A COINTEGRATION ANALYSIS OF WINE STOCK INDEXES

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Abstract

This paper analyzes price patterns and long-run relationships for both fine wine and non-fine wine, with the aim to highlight price dynamics and co-movements between series, and to exploit potential diversification benefits. Data are from Liv-Ex 100 Fine Wine for fine wine, the Mediobanca Global Wine Industry Share Price for normal wine, and the MSCI World Index as a proxy of the overall stock market. Engle-Granger and Johansen tests were used to detect whether and to what extent the series co-move in the long run and which one of the variables contributes proactively to such an equilibrium by reacting to disequilibria from the long-run path. The estimates highlight that i) the two wine indexes have a higher Sharpe ratio compared to the general stock market index, revealing wine stocks as a profitable investment per se, and ii) the absence of cointegration among the three series and the existence of possible diversification benefits. In fact, in the long-run price do not move together and, therefore, investors may be better off by including wine stocks into investment portfolios and take advantage of diversification.

Keywords: Commodity Market, Wine, Portfolio Diversification, Cointegration

1. INTRODUCTION

In the last two decades a rising interest concerning commodity as an alternative asset class has come to light, and the so-called "financialization" of commodity markets have reached renewed levels of interest after the 2008 financial crises. The appeal of investing in commodities is commonly ascribed to low correlation and weak short- and long-run interdependence with traditional stocks, which allows for portfolio diversification benefits and profitable trading strategies. The underlying rationale is that the price of stocks and commodities is driven by different fundamentals, which determine different price patterns and dynamics; this reveal that investors may be better off if they include commodities in their portfolios.

Existing literature has so far focused on the financialization of several types of commodities, such as grain, corn, soybeans, cotton, tobacco, water (Sanning et al., 2007; Masset and Henderson, 2008; Geman and Kharoubi, 2008; Buyuksahin et al., 2010; Chong and Miffre, 2010; Masset and Weisskopf, 2010; Baldi et al., 2014, 2017; Peri et. Al., 2014)[1], but only few works have analyzed wine (Burton and Jacobsen, 2001; Forgarty, 2006; Sanning et al., 2007; Kumar, 2010; Kourtis, 2012; Baldi et al., 2012).

Wine is a commodity of growing importance in the so-called "Old World" countries, such as Italy and France that historically dominated the market, as well as in "New World" countries, like Australia and the United States that more recently have displayed relevant rates of increase. Despite these recent market trends, wine as a financial alternative asset class has been understudied. The goal of the paper is therefore to fill the gap and to contribute to existing literature on investment in commodities by analyzing wine stock prices dynamics and co-movements between series. We distinguish between "fine" wine, traditionally produced in Old World countries, and "non-fine" wine (hereafter "normal" wine), increasingly produced in New World countries and more easily accessible as a class of investment, since New World wineries started to list in stock markets. Fine and normal wine are analyzed in a unique setting and in a global scenario together with stock market indexes, with the ultimate aim to exploit potential diversification benefits. In fact, lack of cointegration among stock prices suggests that series have no tendency to move together in the long run and therefore investors are better off by including them into investment portfolios and take advantage of diversification, that is a reduction of risk for any given level of expected return (Markovitz, 1952; Granger, 1981).

[1] For recent evidences on commodity "financialization" see Baldi et al., 2016.

Monthly data from July 2001 to October 2014 are used. A proxy for the overall stock market is provided by the MSCI World Index, while we use the Liv-Ex 100 Fine Wine Index for fine wine and Mediobanca Global Wine Industry Share Price Index for normal wine to get exposure to commodity asset classes.

Results highlight the diversification properties of both fine and non-fine wine, suggesting a better portfolio performance if fine and non-fine wine stocks are included. Specifically, either fine and non-fine wine stocks show no long-run relationship with the overall market. Moreover, they do not appear to have a long run relationship in common. Indeed, fine wine performed very well until 2011, when it drastically dropped due to a bubble burst. Non-fine wine did not suffered by fine wine drop.

This paper is organized as follows: Section 2 highlights the framework ; Section 3 reviews the empirical literature; Section 4 presents the dataset; Section 5 focuses on the econometric methodology; Section 6 develops the empirical results; Section 7 concludes.

2. FRAMEWORK

The wine market is shared between Old World and New World countries. Wineries in New World countries, as the United States and Australia, entered in the market since the early 1990s. They mainly produce normal, non-fine wine, and their shares are traded on stock exchanges. Investing in normal wine is therefore relatively new, and it is made through stock market indexes representing listed wineries producing normal wine. Conversely, wineries in Old World countries, as France and Italy, are characterized by family ownership and are mostly not listed on stock exchanges. Fine wine investment started in the 18th century in France; historically, it has been the only vehicle to invest in the wine market.

Nowadays, investment in fine wine can be realized in different ways. The first, simplest way to invest in fine wine is to buy it for future resale. Fine wines maturation process can last also 20-40 years, as classified Bordeaux, vintage[2] Port and more recently Australian Barossa Valley and the American Napa Valley wines. As time passes, the number of vintage bottles diminishes, driving up the price of the remaining. Moreover, investment in fine wines is favourably taxed[3] and prices are not considered closely linked to traditional financial assets. Over the 2008 financial crisis, significant return of fine wines and the rapid expansion of the Chinese demand boost the market for fine wines. Only the secondary market, centred mainly in the UK, is currently estimated to account for a global turnover in excess of 1 billion EUR.

Other traditional ways to invest in fine wine are: to buy and sell at wine auctions or purchase with the "en primeur" formula to sell the wine later. Sotheby's and Christie's are the main players in wine auctions. Both have salesrooms across the world and in 2012 Christie's also launched online wine auction[4]. As they are worldwide spread, one can try to exploit the price difference of fine wine in different places, if transaction costs are not too high[5]. Dissimilarly, "en primeur" market is a forward market where wines are sold as futures. Potential buyers are supposed to form quality expectations of the future wine considering the climatic conditions during the grape-growing season and the reputation of the Château.

