ΑΔΣ

Advances in Decision Sciences

Volume 22(A)
22nd Anniversary Special Issue
December 2018

Michael McAleer

Editor-in-Chief
University Chair Professor
Asia University, Taiwan

Is Wine a Safe-Haven? Evidence from a Nonparametric Causality-in-Quantiles Test *

Nikolaos Antonakakis *
Department of Business and Management
Webster Vienna Private University
Vienna, Austria
and
University of Portsmouth
Economics and Finance Subject Group
Portsmouth, UK

Mehmet Balcilar
Department of Economics
Eastern Mediterranean University
Famagusta, via Mersin 10
Northern Cyprus, Turkey

Elie Bouri
USEK Business School
Holy Spirit University of Kaslik
Jounieh, Lebanon

Rangan Gupta
Department of Economics
University of Pretoria
Pretoria, South Africa

September 2018

Abstract

Unlike the extant literature on safe-havens, where one aims to relate the movements in an asset considered with extreme episodes in equity markets, we test this property for fine wine, by relating it to global uncertainty. Using a nonparametric k-th order causality-in-quantiles test, we show that, while uncertainty does affect returns and/or variance of the alternative wine indices considered, this effect is restricted to only certain parts of the conditional distribution. In particular, wine seems to be unaffected by global uncertainty, and hence, acts as a safe-haven at extreme ends of the market, i.e., during bear or bullish times; but not during normal times (around the median of the conditional distribution of returns and/or volatility).

1. Introduction

In the aftermath of the global financial crisis, investors have become more interested in non-traditional assets that could possibly act as safe-havens (e.g., see Bredin et al., 2015; Low et al., 2016, and Bredin et al., 2017, among others), or more precisely be uncorrelated with equities during stress periods (Bouri, 2015). In this regard, fine wine as an alternative investment instrument has recently been the subject of substantial financial media coverage, and more scholars have pointed toward its valuable role in equity portfolios (see, among others, Sanning et al., 2008; Masset and Henderson, 2010; Kourtis et al., 2012; Bouri, 2015; Bouri and Roubaud, 2016). In particular, the growth in the wine industry of 1474 percent since 1988 has outperformed equity, gold and real estate markets (Pruszynski, 2015).

Numerous studies consider the relationships between fine wines and conventional assets, like equities and bonds, to highlight the diversification benefits of fine wine (Sanning et al., 2008; Masset and Henderson, 2010; Kourtis et al., 2012). Interestingly, very recent studies focus on the safe haven property of fine wines by examining the wine-equity correlation during stress periods using DCC-GARCH models (Bouri, 2015; Bouri and Roubaud, 2016), and provide some weak evidence of the safe-haven property of fine wine. Notably, these two recent studies rely on a methodological approach traditionally used to determine whether an asset can be considered a safe-haven that consists of analysing correlation between the particular asset in concern with that of stocks – perceived to be risky, during episodes of financial crisis and market jitters, with these periods of uncertainty being modelled by extreme quantiles of the distribution of equity market returns (see for example, Balcilar et al., (2016) for a detailed review in this regard).

However, recent studies have shown the importance of uncertainty in affecting equity and commodity markets, and the economy in general (see for example, Balcilar et al., (2016, forthcoming) and Chuliá et al., (forthcoming) for a detailed literature reviews). Motivated by these studies, we aim to examine whether movements in uncertainty drive wine returns and volatility using monthly data covering the period of 1997:1-2016:12, and hence to assess the safe-haven property of fine wine. Such an examination would provide us with a more direct test of the safe-haven property of the wine market in comparison to the related works of Bouri (2015), and Bouri and Roubaud (2016), which tends to focus on specific episodes of market turbulence captured through extreme behavior of alternative assets. Methodologically, our study follows the approach undertaken by Balcilar et al., (2016) (while determining the safe-haven property of gold). If the wine market is unaffected by global uncertainty, then we can conclude that the wine market is indeed a safe-haven. While Balcilar et al., (2016) only analyzed the role of various measures of US uncertainty, we instead focus on a measure of *global* uncertainty given the globality of the fine wine market.

