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Multivariate time series analysis of COVID-19 Pandemic and gold price by using Error Corrections Model

Nawzad Muhammed Ahmed, Aras Jalal Mhamad Karim*
Department of Statistics and Informatics/College of Administration and Economics/Sulaimani University

Abstract: Coronavirus (COVID-19) severe acute respiratory syndrome is an infectious disease that has a direct influence on the world's population, as is obvious from the prevalence of COVID-19. However, as the COVID-19 virus continues to proliferate, its impact is becoming more and more significant and extensive. Accordingly, the study's goal is to use the Error Corrections Model (ECM) to examine the relationships between the COVID-19 pandemic and gold prices. An Error Corrections Model was used by the researchers in this investigation. Error Correction Models and long-term equilibrium can be found for non-stationary time series that have been cointegrated together. Two-step estimation can be used to estimate the ECM since a proportion of the imbalance from one period is adjusted in the succeeding period, the system returns to equilibrium. The calculated cointegrating relations are used to create the error correction terms, and the estimation of VAR is done by a first differencing process, and then appears in the model as an explanatory variable, with the term of error correction. The COVID-19 pandemic and gold price data were made available to the general public in a sample data. For the year 2020, it includes data on daily observations for the relevant variables. R-language results show that the COVID-19 pandemic and gold prices have been demonstrated to have a long-term causal relationship. During the most recent period of variance decomposition, 99.76 percent of the variance in covid-19 explains only 0.24 percent of the variance in gold price. This explains that there is no short-term causal relationship between covid-19 and gold price, as indicated by the Wald test results, the granger causality results have shown that the gold price is influenced not only by itself but also by the Covid-19 pandemic. Finally, there is a positive relationship between the Covid-19 pandemic and the price of gold, and this has a negative impact on human life during 2020.

Keywords:
Multivariate time series, ECM model, VAR model, cointegration technique, IRF Analysis.

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*Corresponding author:
Aras Jalal Mhamad Karim
Department of Statistics and Informatics/College of Administration and Economics/Sulaimani University

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تحليل السلاسل الزمنية متعددة المتغيرات لجائحة كورونا -19وسعر الذهب باستخدام نموذج تصحيح الخطأ

نوزاد محمد احمد **ئاراس جلال محمد كريم**
قسم الاحصاء والمعلوماتية كلية الادارة والاقتصاد جامعة السليمانية

المستخلص

يُعَدُّ فايروس كورونا (COVID-19) المُسَبِّب لمرض الجهاز التنفسي الحاد الشديد مرضًا مُعديا يؤثر بشكلٍ مباشر على سُكَّان العالم، كما هو واضح من انتشاره... ومع استمرار انتشار فيروس COVID-19، يزداد تأثيره بشكلٍ متزايد ومتسع. وعليه، يهدف البحث إلى استخدام نموذج تصحيح الأخطاء (Error Correction Model-ECM) لفحص العلاقات بين جائحة COVID-19وأسعار الذهب. تم استخدام نموذج تصحيح الأخطاء (ECM) من قِبَل الباحثين في هذه الدراسة. تُستخدَمُ نماذج تصحيح الأخطاء للعثور على التوازن على المدى الطويل لسلاسل الزمنية الغير مُستقرة التي تم الكشف عنها بالتكامل معًا. يمكن استخدام التقدير المرحلي المكوَّن من خطوتين لتقدير نموذج ECM؛ حيث يتم تعديل جزء من تفاوت الفترة الاولى في الفترة التالية (الثانية)، مما يجعل النظام يعود إلى التوازن. تم استخدام العلاقات التكاملية المحسوبة لإنشاء مصطلحات تصحيح الأخطاء، وتم إجراء تقدير VAR لعملية الفرق الأول، وظهرت في النموذج كمتغير تفسيري مع مصطلح تصحيح الأخطاء. كانت بيانات جائحة COVID-19 وأسعار الذهب متاحة للجمهور العام في عينة البيانات. تضمنت للسنوات 2020 بيانات المراقبات اليومية للمتغيرات ذات الصلة. وقد تم إثبات وجود علاقة قائمة على المدى الطويل بين جائحة-COVID 19وأسعار الذهبك من خلال نتائج اللغة R. خلال فترة تحليل تباين البيانات الأكثر حداثة، أوضح 99.76 بالمائة من التباين في COVID-19 أن 0.24 بالمائة فقط من التباين في أسعار الذهب. يفسر هذا عدم وجود علاقة قائمة على المدى القصير بين COVID-19 وأسعار الذهب، كما أشارت نتائج اختبار غرانجر إلى أن أسعار الذهب تتأثر ليس فقط بنفسها ولكن أيضًا بجائحة COVID-19، وأخيرا هناك علاقة إيجابية بين جائحة كوفيد-19 وسعر الذهب وهذا له تأثير سلبي على حياة الإنسان خلال عام 2020.

الكلمات المفتاحية: متعدد متغيرات السلاسل الزمنية، نموذج ECM، نموذج VAR، تقنية التكامل المشترك، تحليل IRF

1. Introduction

This global economic and financial concern has been sparked by the spread of COVID-19 (Zeren & Hizarci, 2020: 78-84). The virus's global spread and the ensuing lockdowns have had a negative effect on overall demand, resulting in significant short-term volatility in food prices (Albulescu, 2020: 1-13). A 20 to 25 percent drop in economic output is expected as a result of the measures implemented to control the coronavirus, according to OECD estimates. Economic uncertainty and

