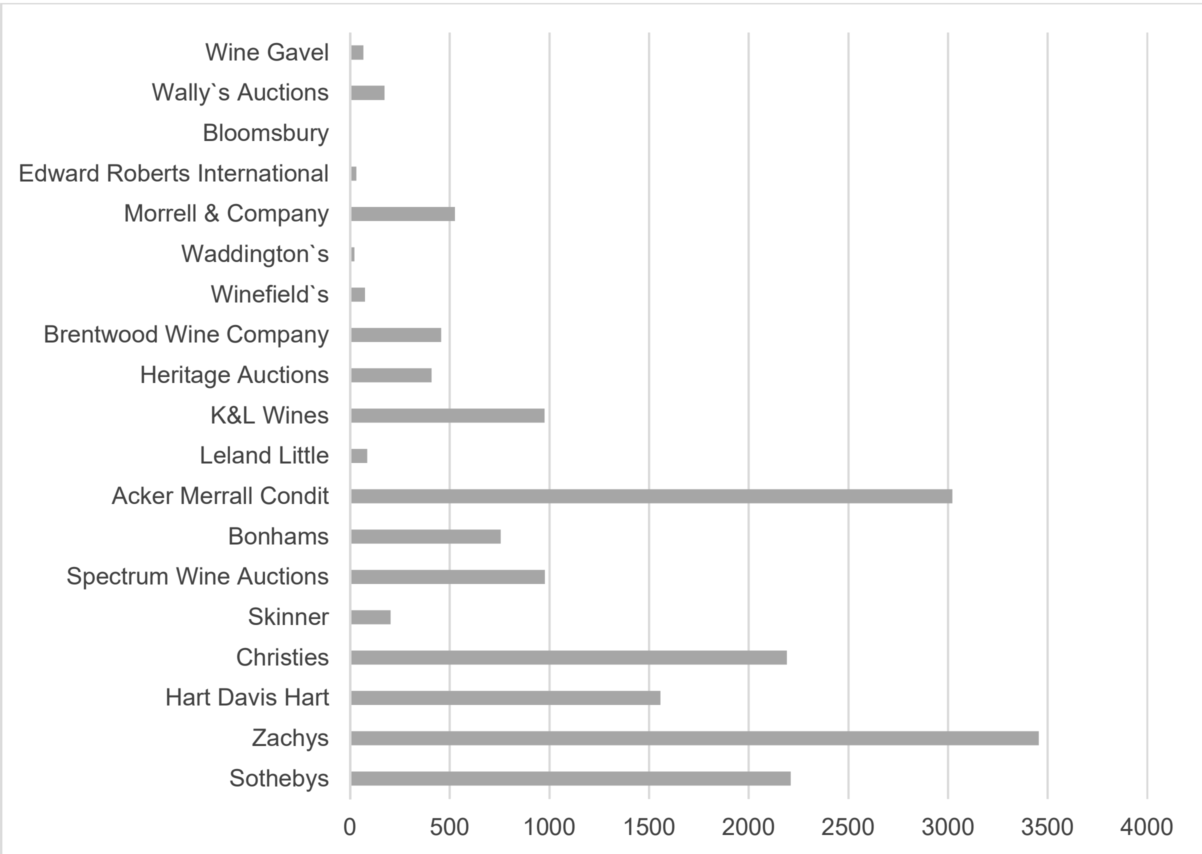


Table I. Hedonic Regression with Auction House Fixed Effect

This table presents estimates from the hedonic regression accounting for auction houses fixed effect. Regression is estimated using OLS. The dependent variable is the natural log of deflated wine hammer prices in US dollars. The auction house dummies Acker, Bloomsbury, Bonhams, Brentwood, Christie's, Edward Roberts, Hart Davis Hart, Heritage, K&L, Leland Little, Morrell, Skinner, Sotheby's, Spectrum, Waddington's, Wally's, Wine Gavel, Winefield's, and Zachys equal one if the sale takes place at Acker Merrall & Condit, Bloomsbury, Bonhams, Brentwood Wine Company, Christie's, Edward Roberts International, Hart Davis Hart, Heritage Auctions, K&L Wines, Leland Little, Morrell & Company, Skinner, Sotheby's, Spectrum Wine Auctions, Waddington's, Wally's Auctions, Wine Gavel, Winefield's, and Zachys, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year of sale level and reported in parentheses beneath the coefficients.