Our second contribution to the wine literature relates to the use of a novel nonparametric causality-in-quantiles test, recently proposed by Balcilar *et al.* (forthcoming) to study whether global uncertainty causes wine returns and volatility. This novel test combines elements of the test for nonlinear causality of *k*-th order developed by Nishiyama et al. (2011), with the causality-in-quantiles test developed by Jeong et al. (2012) and, hence, can be considered as a generalization of the former. The nonparametric causality-in-quantile approach has the following three novelties: First, being a nonparametric test, it detects the underlying dependence structure between the examined variables and, hence, controls for possible misspecification associated with linear tests of causality. Second, it allows us to test for causal effects across all quantiles of the distribution of wine-price movements rather than just at the conditional-mean as in linear models. Therefore, this nonparametric causality-in-quantile test represents implicitly a time-varying approach as it captures

various phases of the wine market (bear (lower quantiles), normal (median) and bull (upper quantiles)). Finally, we are able to test not only for causality in the first moment (returns), but also for higher-order causality in the second moment (volatility) – again not possible in standard linear Granger causality tests. Such an investigation of causality in both returns and volatility is important because, during some periods or market phases, causality in the conditional-mean may not exist while, at the same time, higher-order interdependencies may turn out to be significant.

As indicated earlier, our study is related to a strand of research that focuses on the safe-haven property of wine. However, it differs in several ways. First, and unlike the works of Bouri (2015), and Bouri and Roubaud (2015), we not only use a measure of uncertainty to capture market jitters, instead of extreme behavior of specific equities, but more importantly, we are able to analyze the safe-haven property of the wine market in terms of both returns and volatility at various phases of the wine market – which we show is of paramount importance. Hence, our work is more general than the conditional mean-based (DCC-GARCH) works dealing only with wine returns, so far conducted in the safe-haven literature of the wine market (see also Masset and Henderson, 2010). Second, and unlike most of previous works that used a single wine index as a proxy for the fine wine market, we consider five alternative indices covering different types and numbers of fine wines. In fact, Kourtis et al. (2012) used different wine indices and uncovered some diversification between them which further motivates our choice to use several wine indices. Our main analysis provides suggestive evidence of the safe-haven property of fine wine that interestingly depends on the various phases of the wine market, bear, normal, and bull.

We organize the remainder of this paper as follows: In Section 2, we describe the causality-in-quantiles test, while in Section 3, we discuss our data and empirical results. Finally, in Section 4, we offer some concluding remarks.

2. Methodology

In this section, we present a novel methodology for the detection on nonlinear causality via a hybrid approach developed by Balcilar *et al.* (forthcoming), which in turn, is based on the frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). This approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies.

We start by denoting wine returns by y_t and the predictor variable (in our case the global uncertainty) as x_t.

Let $Y_{t-1} \equiv (y_{t-1}, ..., y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, ..., x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively.

If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t | Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t | Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) | Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the q-th quantile hypotheses to be tested are:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) | Z_{t-1}\} = q\} = 1, \tag{1}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) | Z_{t-1}\} = q\} < 1. \tag{2}$$

Jeong *et al.* (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t | Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \leq Q_\theta(Y_{t-1}) | Z_{t-1}\}] = \theta$ or, equivalently, $1\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\times\}$ is an

6

indicator function. Jeong *et al.* (2012) show that the feasible kernel-based sample analogue of *J* has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{e}_t \hat{e}_s. \tag{3}$$

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{e}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{e}_t = 1\{y_t \pounds Q_q(Y_{t-1})\} - q. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta \mid Y_{t-1}), \tag{5}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1, s^1 t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right) 1(y_s \pounds y_t)}{\sum_{s=p+1, s^1 t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right)}, \tag{6}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