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volatility are periods when investors turn to gold as a safety net. As a safe, liquid, and long-term store of value, gold is ideal for investors who want to achieve their primary goals of safety, liquidity, and return. As a result, gold's price may rise in the future (Grima et al., 2020: 1-31). Whether or not the global COVID-19 pandemic has an ideal influence on gold's price remains to be seen. And how will the COVID-19 pandemic impact the gold price going into the future? Because of that. The theoretical framework of the ECM is used in this study, so we ask three questions: (1) How can one investigate the relationship between the COVID-19 pandemic and gold price time series? (2) Do COVID-19 pandemic affect gold price? (3) How consistent and robust are the different regression approaches in assessing the impacts of questions (1) and (2)? In order to identify the causal effects of the COVID-19 pandemic on gold prices, the researchers set up an Error Corrections Model (ECM) to derive the relationship between the COVID-19 pandemic and gold prices. The study of co-integration has long attracted the attention of econometricians in particular. It is considered to be "cointegrated" when a stationary linear combination of the nonstationary series occurs. "The cointegrating equation" refers to an imbalance long-run relationship between the variables, where the imbalance is a stationary state defined by forces that tend to return a system to balance anytime it deviates from the equilibrium point. The error correction model is based on the assumption that a portion of the disequilibrium from a previous period gets corrected in the next. There are cointegration relations in ECM specification that constrain the long-term behavior of endogenous variables while still permitting short-term dynamic adjustment. Cointegration can be further generalized by applying the nonlinear Wang-Phillips in 2009 model in the case where X_t is stationary at 1^{st} difference and U_t is the stationary disturbance, which was first proposed by Box and Tiao in 1977 and more thoroughly examined by Engle and Granger in 1987. It incorporates a unit-root nonstationary regressor into the model of Linton et al. in 2008 (Lin et al., 2020: 175-191). The Granger causality test and the cointegration approach based on the vector error correction model (VECM) are used to analyze long and short-term correlations between distinct variables (Lahmiri S., 2017: 181-189). To evaluate data on dam monitoring (Li et al., 2013: 12-20) used the cointegration theory and the model of error correction, which depends on an error correction model suggested to reflect long-run balance and short-run imbalance relationships. Scheiblecker proposed a cumulative error correction model for time series dynamics between cointegration and multi-cointegration (Scheiblecker, M., 2013: 511-517). Apergis and Payne were working on the research about Energy consumption and economic growth in Central America: Evidence from a panel cointegration and error correction model (Apergis & Payne., 2009:211-216). GDP and electricity usage in Pakistan are linked by a number of different factors studied by (Jamil & Ahmad., 2010: 6016-6025) which found that there is a unidirectional causality from real economic activity to electricity consumption. So, the error correction model has been seen as a powerful statistical tool to investigate the relationship between variables, that can be used to analyze the relationship between the COVID-19 pandemic and gold price when the variables were stationary at the first difference I (1).

Since the COVID-19 pandemic began, scientists have begun moving away from theoretical models and toward practical studies. As a result, researchers working to construct a theoretical model that may account for the most recent evidence on the association between the COVID-19 pandemic and gold prices. therefore, the study contributions are: Using the most recent data, we'll examine the relationship between these two variables by modern modeling which is the Error Corrections Model (ECM). Secondly, constructing a multivariate time series model to assess the relationship between those two variables. Because the coronavirus affects the price of gold economically, and this situation has a direct impact on the lives of all humanity. Although, the objective of the study is to analyze the relationships between the COVID-19 pandemic and gold prices during 2020 by using the Error Corrections Model (ECM). In addition, the current study consists of four sections, the second section deals with a summary of the theory about ECM. The other section presents the data and results of econometric methodologies. The conclusions and further discussion of the study are examined in section four.

2. Materials and Methods

2-1. Vector AR(p) Model: The following steps can be used to develop a VAR model. As an initial step, can be used either the test of M(i) or the criterion of Akaike information to determine the order of the model. Next, we can estimate a model using the least squares method. Finally, we can

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use the Qk (m) residual statistics to determine whether a fitted model is adequate. Outliers, conditional heteroscedasticity, and other residual series features can also be examined (Lutkepohl, H., 1991:241-283; Tsay, R.S.,2001: 312-318).

The time series Z_t follows a VAR(p) model if it satisfies

$$Z_t = \phi_0 + \Phi_1 Z_{t-1} + \cdots + \Phi_p Z_{t-p} + a_t \qquad (2.1)$$

where ϕ_0 defined as a vector of k-dimensional, and a_t defined as a series of random vectors that don't depend on each other with zero mean and Σ matrix of covariance. The matrix of covariance must have a positive definite in order to lower the dimension of Z_t. Error terms a_t and Φ_j are multivariate normal k×k matrices. The model of VAR of order (p) can be expressed using the back-shift operator B:

$$(I - \Phi_1 B - \cdots - \Phi_p B^p) Z_t = \phi_0 + a_t \qquad (2.2)$$

where I refer to as the k×k identity matrix. The following is a concise version of the following

$$\Phi(B) Z_t = \phi_0 + a_t \qquad (2.3)$$

where $\Phi(B) = I - \Phi_1 B - \cdots - \Phi_p B^p$ is a matrix polynomial. If Z_t is weakly stationary, then we have:

$$\mu = E(Z_t) = (I - \Phi_1 - \cdots - \Phi_p)^{-1} \phi_0 = [\Phi(1)]^{-1} \phi_0 \qquad (2.4)$$

Because the determinant of $[\Phi(1)]$ differs from zero, there must exist an inverse. Let $\tilde{Z}_t = Z_{t-\mu}$. Then the model of VAR of order (p) is defined as:

$$\tilde{Z}_t = \Phi_1 \tilde{Z}_{t-1} + \cdots + \Phi_p \tilde{Z}_{t-p} + a_t \qquad (2.5)$$

Using equation (2.5) below results can be obtained:

- Cov(Z_t, a_t) = Σ, the covariance matrix of a_t;
- Cov(Z_{t-1}, a_t) = 0 for l > 0;

$$\Gamma_I = \Phi_1 \Gamma_{I-1} + \cdots + \Phi_p \Gamma_{I-p} \quad for\ I > 0 \qquad (2.6)$$

The expression (2.6) represents the moment equations of a model of VAR(p) which is the version of the multivariate of the Yule–Walker equation.

