The Causality Relationship Between Financial Constructs with State Space Model

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Abstract. One solution of the state-space model is to see the causal relationship between one and more variables. This model can be used as a statistical basis for modeling movements, for example, carbon variables and other variables that may be related in the form of financial construction. Research looking for this relationship is fascinating to study further. The results show that state space can provide in-depth information about the relationship between constructs. The findings of this study imply that financial construction does not stand alone as a commodity but is also influenced by the sectors above it.

Keywords: State-space · Financial · Causality

1 Introduction

In the area of economics, financial data is data used in making decisions that have an impact on the sustainability of an issuer. Financial data that is widely distributed has a time series type. Autoregressive problems in time series data have been proven. Moreover, dynamic relationships in time series data are observed to understand whether a construct in the form of data is determined by other variables in the same time range. Based on these reasons, the research follows whether the state-space model can be used as a model that shows a causal relationship between financial data is interesting to do. Furthermore, the dynamic and interplay of volatility between the data provide insight into how the times series' financial data works.

2 Literature Review

A. *State-space*

Kalman around 1960 [1], first introduced the State-space model. It is an approach to collectively model and forecast related time series data where these variables have dynamic interactions [2]. State-space models use additional variables (state vectors) to describe the time series of multivariate data. According to [3], the state vector contains a

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summary of all the information of the previous and current values of the time series relevant to forecasting future values. The state-space model represents a stochastic process in a stationary z_t. This model is defined as the state transition equation:

$$zt + 1 = Fzt + Get + 1$$
$$t = 1, 2, \ldots T \tag{1}$$

And the output equation:

$$xt = Hzt \; or \; xt = [Ir, 0]zt \tag{2}$$

B. *Information Criteria (IC)*

Information criteria are used as a reference in selecting the best model. The best model selection criteria used in the state space model is Akaike's Information Criterion (AIC). The best model is the model that has the smallest AIC value [4]. AIC for the VAR model uses the maximum loglikelihood approach as follows

$$Ln(L) - n\ 2\ ln\ ln\ (|\hat{p}\ :|) \tag{3}$$

-order model can be calculated by the equation:

$$AICp = n\ ln\ ln\ |\widehat{pp}| + pr2 \tag{4}$$

C. *Canonical Correlation*

Analysis Canonical correlation analysis is used to simultaneously identify and quantify the relationship between two groups of variables. Variables that are not real are excluded from the state vector. The state vector is uniquely determined through canonical correlation analysis between a set of values for the current and past observations (xn, $xn - 1$,, xnp) and a set of observed values for the current and future events (xn,$xn + 1|n$,, $xn + p|n$) where Pn is a vector of the importance of the present and past events relevant to predicting $xn + 1$ and predictor space ff_n = 〚(x〛 _n, x_(n + 1 |n), x_(n + p|n)) where fn is a vector of the current and future events [5].

In canonical correlation analysis, the submatrix is determined from the covariance matrix based on the Hankel Block:

$$\Gamma = [(0)\ (1)\ (2)\ \Gamma\ (p)\ (1)\ (2)\ (3)\ (p + 1)\ (p)\ (p + 1)\ (p + 2) \vdots (2p)]$$

The choice of p-value refers to the VAR model with the smallest AIC value. The canonical correlation analysis refers to the Hankel Block of the sample covariance matrix, namely;

$$\hat{\Gamma} = [\hat{\Gamma}(0)\ \hat{\Gamma}(1)\ \hat{\Gamma}(2)\ \hat{\Gamma}(p)\hat{\Gamma}(1)\ \hat{\Gamma}(2)\ \hat{\Gamma}(3)\ \hat{\Gamma}(p + 1)$$
$$\hat{\Gamma}(p)\ \hat{\Gamma}(p + 1)\ \hat{\Gamma}(p + 2)\ \hat{\Gamma}(2p)]$$

The canonical correlation analysis forms a series of state vectors, $zn\ j$. Examine a series $fn\ j$ of subvectors fn and form a submatrix $\Gamma\ j$ consisting of rows and columns of Γ corresponding components $fn\ j$, and their canonical correlation values can be calculated. The most minor canonical correlation of $\Gamma\ j$ will be used to select state vector components.