In an extension of Jeong *et al.* (2012)'s framework, Balcilar et al., (forthcoming) develop a test for the *second* moment. In particular, we want to test the volatility causality running from the global uncertainty to wine returns. Adopting the approach in Nishiyama *et al.* (2011), higher order quantile causality can be specified as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_q(Y_{t-1})\,|\,Z_{t-1}\} = q\} = 1 \qquad \text{for } k = 1,2,...,K \qquad (7)$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_q(Y_{t-1})\,|\,Z_{t-1}\} = q\} < 1 \qquad \text{for } k = 1,2,...,K \qquad (8)$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to the* k^{th} *moment* using Eq. (7) to construct the test statistic of Eq. (6) for each k. The causality-in-variance test can be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. However, it can be shown that it is not easy to combine the different statistics for each $k = 1,2,...,K$ into one statistic for the joint null in Eq. (11), because the statistics are mutually correlated (Nishiyama *et al.*, 2011).To efficiently address this issue, we include a sequential-testing method as described Nishiyama *et al.* (2011). First, we test for the nonparametric Granger causality in the *first* moment (*i.e.* $k = 1$). Nevertheless, failure to reject the null for $k = 1$ does not automatically leads to no-causality in the *second* moment. Thus, we can still construct the tests for $k = 2$.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ respectively. In this study, we make use of the Schwarz Information Criterion (SIC) to choose the lag-length. Note that, when it comes to choosing lags, the SIC is considered being parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of overparametrization usually

arising with nonparametric frameworks.[1] The bandwidth value is chosen by employing the least squares cross-validation techniques. [2] Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

3. Data and Empirical Results

Our analysis comprises five alternative wine prices and two measures of global uncertainty, covering the overall monthly period of 1997:01 to 2016:12. We use monthly data on five wine market price indices maintained by London International Vintners Exchange (Liv-ex), which is an exchange for investment-grade wine based in London. Founded in 1999, Liv-ex makes investing in fine wines easier as it provides more transparency and liquidity to the marketplace where wine merchants trade wine. Liv-ex also publishes five leading wine price indices that are used as benchmarks for the "fine wine" market in general by several important wine investment funds (e.g. The Wine Investment Fund in Bermuda, Lunzer Wine Fund in British Virgin Islands, Patrimoine Grands Crus in France). The latter have also accelerated the pace of financialization in the fine wine market. The five indices considered in this paper are:

(a) The Liv-ex Fine Wine 50 (Liv-ex 50) index, which tracks the price movement of the most heavily traded commodities in the fine wine market - the Bordeaux First Growths. It includes only the ten most recent vintages (excluding En Primeur, currently 2004-2013), with no other qualifying criteria applied. The data covers the monthly period of 1999:12-2016:12;

---

[1] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an overparameterized model, while the SIC is asymptotically consistent.
[2] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

(b) The Liv-ex Fine Wine 100 (Liv-ex 100) index is the industry leading benchmark. It represents the price movement of 100 of the most sought-after fine wines on the secondary market. The data period covered in this cases is 2001:08-2016:12;

(c) The Liv-ex Bordeaux 500 is Liv-ex's most comprehensive index and reflects trends in the wider fine wine market. It represents the price movement of 500 leading wines and is calculated using the Liv-ex Mid Price. The index spans the period of 2004:01-2016:12;

(d) The Liv-ex Fine Wine 1000 (Liv-ex 1000) tracks 1,000 wines from across the world using the Liv-ex Mid Price, and covers the period of 2003:12-2016:12;

(e) Finally, the Liv-ex Fine Wine Investables (Liv-ex Investables) index tracks the most "investable" wines in the market around 200 wines from 24 top Bordeaux chateaux. In essence, it aims to mirror the performance of a typical wine investment portfolio. The index data starts in 1990:5 and ends in 2016:12; hence it goes further back than any other Liv-ex indices. However, since the global uncertainty data (details of which we discuss below) only starts in 1997:1, the period of analysis involving Liv-ex Investables can only start at the same point in time.

The data on these five indices have been sourced from Liv-ex. Since our methodology requires stationary data, we work with wine returns, obtained as the first-differences of the natural logarithmic values of a specific wine index expressed in percentage.[3] The squared values of returns measure the volatility of wine returns.