2-2. Cointegration Theory: Cointegration is a statistical property possessed by some time series data that is defined by the concepts of stationarity and the order of integration of the series. it describes the relationship between variables. More specifically, it utilizes cointegration as a form of estimation for describing long-run equilibrium between

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variables. Given that it can estimate the long-run equilibrium, it can also estimate short-run dynamics around the equilibrium to see how a 'pair' of cointegrated variables will revert back to their long-run relationship. Two or more stationary time series can be combined into one linear combination by Granger and Engle (Engle, Granger, 1987: 251-276). Time series that do not follow a stationary linear combination are considered to be cointegrated. "The cointegrating equation" refers to an imbalance long run relationship between the variables, where the imbalance is a stationary state defined by forces that tend to return a system to balance anytime it deviates from the equilibrium point. Definitions based on Engle and Engle (Engle, Granger, 1987: 251-276) are included below. An integration of (d) order is defined as a time series with a stationary, invertible, Auto Regressive Moving Average (ARMA) representation after (d) of the differencing process. For one stationary time series that doesn't have any deterministic elements, a finite ARMA process can be used to approximate the infinite moving average representation. The vector autoregressive (VAR) model framework has been widely applied to model cointegration system. In the modeling of cointegrated systems, the determination of the number of cointegrating relations, or the cointegration rank, is the most important decision. Cointegration is said to exist between two or more non-stationary time series if they possess the same order of integration and a linear combination (weighted average) of these series is stationary. For first differencing I(1) process of series, all of the theoretically infinite variance is derived from the series long-run section. As a result, an I(1) time series is smoother than an I(0) time series, with lengthy swings dominating. When Z_t is distributed as (d) differencing, next $\alpha + \beta Z_t$ is I(d), where α and β represent constants with the value of β differs from zero. It is obvious that a time series is nonintegrated if it cannot be transformed into a stationary time series by infinitely differencing.

2-3. Cointegration test

2-3-1. Engle and Granger: Cointegration tests for nonstationary time series can be performed using a variety of methods. Cointegration can be determined by examining the stationarity of the residuals of a regression model, according to Engle and Granger. In Engle and Ganger's technique, variables are constrained by a common element in their dynamic

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interaction. Regression equation models of the type used to test cointegration are the initial step (Engle, Granger, 1987: 251-276).

$$Z_t = b_1 Z_{1t} + b_2 Z_{2t} + b_3 Z_{3t} + \cdots + b_n Z_{nt} + \varepsilon_t \qquad (2.7)$$

where there is equal integration order of time series (Z_{1t}, Z_{2t},..., Z_{nt}), and the cointegrating vector ($\underline{b}_1$, $\underline{b}_2$, $\underline{b}_3$, …, $\underline{b}_n$) is unknown. The estimated residual values ε_t which are denoted e_t are acquired after the cointegrating vector has been computed from the data. The augmented Dickey–Fuller (ADF) test is used to determine whether ε_t is stationary or not as part of the cointegration test. Cointegration exists in the series if ε_t is stationary. If ε_t is not stationary, the series does not exhibit cointegration (Johansen, 1991: 1551-1580).

In the Engle-Granger analysis, let gold price (Yt) and case of covid-19 (Xt) be I(1) series which means that Yt and Xt are not stationary at the level, but the first difference of the series are stationary. The regression model using Yt and Xt series is as follows

$$Y_t = a_0 + a_1 X_t + u_t \qquad (2.8)$$

where a_0, $a_1 \in \mathbb{R}$ and u_t is error term. If u_t is I(0) or $\Delta\hat{u}_t = \rho_1 \hat{u}_{t-1} + \sum_{i=0}^{p} \zeta_i \Delta\hat{u}_{t-1} + z_t$ where $|\rho_1| < 1$ then Y_t and X_t are cointegrated.

If the series are cointegrated, there is at least one causal relationship between the series. In order for the series to be cointegrated, they must be stationary. The differencing process is applied to ensure stability. However, applying the differencing process causes a loss of long-run information. Therefore, these imbalances are tried to be eliminated by using the error correction model. If there is a long-run relationship between series, an error correction model, which is used to determine the short-run relationship, shows a deviation period from a long-run relationship. The following error correction model (ECM) is used to determine the possible causality relationship between the cointegrated series and to determine the direction.

$$\Delta Y_t = \theta_0 + \sum_{i=0}^{p} \theta_{1i} \Delta Y_{t-i} + \sum_{i=0}^{q} \theta_{2i} \Delta X_{t-i} + \theta_3 \hat{u}_{t-1} + \varepsilon_t \qquad (2.9)$$

Where θ_0 is a constant parameter, θ_3 is error correction parameter or adjustment parameter and $-1 < \theta_3 < 0$ and $\hat{u}_{t-1}$ is equilibrium error term or error correction term where $\hat{u}_{t-1} = Y_{t-1} - a_0 - a_1 X_{t-1}$. The special case of ECM is

$$\Delta Y_t = \theta_0 + \theta_1 \Delta Y_{t-1} + \theta_2 \Delta X_{t-1} + \theta_3 \hat{u}_{t-1} + \varepsilon_t \qquad (2.10)$$

ECM describes how Y and X behave in the short run consistent with a long run cointegrating relationship.

2-4-2. Johansen Cointegration model: The multivariate cointegration test of Johansen conforms to the following format (Johansen, 1991: 1551-1580):

$$\Delta Z_t = \mu + \prod Z_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta Z_{t-i} + \varepsilon_t \qquad (2.11)$$

where Z_t is a 2x1 vector made up of the variables Z_{t1} (gold price) and Z_{t2} (covid-19); μ denotes a 2x1 vector of constant terms; the Γ and Π denote a 2x2 matrix of coefficients; and εt denotes a 2x1 white noise error terms vector. The null hypothesis of no cointegration (rank(r) = 0) is tested against an alternative hypothesis of cointegration (r > 0) in this test, which is dependent on maximum likelihood estimation and trace statistics (λ_{trace}) (Johansen, 1991: 1551-1580).

