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Does fine wine price contain useful information to forecast GDP? Evidence from major developed countries

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ABSTRACT

This study provides the first attempt to examine the ability of the price of fine wine to forecast the Gross Domestic Product (GDP) for the major developed countries. Considering the limitation of a linear Granger causality test in detecting nonlinear causal relationships, a nonlinear Granger causality test is also employed. The results from our nonlinear causality test show that this new variable contains useful information to forecast GDP for the US, the UK, and Australia, suggesting that we may include it as a forecasting variable in GDP forecasting models, especially nonlinear models, for these three countries.

1. Introduction

Successful forecasting of Gross Domestic Product (GDP) is very important for researchers and policy makers. Previous studies have used many different variables to forecast GDP. The variables they use are usually economic variables such as various interest rates, exchange rates, money supply, total exports, total imports, balance of trade, government expenditure, stock market index, unemployment rate and crude oil price. The literature on forecasting GDP using these variables is extensive. For example, Comba-Mendez et al. (2001) use short-term interest rates, real effective exchange rates, stock price indices, etc. to forecast GDP of selected European countries. Fagan et al. (2001) and Dreger and Marcellino (2003) construct medium-scale macroeconometric models for the Euro-area economic variables such as private consumption, fixed capital formation, nominal exchange rate, domestic and foreign nominal interest rate and real interest rate. Banerjee et al. (2005) use not only Euro-area series but also US macroeconomic variables to conduct a detailed evaluation of the properties of a large set of leading indicators for predicting Euro-area GDP. Besides these economic variables, some researchers also use indicators that capture people's expectations about the economy, for example, a consumer sentiment index, consumer confidence index, business confidence index and purchasing managers' index. For example, Mourougane and Roma (2003) find that the confidence indicators (economic sentiment indicator and industrial confidence indicator) are useful to forecast short-run GDP in most of the selected Euro-area countries, including Belgium, Spain, Germany, France, Italy and the Netherlands. Hansson et al. (2005) document that data from business tendency surveys are useful to forecast Swedish GDP in the short run.

This paper contributes to the literature by examining whether a new economic variable, the price of fine wine, contains useful information for forecasting GDP. Fine wine is the type of good that is mainly demanded by rich people, who own most of the world's wealth. It is likely that a rise in the price of fine wine reflects the fact that rich people feel optimistic about the economic outlook. In that case, they will increase their consumption and investment, which in turn will lead to growth in GDP. On the contrary, a drop in the price of fine wine reflects that they feel pessimistic about the economic outlook. Consequently, they will decrease their consumption and investment, which in turn will lead to a drop in GDP. In addition, fine wine is also attractive to wealthier investors, who are usually expertise in economics and participate in stock investment or other alternative investments. When they foresee that the economic situation might be better (worse), they would buy (sell) the fine wine, which leads to a rise (drop) in the price of fine wine.

An empirical investigation of a Granger causal relation from fine wine price to GDP is helpful to answer the aforementioned question. If the price of fine wine Granger causes GDP, it can be shown to contain useful information for forecasting GDP. Consequently, it should be included as a forecasting variable in various GDP forecasting models and should be added into a pool of economic variables to construct a composite leading indicator of economic activity.

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In this paper, we first adopt a standard linear Granger causality test to examine the causal relationship between the fine wine price index, Liv-ex 500, and GDP of the major developed countries. Since the linear Granger causality test has a low power to detect nonlinear causal relationships between economic variables (see, for example, Baek and Brock (1992) and Hiemstra and Jones (1994)), we further adopt a nonlinear Granger causality test, which was developed by Hiemstra and Jones (1994) (hereafter, HJ).[2] This test has high power to detect a nonlinear Granger causal relationship, which could be overlooked by its linear counterpart, between the economic variables. Because of this advantage, it has been widely used in the literature (see, for example, Abhyankar (1998), Huh (2002) and Qiao et al. (2009)). Our empirical results from the linear Granger causality test indicate that there is no causal relationship from price of fine wine to GDP of these countries. But its nonlinear counterpart indicates that a causal relationship from the price of fine wine to the GDP of the US, the UK and Australia does exist, suggesting that we may include it as a forecasting variable in various GDP forecasting models for these three countries, especially nonlinear models.