More recently many financial institutions created specialized wine funds. Minimum investment at wine funds range from a low of 10,000 to 100,000 EUR. Moreover there are wine investment companies which propose themselves as intermediates in buying and selling wine and offer cellar valuation, wine portfolio construction and sometimes management cellar services. Also wine indexes have emerged to cater for fine wine demand from investors. They can be both independent, as the ones reported by Liv-Ex website, or constructed by a financial institution as Monte dei Paschi di Siena with its "MPS Wine Index"[6].

There are not only advantages, but also risks in fine wine investment. The price bottle can change over time due to unanticipated changes in wine quality or the demand for it. One should be warned that as other collectibles market, wine exhibits significant deviations from efficient behavior. There could be asymmetric information regarding valuations (including the potential of fakery) and the presence of many potentially non-profit-maximizing agents, including private collectors. In 2011, Château Lafite Rotschild, which produces wines in Bordeaux, experienced the highest peak of its bottles' selling price. This strong increase was followed by a decline, which lasted well into 2012. Some attributed this price dynamic to a bubble, originated in the Chinese market and fuelled by the elimination of import duty on wine in Hong Kong; according to others, price drop was due to the presence of fakery in the Chinese market, which decreased purchasers' confidence in acquiring the product. Moreover fine wine investment does not generate cash flows, it is less liquid compared to stock markets and it is subject to transaction, insurance and storage costs[7].

Given the differences that characterize investments in fine and normal wine, it is interesting to analyse both types of assets and shed light on their relative performance and long-run dynamics. As highlighted in the next Section, no previous studies have analysed together both types of asset classes.

3. LITERATURE REVIEW

The vast majority of empirical papers regarding wine as an alternative financial investment focuses on fine wine. The literature evolved through time: the first generation of studies tried to evaluate whether wine as an asset could be considered a good investment or not, considering only returns. The

[2] Vintage refers to a wine produced from grapes of a single year, single harvest.

[3] For example, in the UK many investment wines are considered wasting assets (those, which cannot last more than 50 years) and as such investors are not liable to pay Capital Gain Taxes (CGT) on profit from wine investments not exceeding £250,000. If the profit from the sale of a single bottle of wine not considered a wasting asset sold to a single purchaser does not exceed £6,000, CGT does not apply.

[4] See: http://www.christies.com/sales/signature-cellars-april-2013/index.aspx.

[5] Transaction costs using this practice mainly refers to buyer's and seller's premiums, which on average are comprise between 10% and 16% of the overall wine value, VAT included. See Aschenfelter (1989) for other explanations of how wine auctions work.

[6] More info at: https://www.liv-ex.com/home.do and https://www.mps.it/Investor+Relations/ResearchAnalisis/IndiciGrafici/Mps+Wine+Index.htm

[7] Fogarty [2007] tries to estimate these costs for the Australian and the UK market. Insurance and storage cost can reach up to 2% of the bottles value. Transaction costs ranges generally from 10 to 15% of the bottles value.

second generation of studies concentrated more on potential risk diversification benefit of holding wine.

Krasker (1979) was the first to analyze fine wine in a financial perspective. He used data on wine prices from the annual Heublein Wine Auctions for red Bordeaux and Californian Cabernet Sauvignon to study wine rates of return between 1973 and 1977. The author applied the generalized least squares to estimate and compare wine rates of return to a riskless asset[8], finding no risk premium for holding wine.

Jaeger (1981) came to the opposite conclusion. She continued Krasker's study, extending the sample period to eight years beginning in 1969. According to her, the negative result of Krasker was due to the inclusion of two exceptionally bad years from an economic and wine industry's perspective[9]. Moreover she incorporated a significantly lower measure of wine storage costs, published by Freemark Abbey Winery, i.e. $0.449 per 12-bottles case versus $16.80 estimated by Krasker. She also employed a different method to calculate wine rates of return, reversing Krasker's conclusion.

Burton and Jacobsen conducted a similar study in 2001. They used the repeated sales method[10] on data from William Edgerton's wine price file over the period 1986-1996 to calculate the rate of return for holding red Bordeaux, including only wines produced from 1960 onward. The authors compared the wine portfolio with one year Treasury Bill and the Dow Jones index. Results highlighted that wine cannot yield greater return than the other financial assets observed when volatility and transaction costs are taken into account.

With the rise of wines from the "New world" in the market, other studies left Bordeaux focus to concentrate to less traditional investment wines. Fogarty (2006) used adjacent period hedonic price regression approach[11] on Langton's auction house data to estimate the return to storing premium Australian wine during the period 1989-2000, included in the 2001 edition of the Caillard and Langton wine investment guide. He compared wine to Australian All Ordinaries total return index. Index returns were higher than the wine returns, but the same was for the level of risk. The author also compared the rate of return of Australian wine to Bordeaux return reported by Burton and Jacobsen (2001) for a seven-year overlapping period of the two datasets used. According to his results, between 1990 and 1996, Australian wine offered higher return and less risk than Bordeaux wine.

While previous studies focused only on establishing wine return either in absolute terms or relative to a simple market return, Sanning et al. (2007) were the first to analyze the diversification benefit of holding wine, using the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model[12]. They employed monthly auction prices from 1996 to 2003 of The Chicago Wine Company, considering Bordeaux wines from 1893 to 1998, to calculate average monthly return by vintage and producer. Results showed that Bordeaux yielded a positive excess return compared to riskless assets for the period considered and that wine co-varies minimally with commonly accepted market risk factors. Moreover the beta calculated with CAPM resulted near zero (0.007 if calculated by vintage and -0.005 if calculated by vintage and producer), demonstrating that grade wine investment, as Bordeaux, should be considered as a potential way to diversify portfolios.

Kumar (2010) compared the financial performance of the Fine Wine 50 Index[13] to the FTSE 100 Index (FTSE100), the Dow Jones Industrial Average (DJIA), the UK Government Bonds Index (FTGB) and US 30 Year Treasury Bonds for a 20 years period ranging from 1983 to 2003. The results showed that the expected return on the Fine Wine 50 index exceeded that on the other assets considered. Moreover the wine index had a lower volatility than the FTSE 100 Index and the Dow Jones Index, even if higher than the UK Government Bonds and the 30 Years Treasury Bonds index. Segmenting the 20-year period in subsets, the author highlighted that fine wine investment was less volatile than equity investment in the long term, but not in the short term, advising a minimum investment period of five years. Kumar (2010) also focused on the diversification benefit that the wine index could bring to a portfolio. He calculated the correlation and build different portfolios, showing that as government bonds had a lower correlation with the wine index than with equities, the minimum risk portfolio consisted of Fine Wine and government bond with a much smaller weighting held in equities. Kumar also calculated Sharpe ratios for the portfolios, finding higher ratios in portfolios with fine wines than portfolios with only equities and bonds.