The Johansen (1991) technique is adopted to test the long run relationship among variables, The long run relationship could be stated as follows:

$$\beta_1 Z_{t1} + \beta_2 Z_{t2} = 0 \qquad (2.12)$$

In a model with more than two variables there is possibility of the existence of more than one cointegrating vector. In our present model we have two variables, gold price, and covid-19 daily cases. These are represented in the following way

$$Z_{t1} = (Z_{t2})$$

In an unrestricted Vector autoregressive model (VAR) with K lags could be written as:

$$Z_t = \theta + \mu_1 Z_{t-1} + \mu_2 Z_{t-2} + \cdots + \mu_k Z_{t-k} + u_t \qquad (2.13)$$

where, $u_t$is the Gaussian error term, θ is the vector of constant term and $Z_t$is the vector of non–stationary variables. As $Z_t$is a vector of non-stationary variables, it could be reformulated with first difference in a vector error correction framework

$$\Delta Z_t = \theta + \Gamma_1 \Delta Z_{t-1} + \Gamma_2 \Delta Z_{t-2} + \cdots + \Gamma_{k-1} \Delta Z_{t-k-1} + \Pi Z_{t-k} + u_t$$
(2.14)

where

$$\Gamma_i = (I - \mu_1 - \mu_2 - \cdots - \mu_k);\ i = 1, 2, 3, \ldots, k-1$$

and

Doi: www.doi.org/10.25130/tjaes.19.64.1.36

$\Pi = -(I - \mu_1 - \mu_2 - \cdots - \mu_k)$

In our present model, Π is a 2x2 matrix containing information about the long run relationship among the vector of variables.

Johansen describe two separate procedures namely, trace statistics and maximal eigenvalue test to find out the number of cointegrating vectors. The maximal eigenvalue test is the likelihood ratio test for the null hypothesis, presence of r cointegrating vector against the alternative hypothesis r+1 cointegrating vector which can be stated as follows:

$$\lambda_{max}(r, r+1) = -T\, ln(1 - \hat{\lambda}_{r+1}) \qquad (2.15)$$

The second procedure is also based upon likelihood ratio test. Trace statistic verify the increasing tendency of trace as a result of the addition of more eigenvalues beyond the r^{th}. The null hypothesis based on λtrace verify the presence of cointegration vector is less than or equal to r against the alternative hypothesis, presence of more than r cointegrating vectors. It can be estimated as follows:

$$\lambda_{trace} = -T \sum_{i=r+1}^{m} \ln\left(1 - \hat{\lambda}_{r+1}\right) \qquad (2.16)$$

where $\hat{\lambda}_{r+1} \ldots \hat{\lambda}_m$ are $m - r$ smallest estimated eigenvalue. After the conformation of the existence of long run equilibrium relationship.

2-5. Error Correction Model: Error Correction Models can be used to depict nonstationary time series that are cointegrated. The disequilibrium of the previous period is expected to be redressed in the succeeding one. A key feature of the ECM is that it prevents endogenous variables from converging to their cointegration relations over the long term while still permitting short-term adjustment processes. To repair a long-term imbalance by correcting short-term imbalances, the cointegration term has been dubbed the "error correction term." According to the cointegration relation equation, when the y_t and x_t are in long-term equilibrium,

$$Y_t = \mathrm{b}_0 + \mathrm{b}_1 X_t + \varepsilon_t \qquad (2.17)$$

where ε_t defined as a disturbance term that is stationary. Change in one variable can be linked back to earlier equilibrium errors and to previous changes of both variables using a typical ECM, and the analogous ECM is:

$$\Delta Z_t = \mathrm{a}_1 \Delta X_t - \lambda Y_{t-1} + \varepsilon_t \qquad (2.18)$$

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while $Y_{t-1} = Z_{t-1} - (b_0 + b_1 X_{t-1})$ is equal to zero in long-term equilibrium, which is disequilibrium error correction term. The speed with which the error correction term is brought back into equilibrium is used to determine the value of the λ coefficient. Regarding a system with multiple variables, then, suppose that each time series $Z_t = (z_{1t}, z_{2t}, \ldots, z_{nt})'$ is stationary at first difference, so that There is no change in each of the time series' component vectors, indicating that the series is nondeterministic a completely stationary process. The backshift operator for a Finite Vector Autoregression (VAR) representation in terms of B is:

$$Z_t = \boldsymbol{c} + A(B)Z_{t-1} + \mathbf{a}X_t + \varepsilon_t \qquad (2.19)$$

where $A(B) = \sum_{i=1}^{p} A_i B^{i-1}$, $X_t = (x_{1t}, x_{2t}, \ldots, x_{dt})'$ is an exogenous vector of variables, and $c = (c_1, c_2, \_\_\_\_, c_n)'$ is a vector of constant. $\mathbf{a} = (a_1, a_2, \ldots, a_d)'$ is a cointegrating vectors matrix, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{nt})'$ is a multivariate disturbance stationary. Further, formula (2.19) can be defined as follows:

$$\Delta Z_t = \Theta Z_{t-1} + A^*(B)\Delta Z_{t-1} + \mathbf{a}X_t + \varepsilon_t \qquad (2.20)$$

where $\Theta = A(1) - I$, $A^*(B) = \sum_{i=1}^{p-1} A_{i*} B^{i-1}$, $A_{i*} = -\sum_{j=i+1}^{p} A_j$.

The error in each equation is represented as a stationary random variable in an error correction model. ECM expresses Equation (22) as follows:

$$\Delta Z_t = A^*(B)\Delta Z_{t-1} - \lambda Y_{t-1} + a\Delta X_t + \varepsilon_t \qquad (2.21)$$

A vector autoregression-like error correction representation Eq. (2.21) is closer in appearance to Eq. (2.19). It is implied that the variables are cointegrated by the existence of their respective levels. If the variables are cointegrated, incorrectly defining a VAR in differences, and a VAR with levels will forget important restrictions. The dependent variable's response to the independent variables' shocks is used to formulate the error-correcting behaviors (Scheiblecker, M., 2013: 511-517).