Following the work of Baker et al., (2016), the same authors have recently developed a monthly index of Global Economic Policy Uncertainty (GEPU) that runs from 1997:1 to the present. The GEPU Index is a GDP-weighted average of national Economic Policy Uncertainty (EPU) indices

---

[3] Standard unit root tests confirm the stationarity of wine returns and volatility. Complete details of which are available upon request from the authors.

for 16 countries (Australia, Brazil, Canada, China, France, Germany, India, Ireland, Italy, Japan, Russia, South Korea, Spain, the United Kingdom, and the United States), with each national EPU index reflecting the relative frequency of own-country newspaper articles that contain a trio of terms related to the economy, policy and uncertainty. We use both versions of the available GEPU index, i.e., one based on current-price GDP measures, and one based on PPP-adjusted GDP. The 16 countries that enter into the GEPU index account for two-thirds of global output on a Purchasing Power Parity (PPP)-adjusted basis and approximately three-quarters of global output at current prices. The GEPU index, with additional details, is available for download from: http://www.policyuncertainty.com/global_monthly.html. Since the GEPU index is stationary,[4] we work with the natural-logarithms of the two indices namely LEPU1 (GEPU with current price GDP weights) and LEPU2 (GEPU with PPP-adjusted GDP weights). Summary statistics of the series are presented in Table 1.

[TABLE 1]

We now turn to the main focus of the paper, which consists of examining the causality-in-quantile emanating from the two measures of global uncertainty to wine returns and volatility (squared-returns) in order to gauge the safe-haven property of the wine market. The results of the quantile-based test covering the range of 0.05 to 0.95 are reported in Tables 2 and 3. As can be seen from Table 2, global measures of uncertainty fail to cause movements in the returns of Liv-ex Bordeaux 500 and Liv-ex 1000 over the entire of their respective conditional distributions. However, for the returns of Liv-ex 50, Liv-ex 100 and Liv-ex Investables, global uncertainty can predict the movements around the conditional mean of the distribution to the upper quantiles, i.e., specifically between the quantile range of 0.2 to 0.9. In general, the results are consistent irrespective of the

---

[4] Standard unit root tests confirm the stationarity of the natural logarithm of the uncertainty indices. Complete details of these results are available upon request from the authors.

measure of uncertainty we use. These noteworthy findings add to prior studies that generally show a weak correlation between fine wine and equities (Masset and Henderson, 2010; Kourtis et al., 2012), or point toward the safe-haven property of fine wines (Bouri, 2015; Bouri and Roubaud, 2016). Furthermore, the results show evidence of heterogeneity in the relation between uncertainty and fine wine returns that differ across some of the Liv-ex indices, suggesting that investors should not be indifferent toward the choice of a wine index.

[TABLES 2 AND 3]

Next, we turn our attention to Table 3, where we report the causal effect of uncertainty on wine volatility across the various quantiles. We observe that, unlike the returns, global measures of uncertainty affect certain points of the conditional distribution of the volatility for all the five wine indices under consideration, with the volatility of Liv-ex 50 and Live-ex Investables returns being the most affected except at the extreme quantile of 0.95. While, returns of Liv-ex Bordeaux 500 and Liv-ex 1000 were unaffected by uncertainty, now, barring the extreme ends of the respective conditional distribution of volatility, global measures of uncertainty do affect the volatility of these two wine indices. These findings confirm the view that fine wines do not fluctuate according to market risk factors because they are affected, in addition to supply–demand imbalances, by unique factors such age effects, external quality ratings, climate conditions, and grape quality (Hadj et al., 2008). Using different data, methodology, and sample period, our findings corroborate with that reported by Sanning et al. (2008) who, using the CAPM and the Fama–French model, show that the fine wine market and market risk factors are uncorrelated.