Variables	log(p)	Variables	log(p)	Variables	log(p)
supertuscan	0.0943***	vintage2003	-0.770***	Brentwood	0.252***
	(0.0253)		(0.0397)		(0.0504)
case12	0.0841	vintage2004	-0.386***	Christie's	0.417***
	(0.0839)		(0.0479)		(0.0918)
case	-0.319***	vintage2005	-0.399***	Edward Roberts	0.116
	(0.0784)		(0.0706)		(0.0710)
vintage1990	-0.238***	vintage2006	-0.265***	Hart Davis Hart	0.686***
	(0.0300)		(0.0608)		(0.0696)
vintage1991	-1.102***	vintage2007	-0.546***	Heritage	0.357***
	(0.0748)		(0.0499)		(0.0580)
vintage1992	-0.966***	vintage2008	-0.439***	K&L	0.502***
	(0.0888)		(0.0834)		(0.0529)
vintage1993	-0.961***	vintage2009	-0.581***	Leland Little	0.747***
	(0.0664)		(0.0555)		(0.119)
vintage1994	-1.019***	vintage2010	-0.353***	Morrell	0.110
	(0.0766)		(0.0486)		(0.0725)
vintage1995	-0.814***	vintage2011	-0.656***	Skinner	0.380***
	(0.0568)		(0.0721)		(0.0638)
vintage1996	-0.713***	vintage2012	-0.534***	Sotheby's	0.561***
	(0.0618)		(0.0202)		(0.0768)
vintage1997	-0.373***	vintage2013	-0.611***	Spectrum	0.312***
	(0.0372)		(0.0348)		(0.0520)
vintage1998	-0.630***	vintage2014	-0.548***	Waddington's	0.559***
	(0.0500)		(0.0287)		(0.0572)
vintage1999	-0.624***	vintage2015	-	Wally's	0.590***
	(0.0553)				(0.139)
vintage2000	-0.667***	Acker	0.489***	Wine Gavel	0.00373
	(0.0480)		(0.0588)		(0.0495)
vintage2001	-0.313***	Bloomsbury	0.820***	Winefield's	0.289***
	(0.0507)		(0.0367)		(0.0542)
vintage2002	-0.379***	Bonhams	0.302***	Zachys	0.623***
	(0.103)		(0.0707)		(0.0632)
				Constant	5.105***
Observations	18,019				(0.0442)
R-squared	0.205				

Table II. Robustness Check of Aging Effect on Wine Prices: High-Quality Vintage

This table presents results for the hedonic regression similar to equation (3) in Section 1, Chapter 1. In Column 1, the dependent variable is represented by the natural log of deflated hammer price of high-quality vintages. In particular, the hedonic regression only considers those years characterized by favorable weather conditions, and, secondly, those years represented in Table II by an average coefficient lower than 0.5 in absolute terms, i.e. vintage 1990, 1997, 2001, 2002, 2004, 2005, 2006, 2010 and 2015. Column 2 reports the standard errors clustered by year of sale. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Variables	**log(p)**	**se**
age	0.0933**	(0.0407)
agesq	-0.00373	(0.00270)
agecu	0.0000549	(0.000054)
supertuscan	0.107**	(0.0432)
case12	0.215**	(0.0854)
case	-0.364***	(0.0806)
quarter1	-	
quarter2	-0.007	(0.0297)
quarter3	-0.0102	(0.0316)
quarter4	0.0317	(0.0270)
Constant	4.563***	(0.169)
Observations	8,178	
R-squared	0.071	

Figure V: Robustness Check: Aging and Wine Price for High-Quality Vintage

This figure shows the predicted life-cycle price pattern of high-quality vintage as implied by the aging coefficients depicted in Table II, Appendix. The generating model is similar to equation (5) in Section 2, Chapter 1, and it is defined as $y = 4.563 + 0.0933Age_{it} - 0.00373Age_{it}^2 + 0.0000549Age_{it}^3$. Age is expressed in years.