More recently, Kourtis et al. (2012) analysed data from online wine platforms, which became more popular than traditional auctions considered in past papers. They employed wine indexes from the Liv-Ex family and from Wine Prices[14] and used the Wine Price platform from 2005 to 2010 to calculate correlation among different wines. Results showed that further diversification benefits can be achieved by investing in Italian, Australian and Portuguese wines, while it is more limited if one considers only different varieties of French wines. On the overall, all second-generation studies seem to agree with fine wine risk diversification potential.

Baldi et al. [2012] were the first to approach non-fine wine market, using Mediobanca Wine Index. They analyzed the long-run relationships between wine share price indexes and their domestic stock market indexes through a Threshold Vector Error Correction Model (TVECM) to see if wine could act as a financial parachute. Results showed that in more mature markets as France and US, when the gap

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[8] 3-month Treasury bills for the four quarters before the auction.

[9] Krasker analysis coincided with a recession period, due to the oil crisis, and with extreme surplus in the wine industry, due to high inventories, which made wine prices to fall.

[10] The repeat sales model: $p_{j\tau} - p_{jt} = \sum_{t=1}^{T} \gamma_t D_{j\tau} + \varepsilon_{j\tau} + \varepsilon_{jt}$
where D takes the value one if wine j was sold in period τ, minus one if wine j was sold in period t, and is zero otherwise. As with the hedonic model, the return to wine is calculated
from the estimates of ϒ.

[11] The hedonic approach to consumer demand analysis assumes that there exists a (hedonic) function relating the price of a good to the underlying attributes of the good.

[12] Considering one-month bill rate and the weighted month value return on all NYSE, AMEX, and NASDAQ stocks.

[13] He constructed the index from the Wine Price File obtained by Christie's and Sotheby's auction price catalogues (not hammer prices) for fine wines of ten renown Chateaux. It is similar to the Liv-Ex Fine Wine 50.

between the domestic stock index and the wine index exceed a critical threshold, the domestic stock market index responds restoring the long-run equilibrium at a higher speed than the wine index, enabling informed investors to make profitable investments. The authors enlarged the wine investment framework and highlighted that wine diversification benefits is not only a fine wine prerogative, but can be extended to non-fine wine.

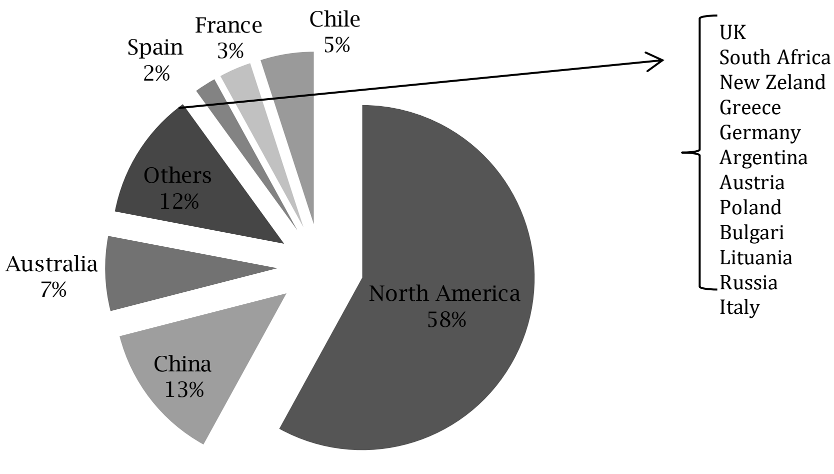
4. DATA ISSUES

The dataset includes the Liv-Ex 100 Fine Wine Index for fine wine, the Mediobanca Global Wine Industry Share Price Index for normal wine, and MSCI World Index as a proxy for the overall stock market. Price series are from July 2001 to October 2014, monthly frequency, in Euro.

The Liv-Ex 100 Fine Wine Index was launched in July 2001 by the UK online platform for wine auction, Liv-Ex. The index currently invests in bottled wines that are physically delivered in the UK. It follows the price movements of 100 of the most sought-after fine wines, ranked at least 95 over 100 in the Robert Parker classification, with a strong secondary market. The wines included in the index are reviewed on a quarterly basis by a committee and they are mainly red Bordeaux vintages, but there are also Bordeaux white wines and wines from other regions, such as Burgundy, the Rhone, Champagne and Italy. The Liv-ex 100 index is based on Liv-ex Mid Prices, which are determined as the mid-point between the current highest bid and lowest offer price on the Liv-ex trading platform. A valuation committee verifies each price to ensure data robustness and this is then multiplied by the wine's average production level, with decreasing weights. In this way, the weighting captures the impact of each component on the overall market in a similar manner as a value-weighted index calculations used for the stock market. When the wine reaches 25 years of vintage, it is removed from the index, as its volume will be too low, according to Liv-Ex policy, to attract a strong secondary market.

The normal wine series is the Mediobanca Global Wine Industry Share Price Index from Mediobanca. It was launched in January 2001 and it is a chain index as MSCI world index. From the dataset, only prices without dividends have been included in the analyses. Mediobanca selected 49 securities representative of 44 listed companies on regulated stock markets, quoted for at least six months and with a minimum 50% turnover coming from wine-related activities. Mediobanca Wine Index is a non-capped index, where large capitalized companies, such as Constellation Brands, the largest North American winery, influence the index. Figure 1 shows the composition by country of the Mediobanca Wine Index.