The remainder of this paper is organized as follows. Section 2 discusses the data and methodology. Section 3 provides empirical results, and Section 4 concludes.

2. Data and methodology

2.1. Data

The fine wine price index adopted in this paper is the Liv-ex 500 Fine Wine Index developed by Liv-ex (*The London International Vintners Exchange*) over the period 2001–2009. Liv-ex is the world's leading exchange for fine wine. It is used by an estimated 300 major fine wine merchants from 26 countries across Europe, Asia, North America and Australasia. These merchants combined account for about 80% of the global turnover in fine wine. Liv-ex advertises comprehensive price data on almost 100,000 fine wines. The Liv-ex index family consists of several indices, such as the Liv-ex 50, Liv-ex 100, Liv-ex 500, Liv-ex Claret Chip, Liv-ex Investable and Bordeaux 2009.[3] Among them, the Liv-ex 500 has the broadest base compared with the other Liv-ex indices and is designed to reflect price trends in a wider fine wine market. Although the majority of the index consists of Bordeaux wine, it also includes Burgundy, the Rhone, Champagne, Port, Italian wine and the new world wine. Since this index is widely acknowledged as the fine wine industry's benchmark, we adopt it in this study. The index data are downloaded from www.Liv-ex.com. In this paper, quarterly GDP data of the 8 economies, namely, Australia, Canada, France, Germany, Italy, Japan, the UK and the US are obtained from Datastream International.

3. Methodology

This section presents the methodology used to investigate the linear and nonlinear causal relationship from Liv-ex 500 index to GDP. The first sub-section briefly introduces the unit root test, which is the prior test to cointegration and causality tests, the second sub-section presents the linear Granger causality test, and the nonlinear Granger causality test will be introduced in the last sub-section.

3.1. Unit root test

Prior to the causality test, we have to certain that the time series are stationary. A time series is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed. If the time series is nonstationary, the deflection from the mean will be permanent. A time series is said to be $I(0)$ if it is stationary at the level form. A time series is said be integrated of order d if it has to be differenced d times to make it stationary. For example if a time series is $I(2)$, then $\Delta\Delta y_t = y_t - 2y_{t-1} + y_{t-2}$ will be stationary. The unit root test based on the Augmented Dickey–Fuller (ADF) test, which is a widely popular used methodology to examine the presence of stationary in the time series, will be first performed. The augmented Dickey–Fuller test may be used regardless of whether the error term u_t is correlated or not. The augment is conducted by adding the lagged values of the dependent variable Δy_t. According to Dickey and Fuller (1979, 1981), ADF test consists the following OLS estimation:

$$\Delta y_t = \beta_0 + \delta y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta y_{t-i} + u_t \tag{1}$$

where u_t is the pure white noise error term and where $\Delta y_{t-1} = (y_{t-1} - y_{t-2})$, $\Delta y_{t-2} = (y_{t-2} - y_{t-3})$, etc. The optimal number of lagged difference terms to be included (m) is determined by Akaike's Information Criteria (AIC) which determines the optimal choice of lag length such that the autocorrelations in the error term may be removed (Akaike, 1970). The unbiased estimate of the coefficient of lagged y_{t-1}, δ, can be obtained then. The null hypothesis in ADF, H_0: $\delta = 1$, indicates that the time series that is nonstationary will be tested against the alternative hypothesis, H_a: $\delta < 1$. The ADF test follows the asymptotic distribution as the DF statistic.