Our results highlight the value added from the use of the higher-order causality-in-quantiles test in terms of not only looking at the entire conditional distribution of returns, but also the same for volatility. While, just based on causality of returns from uncertainty, we would have concluded that

Liv-ex Bordeaux 500 and Liv-ex 1000 are overwhelmingly safe-havens, when analysing volatility, we observe that this is only the case at extreme ends of the distribution. In general, combining the results of both returns and volatility, we can say that the wine market does serve as a safe-haven, but the result is contingent on the state of the market. In particular, the wine market is unaffected by movements in global uncertainty and thus serves as a safe-haven, during bearish (lower quantiles) or bullish (upper quantiles) times, with the result being stronger under the bull phase scenario. However, when the wine market performs in the region of moderate to good, i.e., around the median of the conditional distribution, it fails to serve as a safe-haven, as uncertainty affects both returns and volatility of the market. These results, which add valuable investing knowledge to the existing literature that usually does not distinguish among the three phases of the wine market (bear, normal and bull) seem to suggest, that when the market performs exceptionally well, or alternatively performs poorly, perhaps, the efficient market hypothesis is at work, making the role of uncertainty in determining future movements in the wine market redundant. In such situations, what matters to investors are past behaviour of the wine returns and volatility. But, when the wine market is in average mode, investors require information from global uncertainty in making their investment decisions in the wine market. Alternatively, agents possibly herd when the market is in bearish or bullish modes and, hence, does not require any other information than the past behaviour of wine prices, but around the median, investors aim to use the information content of uncertainty in their decision-making process to potentially make more profits.

4. Conclusion

Following the global financial crisis, while trying to search for alternative assets that are uncorrelated with equities, researchers have started to investigate more whether fine wine, which has a booming market, can serve as a safe-haven. In this regard, some mixed evidence exists. We aim to build on this literature in this paper. But rather than focusing on how the wine market

moves with specific episodes of market turbulence captured through extreme behavior of risky assets, we ask whether a measure of global uncertainty affects wine returns and volatility, accounting for the different phases of the wine market (bear, normal, and bull).

For our purpose, we use a nonparametric causality-in-quantiles test, which is robust to model misspecification being a data-driven approach, and provides evidence of causality or lack of it over the entire conditional distribution of not only returns, but also volatility. Clearly, the nonparametric causality-in-quantiles test is much more general than linear conditional mean based tests of causality dealing only with returns. Using this test, we observe that, while uncertainty does affect returns and/or variance of the alternative wine indices considered, this effect is restricted to only certain parts of the conditional distributions. In particular, wine seems to be unaffected by global uncertainty, and hence, acts as a safe-haven at the extreme ends of the market, i.e., during bearish or bullish times; but not during the normal times (around the median of the conditional distribution of returns and/or volatility).

As part of future research, it would be interesting to extend our study in order to examine if these results continue to hold in an out-of-sample exercise, since in-sample predictability does not guarantee the same in a forecasting set-up (Balcilar et al., 2016), and it is actually real-time forecasts that are required by investors for asset allocation.

References

Baker, S., Bloom, N. and Davis, S., (2016). Measuring Economic Policy Uncertainty. Quarterly Journal of Economics, 131(4), 1593-1636.

Balcilar, M., Bekiros, S. and Gupta, R. (Forthcoming). The Role of News-Based Uncertainty Indices in Predicting Oil Markets: A Hybrid Nonparametric Quantile Causality Method. Empirical Economics, doi: 10.1007/s00181-016-1150-0.

Balcilar, M., Gupta, R., and Pierdzioch, C. (2016). Does Uncertainty Move the Gold Price? New Evidence from a Nonparametric Causality-in-Quantiles Test. Resources Policy, 49(1), 74-80.

Bouri, E. (2015). Fine Wine as an Alternative Investment during Equity Market Downturns. The Journal of Alternative Investments, Spring, 46-57.

Bouri, E., and Roubaud, D. (2016). Fine Wines and Stocks from the Perspective of UK Investors: Hedge or Safe Haven? Journal of Wine Economics, 11(2), 233–248.

Bredin, D., Conlon, T., and Potì, V. (2015) Does gold glitter in the long-run? Gold as a hedge and safe haven across time and investment horizon, International Review of Financial Analysis, 41, 320-328.

Bredin, D., Conlon, T., and Potì, V. (2017) The price of shelter - Downside risk reduction with precious metals, International Review of Financial Analysis, 49, 48-58.