Figure 1. Countries weight in Mediobanca Wine Index

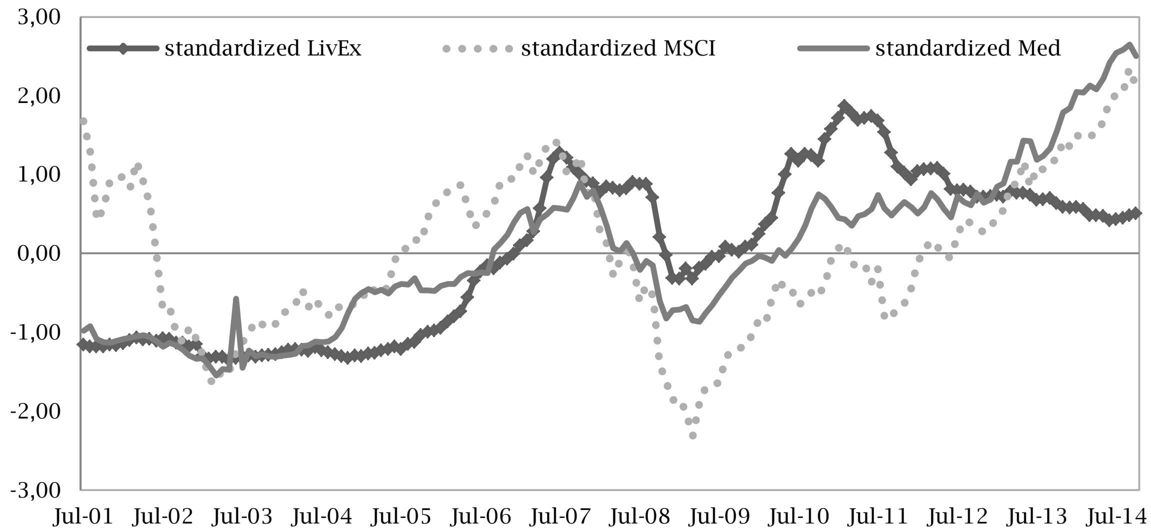


Source: Mediobanca (2015)

Figure 2 shows the price pattern of the indexes over the period under analysis, standardized around zero mean in order to compare the three indexes. Visual inspection highlights a steady price increase for both fine and normal wine until the 2008 financial crisis, when all indexes has been affected by financial turmoil. Besides, fine wine highlights a further price decrease after the beginning 2011, when the fine wine market has been affected by the events described in Section 2. For the general market index MSCI, the most relevant price drops follow the 2001 dot.com bubble, the 2008 financial crisis, and the 2011 sovereign crisis.

Table 1 presents descriptive statistics of the performance of the indexes, for the whole dataset period and for different sub-periods accounting for the most relevant wine price decreases (2008 financial crisis, 2011 fine wine crisis).

Figure 2. Standardized Liv-Ex 100, Mediobanca and MSCI World index graph



Source: elaboration of Liv-Ex 100, Mediobanca and MSCI World data index

Table 1. Indexes descriptive statistics

		Average Returns	SD	Sharpe Ratio	Skewness	Kurtosis
07/2001-10/2014	LIVX100	0,48%	3,27%	0,06	-0,03	-1,43
	MSCI	0,11%	4,95%	-0,03	0,06	-0,73
	MED	0,62%	4,81%	0,07	0,59	-0,13
07/2001-08/2008	LIVX100	0,90%	2,95%	0,21	1,04	-0,57
	MSCI	-0,32%	3,83%	-0,16	-0,04	-1,23
	MED	0,46%	5,84%	0,03	0,45	-1,04
09/2008-12/2010	LIVX100	1,02%	5,13%	0,14	0,53	-1,20
	MSCI	0,52%	5,19%	0,05	-0,20	-1,17
	MED	0,62%	3,91%	0,09	0,36	-0,87
01/2011-10/2014	LIVX100	-0,66%	1,73%	-0,54	1,00	-0,21
	MSCI	0,70%	2,97%	0,14	0,24	-0,96
	MED	0,91%	2,59%	0,24	0,79	-0,82

Source: calculation on Mediobanca data. Risk free rate: 3-Months Tresury Bill

Observing the whole dataset period, Liv-Ex and Mediobanca show the best performance. In particular, the Mediobanca index has the highest average return with a lower volatility than MSCI index. The Sharpe ratio is the highest among the three for Mediobanca and the skewness coefficient is positive, meaning that there are more returns over the average than under it. Kurtosis is the lowest among the three indexes, indicating few extreme returns.

Looking at the first two subsets created to isolate the recent financial crisis, we can concentrate on MSCI World performance over these periods. As highlighted before, during crisis period MSCI World presents lower rate of return and higher volatility compared to Liv-Ex index and the worst Sharpe ratio among the indexes.

Moving to the last subset to offset Liv-Ex bubble burst, we can see the impact of this phenomenon on the index performance, which switch from +1,02% to -0,66% average return. Nevertheless, skewness doubled in a positive way after the bubble burst as Kurtosis, meanwhile, reduces. Results show that Mediobanca index is the best performers.

Diving the latter index by Countries (Table 2), we can noticed that Australia, Chile and China performed worse than total indexes for the overall period, with higher risk and lower rate of return. On the contrary, North America and Other Countries Indexes show higher rate of return compared to total indexes, but with higher risk.

Table 2. Mediobanca Indexes descriptive statistics by Country

07/2001-10/2014	*Average Returns (%)*	*SD (%)*	*Shape Ratio*	*Skewness*	*Courtosis*
World	0,62	4,81	0,07	0,59	-0,13
Australia	0,33	5,52	0,01	1,38	1,76
North America	1,63	9,06	0,15	2,36	5,13
France	0,65	6,66	0,06	0,58	-0,19
Spain	0,43	3,52	0,04	0,54	0,18
Chile	0,37	5,16	0,02	-0,04	-0,42
China	0,22	7,59	-0,01	0,56	-1,00
Others	1,60	9,96	0,13	0,62	-0,24

Source: calculation on Mediobanca data. Risk free rate: 3-Months Tresury Bill

5. ECONOMETRIC METHODOLOGY

Cointegration analysis was then used to focus on the long-run co-movements between fine wine, non-fine wine and stock market indexes. As already mentioned, the absence of cointegration between series of stock prices can be seen as evidence of no long-run relationship between these series. With respect to portfolio diversification, this implies that in the long-run these prices do not move together and, therefore, there may be substantial benefits from portfolio diversification. In the following sections we briefly present the different approaches to test for cointegration carried out in the empirical analysis.