3.2. Cointegration and linear Granger causality

Cointegration test will then be performed to see whether the time-series of Liv-ex 500 and GDP that are individually non-stationary become stationary when they are linearly combined. Two time series are said to be cointegrated if they have a long-term, or equilibrium, relationship between them although they may deviate momentarily from each other in the short run. Existence of cointegration suggests that the two series share the same common trend so that the regression of one on the other will not be necessarily spurious, and the GDP will be subjected to the deviation from the long run movement dictated by the Liv-ex 500. First, we apply the well-known Johansen procedure (Johansen, 1988; and Johansen and Juselius, 1990) to test for possible cointegration between Liv-ex 500 and GDP series. The JJ method does not require a specific variable to be normalized and gives more efficient estimators of cointegrating vectors (Phillips, 1991). The two statistics developed in this approach to determine the number of cointegrating vectors are trace statistics and maximal eigenvalue (Johansen and Juselius, 1990). They are based on a canonical correlation analysis of residuals from two vector autoregressions: (1) Δy_t on $\Delta y_{t-1}, \ldots, \Delta y_{t-p+1}$ and (2) y_t on $\Delta y_{t-1}, \ldots, \Delta y_{t-p+1}$, where y_t is a vector of the variables involved and p is the order of autoregression. Johansen and Juselius (1990) compute the critical values of the test and Osterwald-Lenum (1992) recalculates the critical values for higher dimensions.

Second, Granger causality test will be performed to examine if the indication of presence of cointegration may be due to error correction mechanism; and to determine the presence of short term relationship in the case that the time series are found to be not cointegrated. If any pair of series is not cointegrated, the following bivariate VAR model

[2] Relationships among economic variables can be linear and nonlinear. The nonlinear relationships are more widely observed. Many studies have reported that economic variables exhibit nonlinear dependence (e.g., Granger and Teräsvirta, 1993; Hsieh, 1991; Scheinkman and LeBaron, 1989 etc.). So it is interesting and important to explore both the linear relationship and nonlinear relationship between the two economic variables in this study.

[3] All indices are price weighted and are based on mid prices rather than transaction prices. Mid prices are determined as the mid-point between the current highest bid price and the lowest offer price on the Liv-ex trading platform. Each price is also verified by a valuation committee to ensure data robustness.

will be adopted to test for Granger causality (see Huang et al. (2000), Ciner (2002) and Huh (2002)).

$$\Delta y_{1t} = c_1 + \sum_{i=1}^{m} \phi_{11}^{i} \Delta y_{1,t-i} + \sum_{i=1}^{m} \phi_{12}^{i} \Delta y_{2,t-i} + \varepsilon_{1t} \tag{2}$$

$$\Delta y_{2t} = c_2 + \sum_{i=1}^{m} \phi_{21}^{i} \Delta y_{1,t-i} + \sum_{i=1}^{m} \phi_{22}^{i} \Delta y_{2,t-i} + \varepsilon_{2t} \tag{3}$$

where Δy_{1t} and Δy_{2t} denote the first difference of GDP and the Liv-ex 500 series of one country, respectively, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is the vector of the corresponding error terms, and m is the optimal lag length obtained by using Akaike's information criterion (AIC). The null hypothesis that the Liv-ex 500 does not Granger cause GDP is equivalent to testing $\phi_{12}^{i} = 0$ for all $i = 1, 2, \ldots, m$ in Eq. (2) and it may be indicated by the following Wald's F-statistic:

$$F = \frac{(SSR_R - SSR_{UR}) \big/ m}{SSR_{UR} \big/ n-2m-1} \tag{4}$$

where SSR_R is the sum of squares of residuals of the restricted regression, which assumes all the coefficients ϕ_{12}^{i} equal to zero, and SSR_{UR} is the sum of squares of residuals of the un-restricted regression. The F-statistic follows the F-distribution with m and $n - 2m - 1°$ of freedom. The presence of unidirectional causality implies that the GDP growth is responding to the short-run past changes in the Liv-ex 500.