Chuliá, H., Gupta, R., Uribe, J.M., and Wohar, M.E. (Forthcoming). Impact of US Uncertainties on Emerging and Mature Markets: Evidence from a Quantile-Vector Autoregressive Approach. Journal of International Financial Markets, Institutions and Money, doi: http://dx.doi.org/10.1016/j.intfin.2016.12.003.

Hadj, A., Lecocq, S. and Visser, M. (2008). The Impact of Gurus: Parker Grades and En Primeur Wine Prices. The Economic Journal, 118 (2008), 158-173.

Hurvich, C.M. and Tsai, C-L. (1989). Regression and Time Series Model Selection in Small Samples. Biometrika, 76, 297-307.

Jeong, K., Härdle, W. K. and Song, S. (2012). A Consistent Nonparametric Test for Causality in Quantile. Econometric Theory, 28, 861-887.

Kourtis, A., Markellos, R. and Psychoyios, D. (2012). Wine price risk management: International diversification and derivative instruments. International Review of Financial Analysis, 22, 30-37.

Li, Q. and Racine, J.S. (2004). Cross-validated local linear nonparametric regression. Statistica Sinica, 14, 485-512.

Low, R. K. Y., Yao, Y., and Faff, R., (2016) Diamonds vs. precious metals: What shines brightest in your investment portfolio? International Review of Financial Analysis, 43, 1-14.

Masset, P. and Henderson, C. (2010). Wine as an alternative asset class. Journal of Wine Economics, 5(1), 87-118.

Nishiyama, Y., Hitomi, K., Kawasaki, Y. and Jeong, K. (2011). A Consistent Nonparametric Test for Nonlinear Causality - Specification in Time Series Regression. Journal of Econometrics, 165, 112-127.

Pruszynski, M. (2015). Fine Wine Market Report, Vin-X Fine Wine Investments. Available for download from: https://www.vin-x.com/standalone-forms/vin-x-market-report.

Racine, J.S. and Li, Q. (2004). Nonparametric estimation of regression functions with both categorical and continuous data. Journal of Econometrics, 119, 99-130.

Sanning, L., Shaffer, S. and Sharratt, J.M. (2008). Bordeaux Wine as a Financial Investment. Journal of Wine Economics, 3, 61-81.

Table 1

Descriptive Statistics

	Liv-ex 50	Liv-ex 100	Liv-ex Bordeaux 500	Liv-ex 1000	Liv-ex Investables	LEPU1	LEPU2
Mean	0.1525	0.1366	0.1342	0.1379	0.1464	4.6560	4.6656
St. Dev.	0.5960	0.5357	0.3722	0.2952	0.8845	0.3884	0.3914
Min	-3.1557	-3.0732	-1.8738	-1.3611	-6.1889	3.9217	3.8987
Max	2.2774	2.0088	1.1288	1.1310	6.9702	5.6474	5.6311
Skewness	-0.4249** [0.0292]	-0.7938*** [0.0000]	-0.7126*** [0.0002]	-0.46132** [0.0179]	0.4884** [0.0122]	0.1136 [0.5599]	0.1867 [0.3380]
Excess Kurtosis	6.9068*** [0.0000]	8.6495*** [0.0000]	4.7063*** [0.0000]	3.8580*** [0.0000]	38.131*** [0.0000]	-0.5385 [0.1645]	-0.6006 [0.1210]
JB	312.75*** [0.0000]	499.45*** [0.0000]	156.17*** [0.0000]	101.62*** [0.0000]	9396.4*** [0.0000]	2.2061 [0.3319]	3.2303 [0.1989]

Note: p-values in parenthesis. *, **, *** indicate significance at the 10%, 5% and 1% level.