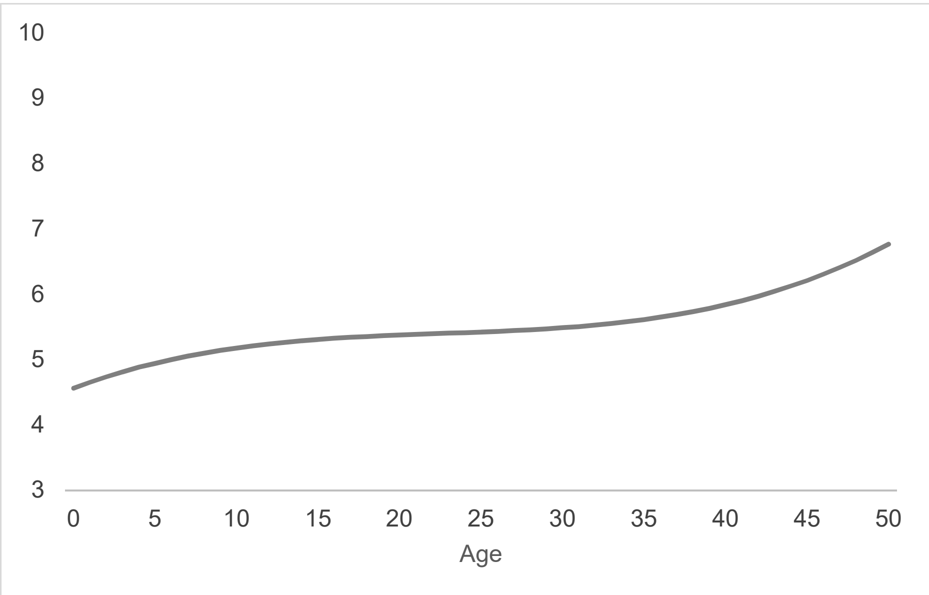


Table III. Quarterly Wine Index based on RSR Method

The table presents the quarterly wine price indices and real returns derived from the repeat-sales regression (20), Section 2.2.1, Chapter 2. Column 1 reports the estimated coefficients of the RSR with the natural log of the price ratio of the final sales price over the initial sales price as dependent variable and the quarterly dummies as explanatory variables. Column 2 shows the standard errors in parentheses. For each quarter, Columns 3 and 4 report the wine price index and the real return, respectively. Market returns, which are derived from first differencing the wine estimated coefficients, are then used in equation (21) in Section 1.1, Chapter 3. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	$\log(p_2/p_1)$			
Variables	**Coef**	**se**	**Index**	**Return**
q4_1997	0		100	-
q1_1998	0.0255	(0.0729)	103	2.55%
q2_1998	0.134	(0.0910)	114	10.90%
q3_1998	0.258***	(0.0913)	129	12.40%
q4_1998	-0.0994	(0.0811)	91	-35.79%
q1_1999	-0.0711	(0.0920)	93	2.83%
q2_1999	-0.0539	(0.0965)	95	1.72%
q3_1999	0.0219	(0.101)	102	7.58%
q4_1999	-0.0568	(0.0991)	94	-7.87%
q1_2000	0.0561	(0.102)	106	11.29%
q2_2000	-0.109	(0.0998)	90	-16.51%
q3_2000	0.0987	(0.107)	110	20.77%
q4_2000	-0.101	(0.105)	90	-19.93%
q1_2001	0.102	(0.105)	111	20.29%
q2_2001	-0.0406	(0.109)	96	-14.29%
q3_2001	-0.0973	(0.111)	91	-5.67%
q4_2001	-0.000716	(0.113)	100	9.66%
q1_2002	0.101	(0.115)	111	10.18%
q2_2002	0.0546	(0.118)	106	-4.65%
q3_2002	0.0455	(0.121)	105	-0.91%
q4_2002	-0.0171	(0.119)	98	-6.27%
q1_2003	-0.0466	(0.121)	95	-2.94%
q2_2003	-0.0335	(0.120)	97	1.31%
q3_2003	0.00323	(0.123)	100	3.67%
q4_2003	0.00744	(0.121)	101	0.42%
q1_2004	0.0366	(0.123)	104	2.91%
q2_2004	-0.0283	(0.122)	97	-6.49%
q3_2004	-0.0687	(0.124)	93	-4.04%
q4_2004	0.0305	(0.124)	103	9.92%
q1_2005	0.0914	(0.124)	110	6.09%
q2_2005	0.128	(0.124)	114	3.70%
q3_2005	0.0503	(0.126)	105	-7.81%
q4_2005	0.0788	(0.126)	108	2.84%
q1_2006	0.129	(0.127)	114	5.06%
q2_2006	0.109	(0.127)	112	-2.01%
q3_2006	0.165	(0.128)	118	5.54%
q4_2006	0.199	(0.127)	122	3.44%
q1_2007	0.320**	(0.129)	138	12.04%
q2_2007	0.255**	(0.129)	129	-6.41%
q3_2007	0.218*	(0.130)	124	-3.79%
q4_2007	0.368***	(0.128)	144	15.03%