If two series are cointegrated, we follow Engle and Granger (1987) to impose the error correction mechanism (ECM) on the VAR to test for linear Granger causality between these variables. The ECM–VAR framework is as follows:

$$\Delta y_{1t} = c_1 + \alpha_1 ect_{t-1} + \sum_{i=1}^{m} \phi_{11}^{i} \Delta y_{1,t-i} + \sum_{i=1}^{m} \phi_{12}^{i} \Delta y_{2,t-i} + \varepsilon_{1t} \tag{5}$$

$$\Delta y_{2t} = c_2 + \alpha_2 ect_{t-1} + \sum_{i=1}^{m} \phi_{21}^{i} \Delta y_{1t-i} + \sum_{i=1}^{m} \phi_{22}^{i} \Delta y_{2,t-i} + \varepsilon_{2t}. \tag{6}$$

Here, the term ect_{t-1} is the error correction term. Thereafter, the Granger causality test is conducted in the usual manner. Granger (1988) indicates that within the ECM, causality may arise from the lagged differences and from the error correction term. The lagged differences of the variables may capture the short-term dynamics and the tests of causality may be carried out based on the significance of these terms. The hypothesis involves two joint-hypothesis tests: the coefficients of lagged variables and the error correction term are jointly zero. Note that, the changes in GDP will depend not only on the changes in Liv-ex 500 but also on the long-run relationship between them, which allows for any previous disequilibrium measured by the error correction term ect_{t-1}, to exert potential influences on the movement of the GDP series. The significance of the error correction term in each equation shows the tendency of Liv-ex 500 to restore equilibrium in GDP. Toda and Phillips (1994) supplemented that ECM may combine the short-run dynamics and long-run adjustment of the series, introducing two channels of causality from Liv-ex 500 to GDP. Since the results of the test are sensitive to the selection of lag length, AIC is adopted again to determine the appropriate lag length.

3.3. Nonlinear Granger Causality

The linear Granger causality test is known to possess a low power for detecting nonlinear causal relationships. To circumvent this problem, we use a nonlinear Granger causality test on the residuals from the linear VAR (ECM–VAR) model as discussed above. This approach enables us to detect the existence of any strictly nonlinear causality relation among the variables being studied, since the VAR (ECM–VAR) has already purged the residuals for linear causality.

The nonlinear Granger causality test developed by Baek and Brock (1992) has been further modified by Hiemstra and Jones (1994). This approach postulates that by removing the linear predictive power in the VAR (ECM–VAR) model given above, any remaining incremental predictive power of one residual series on another should be considered to be a nonlinear predictive power. A nonparametric statistical method is then proposed, using the correlation integral, which is a measure of spatial dependence across time, to uncover any nonlinear causal relation between two time series.

Consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, $t = 1,2,\ldots$ Let X_t^m be the m-length lead vector of X_t, and let $X_{t-L_x}^{L_x}$ and $Y_{t-L_y}^{L_y}$ be the L_x-length and L_y-length lag vectors of X_t and Y_t respectively. For given values of m, L_x, and L_y and for any e, $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ if

$$\begin{aligned} &\Pr\left(\| X_t^m - X_s^m \| < e \,\middle|\, \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e, \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e\right) \\ &\quad = \Pr\left(\| X_t^m - X_s^m \| < e \,\middle|\, \left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e\right) \end{aligned} \tag{7}$$

where $\Pr(\bullet)$ denotes the conditional probability and $\| \bullet \|$ denotes the maximum norm. For given values of m, L_x and $L_y \geq 1$, and $e > 0$, under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$, then

$$\sqrt{n}\left(\frac{C_1\left(m+L_x, L_y, e, n\right)}{C_2\left(L_x, L_y, e, n\right)} - \frac{C_3(m+L_x, e, n)}{C_4(L_x, e, n)}\right) \xrightarrow{a} N\left(0, \sigma^2\left(m, L_x, L_y, e\right)\right) \tag{8}$$