5.1. Engle-Granger and Johansen tests for cointegration

The first contribution in the cointegration literature is the seminal paper by Engle and Granger (2007), that provide a two-step procedure for investigating the long-run relationships of two non-stationary variables. In the first stage a static regression among the variables is performed while in the second stage the presence of a unit root on the residuals is checked through an Augmented Dickey-Fuller (ADF) type test of hypothesis. If the non-stationary series (integrated of order one, i.e. *I(1)*) are effectively cointegrated, the OLS static regression among the levels of the variables allows to consistently estimate the coefficient of the stationary linear combination. Thus, if the residuals of such a regression are stationary, the variables are cointegrated and share a common stochastic trend.

An alternative strategy to verify whether two or more series are cointegrated is the popular multivariate approach proposed by Johansen (1988, 1995). The author suggests to start by estimating a VAR model containing the levels of the variables. An appropriate re-parametrization allows to highlight both the short- and long-run dynamics in a Vector Error Correction (VECM) framework of the form:

$$\Delta y_t = \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_1 \Delta y_{t-1} + \varepsilon_t \quad (1)$$

where y_t represents the *(nx1)* vector of variables, ε_t is a *(nx1)* white noise stochastic process with covariance matrix Σ, and *k* represents the order of the VAR model. The two *(nxr)* matrices α and β represent the adjustment coefficients and the cointegration vectors, respectively, where *r* indicates the number of cointegrating relationships among the variables, or equivalently, *n-r* indicates the number of common stochastic trends characterizing the system.

As all the parameters are unknown, Johansen proposes a very powerful strategy, based on the Maximum Likelihood (ML) estimator, to obtain, within the VAR and the VECM models, the number of cointegrating relationships *r (trace* test or *max-L* test*)*, as well as the coefficients of the cointegrating relationships β. Conditional on these two sets of information, all the other parameters can be estimated consistently through OLS or ML, as the remaining components of the VECM are stationary.

This approach to testing for cointegration allows, thus, to detect whether and to what extent the series co-move in the long run (through the β coefficients) and which one of the variables contributes proactively to such an equilibrium by reacting to disequilibria from the long-run path (through the α coefficients). Interestingly, when the *trace* test or the *max-L* test procedures suggest that *r=0*, it means that there are no cointegrating relationships among the variables and the system is characterized by *n* distinct stochastic trends. This last situation is extremely interesting in our context, indicating that the dynamics of wine indices (Mediobanca Wine Index and Liv-Ex 100 Fine Wine Index) and the proxy of the overall stock market (MSCI World Index) are extremely persistent and do not co-move, neither in the long run.

5.2. Asymmetric cointegration test

The mentioned approaches for dealing with cointegrating time series assume linearity and symmetric adjustment. In particular, in the two-step Engle-Granger procedure the attention is devoted to the static relationship:

$$y_{1t} = \beta_0 + \beta_2 y_{2t} + \cdots + \beta_n y_{nt} + \mu_t \quad (2)$$

where $y_{1t},\ldots,y_{nt}$ are the *I(1)* elements of the vector of variables y_t, and to the related ADF type test on the residuals given, in its simplest form, by:

$$\mu_t = \rho\mu_{t-1} + v_t \quad (3)$$

with being a white noise stochastic process. This cointegration test, however, reveals to be miss-specified if the adjustment is asymmetric. Enders and Siklos (2001) propose an alternative specification based on the threshold autoregressive (TAR) model as follows:

$$\Delta\mu_t = I_t \rho_1 \mu_{t-1} + (1 - I_t)\rho_2 \mu_{t-1} + v_t \quad (4)$$

where I_t is the indicator function defined as:

$$I_t = \begin{cases} 1 \text{ if } \mu_{t-1} \geq \tau \\ 0 \text{ if } \mu_{t-1} < \tau \end{cases} \quad (5)$$

with τ representing a certain threshold level. Clearly, the symmetric standard case represents a particular case of this last specification when .

Enders and Siklos (2001) provide two tests for threshold cointegration based on individual t-statistics for the null hypotheses and and on the joint hypothesis . The largest of the individual t-statistics is called *t-Max*, while the F-statistic for the joint hypothesis is denoted by Φ. Given the complexity of the asymptotic distribution of these two test statistics, the critical values are obtained through simulations (either Monte Carlo or Bootstrap). The authors provide critical values for different combinations of a) number of variables and 2) dimension of the sample, both in the case of known or unknown threshold level .

This specification of the asymmetric adjustment is based on the levels of . Enders and Granger (1998) & Caner and Hansen (1998) suggest to consider the changes of instead of the levels, i.e. . Thus, an alternative specification of the asymmetric adjustment equation can be obtained by substituting the indicator function , with the new rule:

$$M_t = \begin{cases} 1 \text{ if } \Delta\mu_{t-1} \geq \tau \\ 0 \text{ if } \Delta\mu_{t-1} < \tau \end{cases} \quad (6)$$

that is called *momentum*-threshold autoregressive (M-TAR) model. As for the TAR model, Enders and Siklos [2001] define the *t-Max* and Φ statistics, with related simulated critical values, for testing for the presence of cointegration and threshold adjustment.

6. EMPIRICAL RESULTS

In this section we present empirical results obtained by analyzing the time series discussed in Section Data Issues through the econometric techniques presented in Section Econometric Methodology.

Firstly, we formally test whether the time series of wine indices and the overall financial market indicator are effectively non-stationary, as graphically suggested by Figure 2. Table 3 reports the results of the Augmented Dikey-Fuller (ADF) test on the levels of the series, including a) *constant* and b) *constant and linear trend* as deterministic components. In both cases, for all the series it clearly emerges that the null hypothesis of non-stationarity cannot be rejected at standard critical levels.