2-6. Error Correction Model Estimation: Estimating the error correction model can be done using a two-step estimator (Johansen, 1991: 1551-1580), an easy operation. Initially least squares regression procedure is used to estimate the cointegrating vector's parameters on each variable level. The non-cointegration hypothesis is investigated. Long-term relationships can be estimated using cointegrating vector parameter estimations. In the second stage, the regressors show a lagged value of the cointegrating regression's residuals, and this is taken into account in the dynamic specification. Using the calculated cointegrating relations, error correction terms are generated, and a VAR is estimated using the error correction terms as regressors. For both phases, just a single equation least squares approach is necessary because all parameters are consistent. An advantage of an estimator is that it does not necessitate specifying the dynamics until the error correction structure is computed (Johansen, 1991: 1551-1580).

2-7. Impulse Response Functions of Structural Analysis: The dependent variables' responsiveness of vector autoregressive models to shocks can be traced using impulse responses. A one standard deviation positive shock helps to determine the behavior of the variable when the error terms are given a positive shock, as well as how the variables react to each other. It is possible that the original variable can feed back into itself if a shock is delivered to one of the series. Researchers can use the impulse response function method to see how one parameter changes in reaction to a rapid shift in another parameter's expected behavior in the future. This might be referred to as a shock, innovation, or unexpected shift in a variable (Engle, Granger, 1987: 251-276). It's usually referred to as an impulse, which reflects the idea of a one-time shock that takes place at some point along the timeline (Inoue, A., Killian, L., 2013: 1-13).

The general formulation of the VAR(p) model is depicted by the equation (2.22), and the Wald representation of the VAR(p) model is as follows:

$$X_t = \mu + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_s a_{t-s} \qquad (2.22)$$

Where θ_s defined as nxn matrices of moving average. To (i,j)th element interpretation, θ_{ij}^{s} defines the matrix θ_s element as the impulse response:

$$\frac{\partial x_{i,t+s}}{\partial a_{j,t}} = \frac{\partial x_{i,t}}{\partial a_{j,t-s}} = \theta_{ij}^{s}\,, \qquad i,j = 1,2,\ldots\ldots,n \qquad (2.23)$$

var(at)= Σ is a diagonal matrix, which is required for equation (2.22). It indicates that a_t and Σ are uncorrelated if Σ is diagonal. Estimating a triangular structural VAR(p) model is one technique to separate the errors from each other.

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$$\left.\begin{array}{c} X_{1t} = c_1 + \alpha_{11}X_{t-1} + \cdots + \alpha_{1p}X_{t-p} + \eta_{1t} \\ X_{2t} = c_1 + \beta_{21}X_{1t} + \alpha_{21}X_{t-1} + \cdots + \alpha_{2p}X_{t-p} + \eta_{2t} \\ \cdots \\ X_{nt} = c_1 + \beta_{n1}X_{1t} + \cdots + \beta_{n,n-1}X_{n-1,t} + \alpha_{n1}X_{t-1} + \cdots + \alpha_{np}X_{t-p} + \eta_{nt} \end{array}\right\}$$

. (2.24)

The error vector η_t's covariance matrix has been estimated to be a diagonal matrix. Structural errors refer to the non-correlated errors η_t (Engle, Granger, 1987: 251-276). According to orthogonal errors η_t, the Wold representation of X_t can be calculated as follows:

$$X_t = \mu + \Theta_0\eta_t + \Theta_1\eta_{t-1} + \Theta_2\eta_{t-2} + \cdots + \Theta_s\eta_{t-s} \qquad (2.25)$$

Where $\Theta_0 = B^{-1}$ (As can be seen from the equation (2.23), B is the lower triangular matrix of Bi, j. and 1 is the number of B's diagonal elements). Orthogonal shocks' impulse responses η_{jt} are $\frac{\partial x_{i,t+s}}{\partial a_{j,t}} = \frac{\partial x_{i,t}}{\partial a_{j,t-s}} = \theta_{ij}^s$, where θ_{ij}^s define as (i,j)th element of Θ_s. The relationship between θ_{ij}^s's plot and s is known as the orthogonal impulse response function of X_i with regard to η_j (Inoue, A., Killian, L., 2013: 1-13).

2-8. Forecasting: If the fitted model is sufficient, it can be utilized to provide forecasts. The same principles used in univariate analysis can be applied to forecasting. The following steps can be taken to generate forecasts and standard deviations of the corresponding forecast errors. The 1-step ahead forecast at time origin h for a VAR(p) model is $X_h(1) = \phi_0 + \sum_{i=1}^{p} \Phi_i X_{h+1-i}$, and the corresponding forecast error is $e_h = a_{h+1}$. Σ represents the covariance matrix of the forecast error. If X_t is weakly stationary, then as the forecast horizon rises, the 1-step ahead forecast $X_h(1)$ converges to its mean vector μ. If X_t is poorly stationary, then the 1-step ahead forecast $X_h(1)$ converges to its mean vector μ as the forecast horizon increases (Aziz, et al., 2023: 531-543; Tsay, & R.S., 2001: 312-318).

3. Results

3-1. Data Description: In this study, we employ daily observations of the COVID-19 pandemic, for which only case-containing records are included in the statistical modeling method and which are seasonality adjusted. These observations are acquired from the WHO website (covid19.who.int) and an additional variable, gold price, which is also seasonally adjusted and retrieved from the International Energy Agency website (www.gold.org).

Tikrit Journal of Administrative and Economic Sciences, Vol. 19, No. 64, Part (1): 674-693
Doi: www.doi.org/10.25130/tjaes.19.64.1.36

The sample duration is eleven months, beginning in February 2020 and ending in December 2020. Figure 1 depicts the plots of the original time series of two series of the sample study.