where C_1, C_2, C_3 and C_4 are the correlation-integral estimators of the joint probabilities, $n = T + 1 - m - \max(L_x, L_y)$ and $\sigma^2(m, L_x, L_y, e)$ can be estimated by following the approach described by Hiemstra and Jones (1994). A significant positive value of the test statistic implies that lagged values of $\{Y_t\}$ help to predict $\{X_t\}$, whereas a significant negative value suggests that lagged values of $\{Y_t\}$ confuse the prediction of $\{X_t\}$. This test has very good power properties against a variety of nonlinear Granger causal and noncausal relations, and its asymptotic distribution is the same if the test is applied to the estimated residuals from the VAR (ECM–VAR) models. To implement the HJ test, we have to select values for the lead length, m, the lag lengths, L_x and L_y, and the scale parameter, e. Following Hiemstra and Jones (1994), we set lead length $m = 1$ and $L_x = L_y$ for all cases. Also, common lag lengths of 1–4 lags and a common scale parameter of $e = 1.5\sigma$ are used, where $\sigma = 1$ denotes the standard deviation of standardized series.

4. Empirical results

We are testing the series of Liv-ex 500 and GDP of 8 developed countries for stationarity, identifying their order of integration and transforming them to stationary series. The results of ADF unit root tests on both time series and their first-differences of Liv-ex 500 and GDP of 8 countries are reported in Table 1. The time lags are chosen based on the Akaike Information Criteria. The ADF test statistics in the second column suggest that the null hypothesis of the existence of the unit root in time series should not be rejected at 5% level. Therefore all level series of fine wine index and GDP of 8 countries are not stationary in the time series.

The same test was applied for their first differences and the relative results are summarized in the third column of Table 1. The results indicate that they are stationary at 5% significance level. Hence, it is concluded that the time series of Liv-ex 500 and GDP of 8 countries are first-ordered integrated i.e. $I(1)$ series, and thus the level series not the first differences will be subject to cointegration test.

Table 1
ADF test statistics for unit roots in the level and first difference of Live-ex 500 index and GDP of 8 major developed countries.

Variables	Level	First difference
Live-ex 500	1.351 (0.999)	−5.308** (0.001)
Australia GDP	−2.115 (0.529)	−6.900** (0.000)
Canada GDP	−2.267 (0.446)	−6.606** (0.000)
France GDP	−1.662 (0.759)	−8.515** (0.000)
Germany GDP	−1.866 (0.662)	−7.951** (0.000)
Italy GDP	−1.566 (0.798)	−8.502** (0.000)
Japan GDP	−2.413 (0.370)	−8.493** (0.000)
UK GDP	−2.811 (0.197)	−8.050** (0.000)
US GDP	−2.754 (0.218)	−5.363** (0.000)

Notes: The null hypothesis of the ADF test is that the variable has a unit root. ** indicates significance at the 5% level, respectively. *p*-Value is presented in parentheses. The critical values of the ADF tests are based on McKinnon (1996).

Since the series of Liv-ex 500 and GDP of 8 countries are noted to be $I(1)$, there exists the possibility that they share a long-run equilibrium relationship. Thus we apply the Johansen procedure to look for evidence of cointegration for pairs of Liv-ex 500 index and any one of the GDP of 8 countries, and the results are presented in Table 2. The time lags in the unit root test for the residuals got from the cointegrating regression are determined similarly based on Akaike Information Criteria. As indicated in Table 2, there is no cointegration relation in these eight pairs. Thus, for these pairs, we adopt the usual VAR displayed in Eqs. (2) and (3) to test Granger causality.[4]

The conventional linear Granger causality test builds upon the previous unit root and cointegration tests to assess the interactions between the Liv-ex 500 index and GDP of 8 countries. The main focus of this study is to evaluate whether Liv-ex 500 series Granger cause the GDP of 8 countries; the feedback from the GDP to Liv-ex 500 index will not be evaluated. The results of linear causality test are presented in Table 3. As can be seen from the table, wine price index cannot Granger cause GDP of 8 countries, implying that it cannot be used to forecast the GDP of these countries. However, nonlinear causality may exist, which may not be captured by conventional causality test. Because of this, we proceed to nonlinear causality analysis.