Table 3. ADF test for stationarity: Empirical results

	Constant		*Constant and Trend*	
	Test Stat.	***P-value***	***Test Stat.***	***P-value***
Liv-Ex 100	-1.480	0.541	-1.851	0.675
Mediobanca	0.400	0.982	-1.633	0.775
MSCI World	-1.162	0.690	-1.878	0.662

Note: The number of lags is determined automatically from a maximum of 12 using the BIC. "Constant" and "Constant and Trend" indicate the deterministic component used in the ADF regression.

Table 4 and Table 5, instead, report the results for the Engle-Granger and Johansen tests for cointegration among the series, respectively. In particular, for both approaches, we test whether wine indices and the market index, taken two-by-two, are effectively cointegrated. The analysis is based on the entire sample, from January 2001 to October 2014, monthly frequency.

Table 4. Engle-Granger test for cointegration: Empirical results

Liv-Ex 100 - MSCI World			*Mediobanca – MSCI World*			*Liv-Ex 100 - Mediobanca*		
Dep. Variable: Liv-Ex 100	Coeff.	Std. Error	Dep. Variable: Mediobanca	Coeff.	Std. Error	Dep. Variable: Liv-Ex 100	Coeff.	Std. Error
Const	115.341	24.707	const	−3.602	4.795	const	109.785	21.138
MSCI World	0.017	0.026	MSCI World	0.113	0.005	Mediobanca	0.214	0.203
Time	1.547	0.092	time	0.680	0.018	time	1.394	0.183
	Test Stat.	P-value		Test Stat.	P-value		Test Stat.	P-value
Cointegration test	-3.733	0.057		-4.204	0.015		-3.6011	0.0784

Note: Sample 2001:01-2014:10

Table 5. Johansen test for cointegration: Empirical results

Liv-Ex 100 - MSCI World VAR model with 2 lag (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.025	5.359	0.770	3.975	0.855
1	0.009	1.384	0.240	1.384	0.240
Mediobanca - MSCI World VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.051	8.633	0.408	8.265	0.361
1	0.002	0.369	0.544	0.369	0.544
Liv-Ex 100 - Mediobanca VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.023	4.627	0.843	3.629	0.888
1	0.006	0.998	0.318	0.998	0.318

Note: Sample 2001:01-2014:10. Lag selection of the VARs performed through the BIC from a maximum of 12 lags

The two-step Engle-Granger approach suggests that, for all pairs of variables, the null hypothesis of no cointegration cannot be rejected, at least at the 1% critical level. Given the positive long-run path of the series observed in Figure 2 (more clear for the wine indices Liv-Ex and Mediobanca, much less for the overall market index MSCI World), these first battery of results has been obtained by including a linear trend in the static regression of the Engle-Granger approach. Stronger results in favor of the hypothesis of no cointegration, not reported for saving space, but available upon request, are obtained including the constant term only.

All these results are confirmed, or better strengthened, by the Johansen test for cointegration, reported in Table 5. In fact, considering a specification of an unrestricted constant term as the deterministic component of the VAR model, both the *trace* test and the *L-max* test always suggest to not reject the null hypothesis of $r=0$, i.e. no cointegration. Similar results, available upon request, can be obtained for a) *restricted constant* or b) *restricted trend* as possible alternatives for the deterministic component of the VAR model.

The last attempt to verify whether there is any long-run relationship between the variables has been performed through the threshold cointegration test provided by Enders and Siklos (2001) and briefly presented in Section Econometric Methodology. This strategy provides a test for cointegration among the series but allowing for a possible asymmetric adjustment.

Table 6 provides the results of the analysis considering both the *threshold* (TAR) and *momentum* (M-TAR) specification of the adjustment function. The table reports, in the upper part, the and coefficients of equation (4), as well as the coefficients of lagged values of included to obtain no more autocorrelated residuals, both for the *threshold* (TAR) and *momentum* (M-TAR) specifications. In the lower part, instead, the table reports the *t-Max* and Φ statistics, together with the simulated 5% critical values (Monte Carlo with 10,000 replications). Using this alternative approach does not alter the previous results and highlights the absence of cointegration even when considering possible non-linearities in the adjustment process.

In addition, we test for cointegration for all subperiods presented in Section Data Issues as a robustness check. Also for the sub-periods, all results, reported from Table 9 to Table 17, strongly confirm that there is no evidence of co-movements among the series in the long-run, neither among Liv-Ex 100 and Mediobanca wine indices, nor among the wine indices and the overall market index proxied by the MSCI World.

Table 6. Threshold cointegration analysis: Empirical results

	Liv-Ex 100 - Mediobanca				***MSCI World - Liv-Ex 100***				***Mediobanca - MSCI World***			
	Threshold		***Momentum***		***Threshold***		***Momentum***		***Threshold***		***Momentum***	
Lags (determined by data):	2		2		2		2		2		2	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Above Threshold	-0.031	0.023	0.011	0.028	-0.006	0.026	-0.013	0.022	-0.008	0.026	-0.033	0.022
Below Threshold	-0.014	0.026	-0.043	0.021	-0.031	0.025	-0.030	0.031	-0.043	0.024	-0.018	0.029
Differenced Resid. (t-1)	0.123	0.080	0.102	0.081	0.128	0.078	0.133	0.078	-0.082	0.079	-0.074	0.079
Differenced Resid. (t-2)	0.180	0.081	0.165	0.081	0.052	0.078	0.055	0.078	0.067	0.078	0.083	0.078
	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%
Threshold value (tau):	0		0		0		0		0		0	
F-equal:	0.259	(2.753)*	2.421	(3.840)*	0.524	(2.766)*	0.188	(3.691)*	0.957	(2.776)*	0.159	(3.835)*
T-max value:	-0.545	(-2.123)*	0.405	(-2.007)*	-0.228	(-2.121)*	-0.610	(-2.011)*	-0.301	(-2.109)*	-0.637	(-1.975)*
F-joint (Phi):	1.048	(5.912)*	2.142	(6.399)*	0.810	(5.926)*	0.641	(6.321)*	1.675	(5.817)*	1.270	(6.318)*

*Note: Sample 2001:01-2014:10. *: significant at 5% critical values simulated using 10,000 iterations*