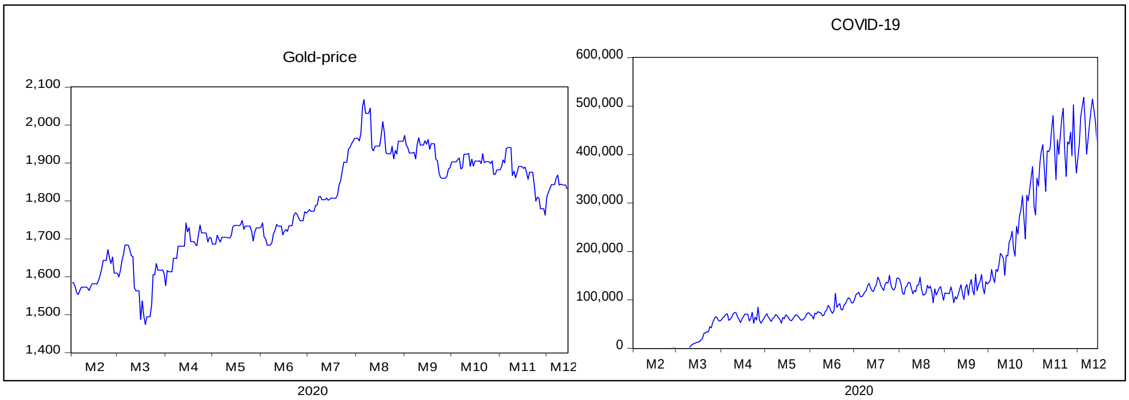


Figure (1): Time Series Plots of the Variables (R-Studio v.4.5.1)

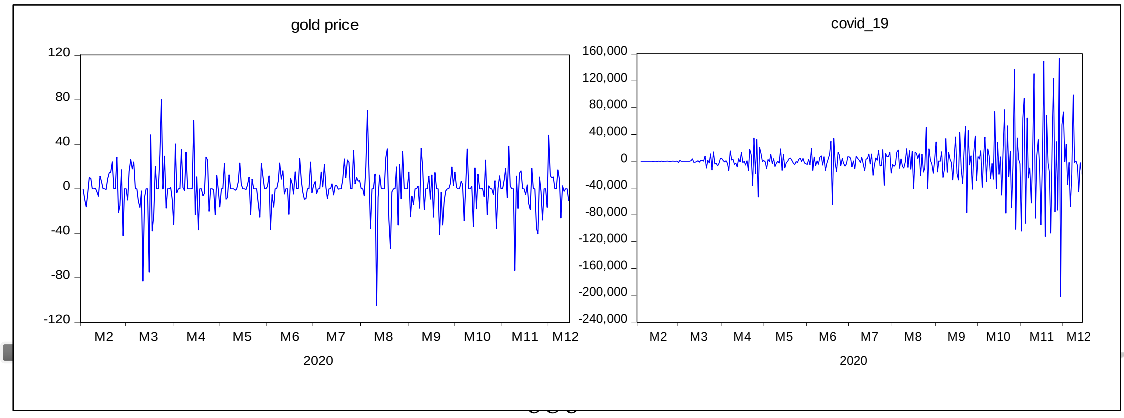
In order to construct a suitable model, all series included in the study must have been stationary; consequently, the researchers must examine the structure of unit-root of the data. Even though the following graph offers us a general sense of the stationarity structure of the series, to test for unit roots, we applied the Augmented Dickey-Fuller test to the series. Table 1 displays the results of the ADF test applied to the levels and the first differences of the series.

Table (1): Unit root results of lag variables

Variables	Lags	Test Value	p- value
COVID-19	Level	-0.3052	0.9211
	First	-18.2053	0.000
Gold price	Level	-1.6918	0.4345
	First	-19.1885	0.000

Source: Prepared by researchers based on the statistical program.

The ADF test findings show that all variables are not stationary through not rejecting the hypothesis of unit-root at all levels, they were all found to be stationary after first differencing. Figure 2 shows the differenced series in time series plots.



Doi: www.doi.org/10.25130/tjaes.19.64.1.36

Figure (2): Plot of series of the differenced variables (R-Studio v.4.5.1)

3-2. Lag order selection: In accordance with Lutkepohl (Lutkepohl, H., 1991: 241-283), using a higher order lag length than the actual lag lengths increase the mean square forecast errors of the VAR, whilst selecting a smaller order lag length than the actual lag lengths often result in autocorrelated errors. Therefore, the precision of forecasts given by VAR models is highly dependent on the choice of actual lag lengths. Using penalty selection techniques such as the log likelihood (LogL), sequential modified LR, Final prediction error (FPE), Akaike Information Criterion (AIC), Schwarz information (SC), and the Hannan-Quinn (HQ), we found a VAR(p) and ECM model for the analysis (HQ). Table 2 illustrates the results of the selection criterion.

Table (2): Order selection criteria of model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6391.04	NA	2.05E+14	38.62865	38.65163	38.63782
1	-5550	1666.848	1.30E+12	33.57097	33.63989*	33.59846
2	-5538.48	22.68820*	1.24e+12*	33.52554*	33.64041	33.57136*
3	-5537.36	2.184211	1.27E+12	33.54297	33.70378	33.60711
4	-5537.17	0.377737	1.30E+12	33.56597	33.77273	33.64843

Source: Prepared by researchers based on the statistical program.

The table 2 provides for the selection of an acceptable lag for the model, the above table reveals that majority of lag selection criteria identified the optimum lag to be 2. Although AIC, FPE, HQ and LR indicating the optimum lag to be consider as 2, the SC criteria suggest lag 1 as the optimum. Based on the majority view we have selected lag 2 for further analysis, this indicates that the best model for our data is order 2.

3-3. Co-integration test: The next stage, following the selection of the ideal lag duration, is to determine the existence of a long-term relation among variables. To test for co-integration, the co-integration test developed by Johansen (1998) is used to identify the long-term relationship among the variables. Table 3 displays the outcomes of the Johansen multivariate co-integration test for both equation systems.