Before testing for nonlinear Granger causality in the residuals from the VAR, the Ljung–Box *Q*-test is conducted on the residuals from the VAR models to determine whether any linear dependency remains in the residuals. The null hypothesis of the *Q*-test is that serial correlation does not exist in the residuals. The results of this diagnostic test, as reported in Table 3, show that the VAR models successfully account for linear dependency, as indicated by insignificant values of the *Q*-test.[5]

We then apply the HJ test to the residuals from the above VAR models. The results of the HJ test are reported in Table 4. In contrast to the results for its linear counterpart, the results for the nonlinear test indicate that there is causal relationship running from Liv-ex 500 index to GDP of the US, the UK, and Australia. Overall, our empirical test results indicate that wine price index can be very useful in predicting GDP in these countries and should be included as forecasting variables in corresponding forecasting models, especially nonlinear forecasting models. The economists may use the movements in Liv-ex 500 index as a predictor of future movements in GDP of these three countries. The fine wine investors are usually expertise in investments and predicting economic climate, they may foresee the coming grows (falls) in economic climate and subsequently increase (decrease) the bidding activities in fine wine auction.

[4] To save space, the complete estimation results for the VAR are not reported here but are available upon request.
[5] To save space, we do not report the complete set of estimation results for the VAR here, but it is available upon request.

Table 2
Johansen cointegration test results.

Variables	H_0	Eigenvalue	*p*-Value	Trace stats	*p*-Value
Australia — Live Ex 500	$r = 0$	5.260	(0.708)	5.276	(0.778)
	$r \le 1$	0.015	(0.901)	0.015	(0.901)
Canada — Live Ex 500	$r = 0$	7.043	(0.484)	7.051	(0.571)
	$r \le 1$	0.009	(0.924)	0.008	(0.924)
France — Live Ex 500	$r = 0$	4.889	(0.755)	4.898	(0.819)
	$r \le 1$	0.008	(0.927)	0.008	(0.927)
Germany — Live Ex 500	$r = 0$	5.260	(0.708)	5.276	(0.778)
	$r \le 1$	0.015	(0.901)	0.015	(0.901)
Italy — Live Ex 500	$r = 0$	5.406	(0.689)	5.409	(0.763)
	$r \le 1$	0.003	(0.953)	0.003	(0.953)
Japan — Live Ex 500	$r = 0$	3.826	(0.877)	4.230	(0.884)
	$r \le 1$	0.403	(0.525)	0.403	(0.525)
UK — Live Ex 500	$r = 0$	9.269	(0.264)	9.615	(0.311)
	$r \le 1$	0.347	(0.556)	0.346	(0.556)
US — Live Ex 500	$r = 0$	6.837	(0.508)	7.375	(0.534)
	$r \le 1$	0.538	(0.463)	0.538	(0.463)

Note: This table reports Johansen cointegration test λ_{trace} statistics and corresponding *p*-values. The test results are qualitatively the same when we use $\lambda_{\max}$ statistics. *r* denotes the number of cointegrating relations in the null hypothesis. *p*-Values are given in parentheses. The lag length selection in the Johansen cointegration test procedure is based on AIC.