	(1)	(2)	(3)	(4)
	$\log(p_2/p_1)$			
Variables	**Coef**	**se**	**Index**	**Return**
q1_2008	0.295**	(0.129)	134	-7.25%
q2_2008	0.358***	(0.130)	143	6.29%
q3_2008	0.323**	(0.130)	138	-3.57%
q4_2008	0.261**	(0.130)	130	-6.19%
q1_2009	0.276**	(0.131)	132	1.49%
q2_2009	0.344***	(0.130)	141	6.85%
q3_2009	0.438***	(0.132)	155	9.43%
q4_2009	0.465***	(0.131)	159	2.63%
q1_2010	0.448***	(0.131)	157	-1.66%
q2_2010	0.526***	(0.131)	169	7.82%
q3_2010	0.525***	(0.132)	169	-0.12%
q4_2010	0.480***	(0.132)	162	-4.49%
q1_2011	0.463***	(0.132)	159	-1.69%
q2_2011	0.456***	(0.132)	158	-0.77%
q3_2011	0.477***	(0.133)	161	2.13%
q4_2011	0.438***	(0.133)	155	-3.86%
q1_2012	0.537***	(0.133)	171	9.90%
q2_2012	0.529***	(0.133)	170	-0.84%
q3_2012	0.546***	(0.133)	173	1.73%
q4_2012	0.526***	(0.133)	169	-1.99%
q1_2013	0.684***	(0.134)	198	15.78%
q2_2013	0.572***	(0.134)	177	-11.16%
q3_2013	0.537***	(0.134)	171	-3.50%
q4_2013	0.565***	(0.134)	176	2.74%
q1_2014	0.622***	(0.135)	186	5.75%
q2_2014	0.583***	(0.135)	179	-3.96%
q3_2014	0.649***	(0.136)	191	6.60%
q4_2014	0.667***	(0.136)	195	1.84%
q1_2015	0.615***	(0.136)	185	-5.16%
q2_2015	0.641***	(0.137)	190	2.57%
q3_2015	0.642***	(0.137)	190	0.08%
q4_2015	0.587***	(0.137)	180	-5.46%
q1_2016	0.657***	(0.138)	193	6.97%
q2_2016	0.672***	(0.138)	196	1.45%
q3_2016	0.701***	(0.139)	202	2.99%
q4_2016	0.663***	(0.139)	194	-3.88%
q1_2017	0.684***	(0.140)	198	2.18%
q2_2017	0.675***	(0.140)	196	-0.95%
q3_2017	0.773***	(0.140)	217	9.81%
q4_2017	0.788***	(0.140)	220	1.51%
q1_2018	0.815***	(0.141)	226	2.73%
q2_2018	0.828***	(0.142)	229	1.27%
q3_2018	0.842***	(0.142)	232	1.34%
q4_2018	0.829***	(0.143)	229	-1.24%
Arithmetic mean				**0.99%**
Geometric mean				**0.99%**
St.dev.				**8.36%**
Observations	5,980			
R-squared	0.081			

Figure VI: Quarterly Wine Price Index from the RSR Method

The figure presents the Italian wine price index from the fourth quarter of 1997 to the fourth quarter of 2018, as detailed in Table III above. The initial index value is set to 100 in the last quarter of 1997.