Table (3): Test of Johansen's maximum likelihood for relationships of multiple co-integrating

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 0.05	Prob	Max-Eigen Statistic	Critical Value 0.05	Prob
None *	0.057994	19.92448	15.49471	0.01	19.8349	14.2646	0.0059
At most 1 *	0.00027	0.089573	3.841465	0.7647	0.089573	3.841465	0.7647

Source: Prepared by researchers based on the statistical program.

Table 3 illustrates that the trace value (19.92) exceeds the critical Value (15.495), which allows us to reject the hypothesis which means there is no cointegration among variables at the level of significance 5%. However, the trace value (0.0896) is less than the critical Value (3.841) at the level of significance 5% for testing at most one cointegration, and the maximum eigen test indicates that we should reject the null which means there is no at least one cointegration vector. The value of the maximum eigen test is (19.83), which is more than the critical values (14.26), hence the null hypothesis can be rejected, While, the value of the maximum eigen test is (0.0896) for testing at most one cointegration, which is less than the critical Value (3.841) at the level of significance 5%. Thus, there is only one cointegration among variables, and the co-integration regression vector for the gold price is equal to:

GOLD_PRICE = 0.995151 + 0.000791*covid-19
S.E. (4.45159) (0.00022)
t-stat [0.22355] [3.57438]

In addition, to confirm the cointegration of variables, the distribution of the residuals must be stationarity, which is shown in table (4)

Table (4): Results of residual unit root

Variable	Level of Sig.	Test Value	p- value
Residual		-4.93941	0.000
	1% level	-3.4498	
	5% level	-2.87	
	10% level	-2.57135	

Source: Prepared by researchers based on the statistical program.

Table 4 presents the findings of the ADF test, which demonstrate that residual is stationary through rejecting the hypothesis of unit-root at levels, i.e., there is additional evidence of cointegration between the variables under investigation.

3-4. Estimation of ECM model: After identifying an order Lag and cointegration test, we proceed to model estimate. The model estimation findings are presented in the table below.

Table (5): Estimation parameters for Error Correction Model (ECM)

Coefficients	Coefficient	Std.Error	t-test	Sig.
$\hat{e}_{t-1}$	-0.176328	0.039502	-4.46372	0.000
Δ GOLD_PRICE (-1)	-0.292221	0.058636	-4.98365	0.000
Δ GOLD_PRICE (-2)	-0.080997	0.054976	-1.47332	0.1416
Δ COVID_19(-1)	0.000212	0.000328	0.646341	0.5185
Δ COVID_19(-2)	-0.00001761	0.000328	-0.05368	0.9572
Constant	0.995151	4.451595	0.223549	0.8232
Akaike info criterion	11.62712			
Schwarz criterion	11.69588			
Hannan-Quinn criter.	11.65454			
Durbin-Watson stat	1.996483			
F-statistic	15.77856 [0.000]			

Source: Prepared by researchers based on the statistical program.

In terms of t-value, the parameter of lagged residual is negative and statistically significant, indicating a long-run causal relationship between covid-19 and gold price. This coefficient suggests that daily changes in the COVID-19 variable may correct 17.6% of the imbalance in the gold price, which is another proof that the variables are co-integrated and that the model is accurate:

$$\begin{aligned}\Delta(Gold\ Price) &= -0.17633(Gold(-1) - 0.00079\ COVID(-1) \\ &- 1644.24) - 0.2922\Delta(Gold(-1)) \\ &- 0.08099\Delta(Gold(-2)) \\ &+ 0.000212\Delta\big(\mathrm{COVID}(-1)\big) - 0.000018\Delta\big(\mathrm{COVID}(-2)\big) \\ &+ 0.9952\end{aligned}$$

We can use the Wald test to check short-run causality which follows chi-square distribution and the results the flowing below:

Table (6): wald test result

Test Statistic	Value	df	Sig.
Chi-square	0.421401	2	0.81

Source: Prepared by researchers based on the statistical program.

Tikrit Journal of Administrative and Economic Sciences, Vol. 19, No. 64, Part (1): 674-693
Doi: www.doi.org/10.25130/tjaes.19.64.1.36

From Table 6, it is clear that the test is non-significant and cannot reject the null hypothesis which states that the coefficients of (Δ COVID_19) are equal, meaning that there is no short-term causality running from COVID-19 to gold price.

3-5. Diagnostic checks for residuals: After estimating a suitable model for the variables, this phase of the study focuses on diagnostic checking. There are numerous approaches for controlling the robustness of the model; for diagnostic checks, we have employed statistical tests for the residuals. Table 7 shows the outcomes of the serial correlation and heteroskedasticity tests on the residuals.

Table (7): residuals diagnostic checks

Tests	Statistic test	Sig.
Serial Correlation	3.2937	0.1926
Heteroskedasticity	1.4391	0.9634

Source: Prepared by researchers based on the statistical program.

The heteroskedasticity test results in Table 7 indicate that the application of the model for the series is homoskedasticity, and we can argue that the gold price model could have been a good model because that reduces serial correlation.

3-6. Impulse Response Function Results: Impulse response functions (IRFs) illustrate how a system responds to exogenous shocks (Inoue, & Kilian, 2013: 1-13). Figures 3 depict the estimated COVID-19 and gold price response functions, respectively. the lines represent point estimates of the IRFs.