5. Conclusion

This paper provides the first attempt to examine the ability of the price of fine wine to forecast the GDP of the major developed countries. ADF unit root test is first employed to test the stationarity of price levels and first difference of Liv-ex 500 Fine Wine Index and the series of GDP of 8 major developed countries, the results indicate that all of them are first order integrated, i.e. their first differences are stationary. Cointegration and causality tests are then performed on the levels rather than the first differences. The results from bivariate cointegration test suggest that no series of GDP of 8 major developed countries respond to deviations from the long-run equilibrium path traced between the Liv-ex 500 series. VAR model is thus constructed for these non-cointegrated series to test the causal relationship between the Liv-ex 500 and GDP of these 8 countries. By adopting VAR model, we do not find that the Liv-ex 500 Fine Wine index Granger cause the GDP growth in these countries. Since the linear Granger causality test has a low power for detecting nonlinear causal relationships, this study also uses a nonlinear Granger causality test. We find that the linear Granger causality test overlooks the causal relationships from the price of fine wine to the GDP of the US, the UK and Australia, but such relationships can be detected by the nonlinear Granger causality test. Overall, our empirical results show that the price of fine wine contains useful information for forecasting the GDP of the US, the UK, and Australia, suggesting that we may include it as a forecasting variable in GDP forecasting models, especially nonlinear models, for these three countries.

Table 3
Testing for linear Granger causality from Live-ex 500 to GDP of 8 major developed countries.

Null hypothesis: Live-ex 500 does not Granger cause GDP		
Variables	Wald statistics	LB(6)
Live-ex 500 → Australia	1.756 (0.190)	5.728 (0.454)
Live-ex 500 → Canada	0.105 (0.900)	3.730 (0.713)
Live-ex 500 → France	0.422 (0.659)	5.044 (0.538)
Live-ex 500 → Germany	0.558 (0.578)	4.934 (0.552)
Live-ex 500 → Italy	0.282 (0.755)	4.203 (0.649)
Live-ex 500 → Japan	2.716* (0.082)	1.619 (0.951)
Live-ex 500 → UK	0.283 (0.754)	0.933 (0.988)
Live-ex 500 → US	0.904 (0.415)	6.746 (0.345)

Note: This table reports the results for testing linear Granger causality from the Live-ex 500 index to GDP. LB(6) is the Ljung–Box *Q* statistic based on the residual series of dependent variables in Eq. (1), up to the 6th lag. *p*-Values are in parentheses. * indicates significance at the 10% level.

Table 4
Testing for nonlinear Granger causality from Live-ex 500 to GDP of 8 major developed countries.

Null hypothesis: Live-ex 500 does not Granger cause GDP				
Variables	Lx = Ly			
	1	2	3	4
Live-ex 500 → Australia	1.971 (0.024)**	2.137 (0.016)**	1.698 (0.045)**	1.306 (0.096)*
Live-ex 500 → Canada	0.915 (0.180)	1.591 (0.056)*	0.818 (0.207)	0.000 (0.500)
Live-ex 500 → France	0.607 (0.272)	−0.344 (0.366)	−0.855 (0.196)	−0.029 (0.488)
Live-ex 500 → Germany	−0.113 (0.455)	0.190 (0.425)	−0.442 (0.329)	0.399 (0.345)
Live-ex 500 → Italy	1.086 (0.139)	0.354 (0.362)	−0.989 (0.161)	0.414 (0.340)
Live-ex 500 → Japan	1.307 (0.096)*	1.482 (0.069)*	0.133 (0.447)	0.627 (0.265)
Live-ex 500 → UK	1.525 (0.064)*	1.977 (0.024)**	1.350 (0.088)*	1.136 (0.128)
Live-ex 500 → US	1.890 (0.029)**	1.369 (0.086)*	1.423 (0.077)*	1.200 (0.115)

Notes: This table reports the results for testing nonlinear Granger causality from the Live-ex 500 index to GDP. Each cell contains two numbers: numbers without parentheses are the standardized HJ test statistic, as in Eq. (8), and numbers in parentheses are the corresponding p-values. Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed as N(0, 1) and is a one-tailed test. A significant positive test statistic implies that lagged values of $\{Y_t\}$ nonlinear Granger cause $\{X_t\}$. ** and * denote significance at the 5% and 10% levels, respectively.

Economists may also consider adding it to a pool of economic variables when constructing a composite leading indicator of the economic activity of these three countries. Further research may be done on the causal relationship between GDP and other luxury commodity prices.

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