Table 1. Series of Research Methods

	Activities	**Outcomes**	**Success Indicators**
1	Collection Data	Daily Data on Carbon and Gas. Carbon and Gas Daily plot graph.	Complete data in the research period. The data is visually seen in terms of reasonable volatility.
2	Descriptive Statistics & Stationarity Descriptive	Statistics Initial level correlation test Stationarity & Differing	Descriptive Statistics Stationary Data can be continued with the differentiation process.
3	Differencing Data	Data After Differencing	Data and Table after Differencing
4	AIC Criteria	Table *Schematic Representation of Partial Autocorrelation s*	Data *Schematic Representation of Partial Autocorrelation s*
5	Determinatio n *of StateVector*	Table *Canonical Correlations Analysis* Table *Selected State-space Form and* Table *Preliminary Estimates*	*Canonical Correlations Analysis* *Selected State- space Form and* *Preliminary Estimates*
6	State Space Model	Results *IterativeFitting: Maximum Likelihood Estimation*	Table *Iterative Fitting: Maximum Likelihood Estimation.*
7	Selected State Space	Table *Model* Forecasting Table	Form and Fitted Model Forecasting

3 Methodology

Each step in the research process has determined outcomes and indicators of achievement. Table 1 shows the outputs and achievement indicators in detail:

4 Results and Discussion

We perform steps or valid methods to fulfill the procedures in this research. We will test the correlation between variables. In economic research, such a step is to ensure that the variables are related early. The results of the correlation test, taking into account the value of Pearson Correlation are presented in more detail:

Table 2a and b shows that the variables in the study, namely gas and carbon prices (Table 2a) as well as gold and the exchange rate (Table 2b), have a positive and nearperfect relationship by looking at the Pearson correlation coefficient value of 1.0000. In research using state-space models, the classical problem of non-stationary time series data is one that also comes early and is essential to solve. Several considerations can be selected

Table 2a and b. Test Correlation Pearson.

Correlation Coefficient Correlation Test, N = 90 Prob > |r| under H0: Rho = 0		
	GP	**CO_2**
GP	1.0000	0.31241 0.0027
CO_2	0.31241 0.0027	1.0000
Pearson Correlation Coefficients, N = 298 Prob > |r| under H0: Rho = 0		
	ANTM	IDR
ANTM	1.0000	0.23956 <.0001
IDR	0.23956 <.0001	1.0000

and then used to ensure the data is stationary, for example, the ADF test and visuals from the ACF graph (Table 3).

Differencing the impact on the stationary gold price and exchange rate data by looking at the value of Pr < Rho and Pr < Tau significant 0.0001. Further consideration of the very important stationary, we can confirm this by looking at the ACF graph as follows:

Figure 1 shows that the data rapidly drops in df. This provides additional information that confirms the data is stationary and ready to be processed at the next stage. A further series of steps will consider canonical correlation's value. The canonical correlation is used in determining the state vector, while at the same time it also has the aim of investigating the relationship between two variables or multivariate vectors in an average

Table 3. Dickey-Fuller Unit Root Tests

Typ e	**La gs**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	0	-284.773	0.0001	-16.53	<.0001		
Single Mean	0	-285.124	0.0001	-16.53	<.0001	136.58	0.0010
Trend	0	-285.271	0.0001	-16.51	<.0001	136.25 0.0010	Table

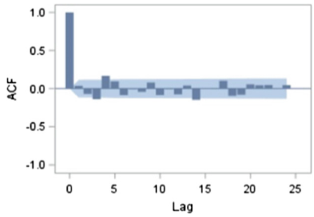

Fig. 1. ACF graph

Table 4. Canonical Correlations Analysis.

antm(T;T)	idr(T ;T)	idr(T + 1;T)	idr(T + 2;T)	Information Criterion	Chi Square	D F
1	1	0.7194 08	0.3730 41	6.35457 2	42.93 103	1 9

Table 5. Canonical Correlations Analysis

Price(T; T)	CO2CO2(T ;T)	(Criteria(T + 1;T)	inform ation	Chi- square	D F
1	1	0.4032 26	3.79242	15.260 09	6

or the same data set size. IC reference values in negative conditions will be removed from the state vector, while positive ICs are included (Table 4).

Based on the significance test using chi-square (X2) gets X2hit = 42.93103 > X(0.05(19))^2 = 30.14. This means that the canonical correlation is significant so that the component can be included in the state vector. From the significance test of canonical correlation analysis, the real components are xt, yt, yt + 1|t these components become the final state vector components, as follows:

$$zt = \left[xt\ yt\ yt + 1\ |t\ yt + 2|t\right]$$

Meanwhile, the carbon data which is suspected to have a relationship with the main structure, namely gas, is proven not to be valid. Furthermore, the insignificant relationship is shown in Table 5.

5 Conclusion

Causality relationships have many advantages in investigating financial research. Understanding the factors that influence an economic variable is an attempt to ensure that other factors can influence its movement. The state space model proves its ability in this manuscript, although it is possible that the state space model also has limitations that affect the results of the study. On carbon and gas data, the state space model does not work perfectly because the vector is removed from the primary model, while for the daily gold price data associated with foreign exchange, the state space model shows the desired capability.

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