Table 7. Engle-Granger test for cointegration: Empirical results

Liv-Ex 100 - MSCI World			***Mediobanca – MSCI World***			***Liv-Ex 100 - Mediobanca***		
Dep. Variable: Liv-Ex 100	Coeff.	Std. Error	Dep. Variable: Mediobanca	Coeff.	Std. Error	Dep. Variable: Liv-Ex 100	Coeff.	Std. Error
const	–42.935	29.742	const	19.950	6.748	const	-66.959	27.831
MSCI World	0.150	0.032	MSCI World	0.082	0.007	Mediobanca	1.692	0.286
time	2.262	0.182	time	0.851	0.041	time	0.842	0.330
	Test Stat.	P-value		Test Stat.	P-value		Test Stat.	P-value
Cointegration test	-2.726	0.398		-2.538	0.499		-1.313	0.953

Note: Sample 2001:01-2008:08

Table 8. Johansen test for cointegration: Empirical results

Liv-Ex 100 - MSCI World VAR model with 2 lag (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.098	9.561	0.322	8.677	0.321
1	0.010	0.884	0.347	0.884	0.347
Mediobanca - MSCI World VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.078	7.498	0.528	6.805	0.521
1	0.008	0.693	0.405	0.693	0.405

Liv-Ex 100 - Mediobanca VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.083	8.214	0.450	7.241	0.470
1	0.012	0.973	0.324	0.973	0.324

Note: Sample 2001:01-2008:08. Lag selection of the VARs performed through the BIC from a maximum of 12 lags.

Table 9. Threshold cointegration analysis: Empirical results

	Liv-Ex 100 - Mediobanca				***MSCI World - Liv-Ex 100***				***Mediobanca - MSCI World***			
	Threshold		***Momentum***		***Threshold***		***Momentum***		***Threshold***		***Momentum***	
Lags (determined by data):	2		2		2		2		2		2	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Above Threshold	-0.030	0,083	-0,004	0,073	-0,066	0,049	-0,018	0,048	-0,037	0,053	-0,069	0,046
Below Threshold	-0.109	0,071	-0,160	0,078	-0,024	0,048	-0,072	0,048	-0,063	0,053	-0,016	0,063
Diff. Resid. (t-1)	0.132	0,120	-0,123	0,117	0,184	0,106	0,196	0,105	-0,228	0,111	-0,224	0,109
Diff. Resid. (t-2)	0.150	0,116	0,160	0,114	-0,015	0,106	-0,008	0,105	0,075	0,108	0,093	0,108
	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%
Threshold value (tau):	0		0		0		0		0		0	
F-equal:	0,571	(2.859)*	2,382	(3.952)*	0,380	(2.738)*	0,643	(3.972)*	0,124	(2.884)*	0,459	(3.906)*
T-max value:	-0,361	(-2.115)*	-0,049	(-1.983)*	-0,497	(-2.122)*	-0,362	(-2.000)*	-0,704	(-2.117)*	-0,248	(-1.972)*
F-joint (Phi):	1,185	(5.812)*	2,111	(6.347)*	1,035	(5.960)*	1,169	(6.315)*	0,983	(5.847)*	1,154	(6.283)*

*Note: Sample 2001:01-2008:08. *: significant at 5% critical values simulated using 10,000 iterations*

Table 10. Engle-Granger test for cointegration: Empirical results

Liv-Ex 100 - MSCI World			***Mediobanca – MSCI World***			***Liv-Ex 100 - Mediobanca***		
Dep. Variable: Liv-Ex 100	Coeff.	Std. Error	Dep. Variable: Mediobanca	Coeff.	Std. Error	Dep. Variable: Liv-Ex 100	Coeff.	Std. Error
Const	−188.269	53.577	const	−53.652	16.523	const	-92.645	67.280
MSCI World	0. 364	0. 069	MSCI World	0.103	0.021	Mediobanca	2.249	0.506
Time	1. 956	0. 847	time	1.240	0.261	time	0.447	1.262
	Test Stat.	P-value		Test Stat.	P-value		Test Stat.	P-value
Cointegration test	-1.482	0.935		0.253	0.9995		-1.335	0.947

Note: Sample 2008:09-2010:12.

Table 11. Johansen test for cointegration: Empirical results

Liv-Ex 100 - MSCI World VAR model with 2 lag (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.194	6.374	0.656	6.051	0.613
1	0.011	0.323	0.570	0.323	0.570
Mediobanca - MSCI World VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.402	15.528	0.048	14.414	0.045
1	0.0390	1.114	0.291	1.114	0.291
Liv-Ex 100 - Mediobanca VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.306	10.837	0.226	10.243	0.200
1	0.0210	0.593	0.441	0.593	0.441

Note: Sample 2008:09-2010:12. Lag selection of the VARs performed through the BIC from a maximum of 12 lags.

Table 12. Threshold cointegration analysis: Empirical results

	Liv-Ex 100 - Mediobanca				***MSCI World - Liv-Ex 100***				***Mediobanca - MSCI World***			
	Threshold		***Momentum***		***Threshold***		***Momentum***		***Threshold***		***Momentum***	
Lags (determined by data):	2		2		2		2		2		2	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Above Threshold	-0,506	0,209	-0,487	0,206	-0,169	0,164	-0,164	0,177	-0,583	0,201	-0,524	0,195
Below Threshold	-0,337	0,192	-0,348	0,195	-0,233	0,195	-0,228	0,185	-0,641	0,228	-0,728	0,224
Diff. Resid. (t-1)	0,481	0,193	0,487	0,194	0,342	0,209	0,340	0,209	0,547	0,204	0,526	0,203
Diff. Resid. (t-2)	0,113	0,229	0,106	0,229	-0,195	0,199	-0,188	0,206	0,356	0,224	0,369	0,217
	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%
Threshold value (tau):	0		0		0		0		0		0	
F-equal:	0,433	(3.0671)*	0,293	(4.096)*	0,072	(3.262)*	0,067	(4.091)*	0,047	(2.966)*	0,619	(4.160)*
T-max value:	-1,758	(-2.226)*	-1,784	(-2.082)*	-1,030	(-2.238)*	-0,926	(-2.082)*	-2,813	(-2.265)*	-2,691	(-2.071)*
F-joint (Phi):	3,842	(6.051)*	3,749	(6.671)*	1,110	(6.190)*	1,107	(6.739)*	6,762	(6.094)*	7,232	(6.635)*