Table 2

Results of Causality-in-Quantiles Test from Uncertainty to Wine Returns

Wine	Uncertainty	Quantile										
		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
Liv-ex 50	LEPU1	1.0487	1.6390	1.9524	**2.3130**	**2.8535**	**2.7937**	**2.7088**	**2.9740**	**3.1753**	**2.0461**	1.0566
	LEPU2	0.8684	1.3503	1.5626	**2.1082**	**2.5904**	**2.4714**	**2.4753**	**2.5832**	**2.9567**	**2.0628**	1.0218
Liv-ex 100	LEPU1	1.1401	1.6137	1.9259	1.9534	**2.0052**	**2.3798**	**2.3625**	**2.8604**	**2.1337**	1.3677	1.0121
	LEPU2	1.0789	1.4807	**2.0962**	**1.9832**	1.9139	**2.5858**	**2.3250**	**2.7240**	1.9012	1.3928	1.0315
Liv-ex Bordeaux 500	LEPU1	0.4902	0.8617	0.3636	0.3377	0.5413	0.7709	1.0854	0.8478	0.8603	0.8722	0.7438
	LEPU2	0.5075	0.8420	0.3372	0.3275	0.5645	0.8240	1.0870	0.8033	0.8306	0.8657	0.7055
Liv-ex 1000	LEPU1	0.1855	0.3933	0.2642	0.2920	0.6568	0.3689	0.6406	0.4497	1.0215	0.8315	0.2240
	LEPU2	0.1725	0.4475	0.3173	0.3153	0.6551	0.3811	0.5688	0.3732	0.9099	0.7528	0.2118
Liv-ex Investables	LEPU1	0.9426	1.0617	1.9150	**2.6801**	**3.1238**	**4.2344**	**3.3938**	**3.6021**	**3.3430**	1.6657	1.0249
	LEPU2	0.9070	0.9366	1.8131	**2.6380**	**2.8391**	**3.8083**	**3.2740**	**3.3660**	**3.2507**	1.5124	1.0274

Note: Bold entries indicate the rejection of the null of no causality from uncertainty to wine returns at 5 percent (1.96) level of significance.

Table 3

Results of Causality-in-Quantiles Test from Uncertainty to Squared Returns (Volatility) of Wine

		Quantile										
Wine	Uncertainty	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
Liv-ex 50	LEPU1	**2.3268**	**2.5395**	**3.4774**	**4.0827**	**4.3922**	**4.4181**	**4.3188**	**4.2563**	**3.6005**	**2.1686**	1.7082
	LEPU2	**2.5774**	**3.3725**	**4.1797**	**4.0294**	**4.2087**	**4.2629**	**4.1243**	**3.9734**	**3.2246**	**2.1849**	1.6901
Liv-ex 100	LEPU1	1.3133	**2.0014**	**2.1399**	**2.5497**	**3.0383**	**3.1172**	**3.3371**	**2.8129**	**2.3310**	1.7532	0.9819
	LEPU2	1.0110	1.5228	**2.2878**	**2.7753**	**2.7145**	**3.0036**	**3.0790**	**2.7237**	**1.9760**	1.6270	1.0223
Liv-ex Bordeaux 500	LEPU1	0.1910	0.7180	1.3606	1.4134	**3.4835**	**2.7070**	**2.8578**	**2.2593**	1.5127	0.7376	0.3930
	LEPU2	0.1534	0.6464	1.1675	1.2601	**3.1475**	**2.5518**	**2.7087**	**2.3450**	1.6369	0.7141	0.3965
Liv-ex 1000	LEPU1	1.8732	**2.1491**	**2.6966**	**3.3960**	**3.5213**	**4.1461**	**3.9469**	**3.6872**	**2.8168**	1.8553	1.3199
	LEPU2	1.9058	**3.0131**	**2.7738**	**3.1993**	**3.5994**	**3.9593**	**3.8467**	**3.9038**	**2.9730**	1.8839	1.3050
Liv-ex Investables	LEPU1	**2.0348**	**3.0105**	**3.8984**	**4.4267**	**5.1471**	**5.2076**	**4.6387**	**4.3492**	**3.8877**	**2.9333**	1.8644
	LEPU2	**2.0293**	**2.8047**	**3.8517**	**4.5046**	**4.8210**	**4.9839**	**4.8860**	**4.5132**	**3.8685**	**2.8660**	1.8408

Note: Bold entries indicate the rejection of the null of no causality from uncertainty to wine returns volatility at 5 percent (1.96) level of significance.