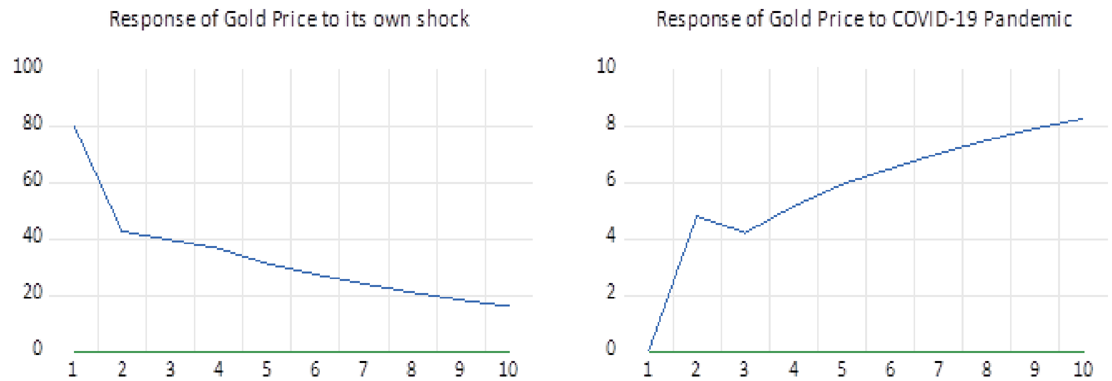


Figure (3): Impulse Response Function (R-Studio v.4.5.1)

From Figure 3, it can be inferred that when one standard deviation shock is applied to the gold price, the response of the gold price to its own shock is

Doi: www.doi.org/10.25130/tjaes.19.64.1.36

a dramatic decline from period one to period two, followed by near-uniformity from period three to the end. Although the response of gold price to a one-standard-deviation shock to covid-19 instances is a significant, moderate increase, it remains the same from period two to the conclusion.

3-7. Results of Variance Decomposition: The variance decomposition reveals the forecast error variance. In the short term, for example over two periods, the impulse or shock to gold price accounts for 99.72 percent of the variation in the gold price in the variance decomposition of gold price (own shock), but only 0.11 percent in the variance decomposition of covid-19 (shock of another variable). Table 8 (b) demonstrates that 99.86 percent of the variance in covid-19 explains 0.14 percent of the variance in the gold price during the fifth period. 0.24 percent of the volatility in gold price during the tenth lag period is explained by 99.76 percent of the variance in COVID-19, This explains that there is an insignificant short-term causal relationship between COVID-19 and gold price, as indicated by the Wald test results.

Table (8): variance decomposition analysis

Variance Decomposition of GOLD Price			
Period	**S.E.**	**GOLD Price**	**COVID-19**
1	80.29173	100.000	0.00000
2	90.98387	99.72207	0.277926
3	99.27009	99.58677	0.413232
4	105.8706	99.40007	0.599931
5	110.4844	99.16165	0.83835
6	113.989	98.88883	1.111165
7	116.6793	98.57712	1.422882
8	118.7665	98.2287	1.771296
9	120.4163	97.84629	2.153706
10	121.7425	97.4323	2.567704
Variance Decomposition of COVID-19			
Period	**S.E.**	**GOLD Price**	**COVID-19**
1	13655.49	0.093877	99.90612
2	19305.11	0.112546	99.88745
3	23634.38	0.103083	99.89692
4	27298.96	0.118509	99.88149
5	30531.88	0.136534	99.86347
6	33459.44	0.155795	99.84421
7	36155.43	0.17619	99.82381

8	38667.72	0.196739	99.80326
9	41029.73	0.217091	99.78291
10	43265.73	0.237013	99.76299

Source: Prepared by researchers based on the statistical program.

Finally, Granger causality is employed to examine two tests. The first is to examine the null hypothesis that the COVID-19 pandemic does not Granger Cause gold prices. The second experiment tests the hypothesis that the gold price does not Cause the COVID-19 pandemic.

Table (9): Granger Causality Test

Test	Group	F-Statistic	Prob.
Test 1	Group 1 variable: COVID-19	5.21707	0.0059
	Group 2 variable: GOLD Price		
Test 2	Group 1 variable: GOLD Price	0.01961	0.9806
	Group 2 variable: COVID-19		

Source: Prepared by researchers based on the statistical program.

Depending on the outcomes of the Granger causality tests, Table (8) reveals that Test 1, F-test is equal to 5.22 with a P-value equal to 0.0059; therefore, the null hypothesis can be rejected, and we conclude that the gold price is influenced not only by itself but also by the Covid-19 pandemic. Although. For Test 2, the F-test is 0.0196 with a p-value equal to 0.980; therefore, the null hypothesis cannot be rejected, and we infer that the Covid-19 pandemic is exclusively influenced by itself and not by gold price.

4. Discussions: The global economy and finances in the world are faced the effect of coronavirus especially during 2020, whereas, the result of this virus's proliferation, the impact of the virus on human existence is growing increasingly widespread.

As a result, investors may continue to seek sanctuary in gold for a considerable amount of time if the COVID-19 pandemic causes a global recession. Consequently, the goal of this study is to use the Error Correction Model (ECM) to assess and examine the relation between the COVID-19 pandemic and the gold price, Error correction models can be used to depict long-run equilibrium of cointegrated nonstationary time series. This sample analysis utilized the daily number of COVID-19 pandemic cases and the daily gold price in the world. The results indicate that COVID-19 and gold prices are cointegrated over the long term. Despite this, the residual lagged coefficient in the model is negative and

Doi: www.doi.org/10.25130/tjaes.19.64.1.36

statistically significant, indicating that COVID-19 is causally related to gold prices in the long run. This coefficient suggests that 17.6 percent of the imbalance in the gold price will be adjusted daily by changes in the COVID-19 variable. In addition, it is possible to conclude that when one standard deviation shock is applied to the gold price, the response to its own shock (by the gold price) is a decline in gold price over time. Although a one-standard-deviation shock to covid-19 cases results in a large increase in gold price, this trend continues from period two until the end. In the fifth period, 99.86 percent of the volatility in covid-19 explains 0.14 percent of the variance in the gold price, therefore, we argued that there is no causal relationship between covid-19 and gold price in the short term, as indicated by the Wald test results in table (6). Finally, the Granger causality results show that the gold price is influenced not only by itself but also by the Covid-19 pandemic. Future studies will be able to employ a variety of factors in many fields and uncover their integration. Incorporating tourism demand and industry variables in modeling is another approach that might be examined.

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