*Note: Sample 2008:09-2010:12. *: significant at 5% critical values simulated using 10,000 iterations*

Table 13. Engle-Granger test for cointegration: Empirical results

Liv-Ex 100 - MSCI World			***Mediobanca – MSCI World***			***Liv-Ex 100 - Mediobanca***		
Dep. Variable: Liv-Ex 100	Coeff.	Std. Error	Dep. Variable: Mediobanca	Coeff.	Std. Error	Dep. Variable: Liv-Ex 100	Coeff.	Std. Error
const	749.475	19.696	const	–41.612	17.457	const	763.457	19.828
MSCI World	0.216	0.035	MSCI World	0.135	0.031	Mediobanca	0.931	0.138
time	-4.667	0.358	time	0.779	0.317	time	-4.508	0.311
	Test Stat.	P-value		Test Stat.	P-value		Test Stat.	P-value
Cointegration test	-2.530	0.528		-1.614	0.905		-2.303	0.644

Note: Sample 2011:01-2014:10.

Table 14. Johansen test for cointegration: Empirical results

Liv-Ex 100 - MSCI World VAR model with 2 lag (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.278	15.198	0.054	14.972	0.037
1	0.005	0.225	0.635	0.225	0.635
Mediobanca - MSCI World VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.107	6.321	0.662	5.218	0.716
1	0.024	1.103	0.294	1.103	0.294
Liv-Ex 100 - Mediobanca VAR model with 2 lags (unrestricted constant)					
Rank	Eigenvalue	Trace test	P-value	L-max	P-value
0	0.110	5.374	0.768	5.351	0.700
1	0.0004	0.023	0.880	0.023	0.880

Note: Sample 2011:01-2014:10. Lag selection of the VARs performed through the BIC from a maximum of 12 lags.

Table 15. Threshold cointegration analysis: Empirical results

	Liv-Ex 100 - Mediobanca				***MSCI World - Liv-Ex 100***				***Mediobanca - MSCI World***			
	Threshold		***Momentum***		***Threshold***		***Momentum***		***Threshold***		***Momentum***	
Lags (determined by data):	2		2		2		2		2		2	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Above Threshold	-0,106	0,070	-0,076	0,072	-0,117	0,112	-0,229	0,091	-0,138	0,110	-0,185	0,120
Below Threshold	-0,107	0,078	-0,138	0,074	-0,139	0,090	0,001	0,105	-0,238	0,132	-0,172	0,121
Diff. Resid. (t-1)	0,320	0,149	0,330	0,147	0,186	0,152	0,152	0,148	0,026	0,153	0,023	0,154
Diff. Resid. (t-2)	0,035	0,146	0,021	0,147	0,226	0,156	0,137	0,158	-0,138	0,110	-0,185	0,120
	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%	Test Stat.	Std. Error 5%
Threshold value (tau):	0		0		0		0		0		0	
F-equal:	0,000	(2.925)*	0,370	(4.041)*	0,026	(3.128)*	2,761	(3.926)*	0,354	(2.819)*	0,006	(4.0580)*
T-max value:	-1,372	(-2.170)*	-1,049	(-2.006)*	-1,038	(-2.173)*	0,007	(-1.998)*	-1,251	(-2.158)*	-1,427	(-2.044)*
F-joint (Phi):	2,100	(6.063)*	2,305	(6.521)*	1,677	(5.922)*	3,161	(6.580)*	2,328	(6.227)*	2,137	(6.744)*

*Note: Sample 2011:01-2014:10. *: significant at 5% critical values simulated using 10,000 iteration*

7. CONCLUSION

Over the last years investment in commodities as an alternative asset class has grown rapidly. Existing economic literature mainly focuses on fine wine, with the aim to evaluate whether wine as an asset could be considered a good investment or not, considering only returns. More recent studies have the goal to assess potential risk diversification benefits of holding wine, using the Capital Asset Pricing Model (CAPM) or other more sophisticated multi-factor models. In our paper we enlarged the wine investment framework by focusing both on fine wine and non-fine wine and by highlighting that wine diversification benefits are not only a fine wine prerogative, but can be extended to non-fine wine. The interest on non-fine wine stocks as an asset class that traders can use for investing purposes is particularly relevant, due to the growing size of the wine market in countries not historically suited to the production of wine, the increasing stock price volatility, the higher performances, and, more in general, the renewed levels of interest over the role of the “financialization” of commodity markets during the 2008 economic crises.

This paper focuses on fine and normal wine stock price series and apply a cointegration analysys with the aim to investigate the potential of wine as a financial investments. The Liv-Ex 100 Fine Wine Index is used for fine wine, the Mediobanca Global Wine Industry Share Price Index for normal wine, and MSCI World Index as a proxy for the overall stock market. The dataset is from July 2001 to October 2014 and prices are on a monthly frequency.

A first-step empirical investigation of fine and non-fine wine abnormal returns highlighted that wine indexes have performed better than the overall stock market. Investors could have earned greater returns with less risk by investing in wine, especially non-fine wine, revealing investment in wine stocks as a profitable investment *per se*.

A second-step analysis focused on the long-run relationship between fine wine, non-fine wine and the general stock market with the specific goal to highlight different price dynamics and co-movements in the long-run and to exploit potential diversification benefits. The results highlight a lack of long-run relationship between fine wine and non-fine wine. Besides, both indexes are not cointegrated with the stock market, that is are driven by different fundamentals, and therefore they can offer a diversification benefit to investors, suggesting a better portfolio performance if fine and non-fine wine stocks are included.

The topic is relevant in the light of the need to properly understand the fluctuating pattern of agricultural prices, the relationship between commodity prices and stock market indexes, and the appeal (and risk) of investing in commodities. From a financial perspective, further research on wine as an asset class should quantify the effect of diversification and investigate financial mechanisms behind the profitability of wine companies and the pattern of their stock prices, to identify possible investment opportunities and portfolio strategies.

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