Journal Title
XX(X):1–5

DOI: 10.1177/ToBeAssigned
www.sagepub.com/
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Stock Price and Job Growth: A Causal Inference Study

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Abstract

Stock prices and job growth are believed to be negatively correlated. However, stock prices are a leading indicator, whereas job growth is a lagging indicator. With the economy being ever-changing, standard statistical tools fall short to accurately predict one from the other and establish the direction of information flow. Both of these problems can be solved by conducting a causal inference study. The paper makes use of the Granger-causality and transfer entropy to establish cause-and-effect relationships between stock price and job growth. The Transfer Entropy test was used for all combinations of Y and X on the dataset, both intra-country as well as inter-country. Interpolation was also done on the individual datasets. Various techniques such as MinMaxScaler, Standard Scaler, log of values, along with vanilla TE techniques were used to obtain robust results.

Keywords

Causal Inference, Transfer Entropy, Granger-causality, entropy, Stock market, Job market, correlation, causation

Introduction

It goes without saying that there exists a stock market - unemployment correlation. Unemployment in the economy leads to negative sentiment in the stock market, which in turn leads to overall reduced stock prices. Similarly, when the unemployment rate drops, people invest more, the market sentiment improves and the stock prices rise. There is plenty of empirical backing to this claim, as seen in the dot-com bubble burst, the global financial crisis of 2007-08, and the Harshad Mehta scam of 1992 in India. It is evident that the job market and the stock market are closely correlated, and the condition of today's job market could play a crucial role in determining tomorrow's stock market.

However, the correlation might not always be visible in the economy. This is because the stock prices are a leading indicator of the economy, while unemployment is a lagging indicator. This implies that while changes in sentiment, improvements in economy, or introduction of new policies reflect immediately in the stock prices, unemployment rates will typically not respond immediately, but in the long term, as conditions improve.

Thus, a stronger relationship between stock prices and job growth is required. Literature shows that several countries demonstrate a correlation between stock prices of the country and job growth. The literature has, however, neglected transfer entropy as an important tool to find the direction of information flow. Moreover, the literature has not investigated causal relationships between the stock markets and economic growth of different countries. Thus, in this paper we approach the problem through a causal inference study over several countries. To the best of our knowledge, such a study has not been conducted before.

There might exist a bi-directional cause-and-effect relationship between job growth and stock prices. Causal inference is a statistical tool for inferring causal effects based on the conditions of the occurrence of the effect. Causal inference based analysis differs from typical statistical based analysis, such as regression, by not just estimating the beliefs under static conditions, but also the dynamics of the belief under changing conditions. The aim of a causal inference study is to establish relationships between two variables that continue to exist despite changes in external conditions. Given the ever-changing nature of the economy, causal inference was determined to be the appropriate tool for the study.

Related Works

Barnett et al 2009 (1) show that for Gaussian variables, Granger causality and transfer entropy are completely equivalent. Huang et al 2015 (5) present a causal inference framework for time series datasets that can improve the accuracy of inferences in time series data and enable faster computation of causal significance. Syczewska et al 2015 (3) emphasize the importance of other variants of Granger Causality to be of relevance for the analysis of financial variables. Mamun et al 2018 (2) investigate time series data on the influence of the stock market on the economic growth of Bangladesh from 1993-2016 using ARDL Bounds Tests. The paper observe that the stock market impacts the economy in both the short-run as well as the long run. Osakwe et al 2017 (4) similarly observe the short-run and long run causal relationship between stock market and economic growth in the context of Nigeria and South Africa. Anokye-Wusu et al 2015 (9) observed significant causal relations, both unidirectional and bidirectional between indicators of stock markets and indicators of economic

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growth in Ghana. Okodua et al 2013 (10) did not find a strong relationship between the stock market of Nigeria and economic growth, suggesting that the stock market in Nigeria is not developed enough to sufficiently move the economy. Türsoy 2017 (7) confirms that for the dataset derived from Turkey, there exists a bidirectional Granger causality relation between stock prices and GDP, and a unidirectional Granger causality from GDP to stock prices in the short-run. The paper demonstrates that stock prices and economic growth are strongly linked with each other. Altarturi et al 2016 (8) demonstrate a bidirectional relationship between Islamic stock markets and economic performance in Malaysia. Paramati et al 2013 (6) establish similar causal relationships for India, while Imam alam et al 2003 (11) demonstrate the same for USA.

Research Gaps

Various studies examining different countries have been conducted to find the direction of causality. However, Transfer Entropy (TE) as an important tool to determine causality has been neglected in the literature. Moreover, only a few markets such as North America, Turkey, India etc were studied in detail. Our research takes into account several markets, and studies not only the links between stock price and economic growth in the country, but also across countries. Moreover, we make use of several techniques such as MinMaxScaler, Standard Scaler, log of values, along with vanilla TE techniques to obtain robust results. To the best of our knowledge, such a study has not been conducted before.

Overview

Granger Causality and Transfer Entropy

Causality can be quantified through the notion of causal relation introduced by Granger (Wiener 1956; Granger 1969). An indicator/random variable X is said to Granger-cause Y if the future values of Y can be explained better using both the lag values of X and Y, as opposed to lag values of Y alone. If the inclusion of lag values of X improves the prediction power of Y, then X is said to Granger-cause Y.

More formally, consider a random variable X. Let the value of the random variable X at time t be denoted by X_t. Let X^t denote the collection of random variables sampled at different time periods upto time t. Let $X_t, Y_t and Z_t$ represent three stochastic processes. Let the predicted/forecasted value at time $t+1$ of Y be $\hat{Y_{t+1}}$. Thus, the expected value of a loss function $g(e)$ with the error $e = \hat{Y}_{t+1} - Y_{t+1}$ of two models will be as follows:

- The expected value of the prediction error given only Y^t
  $R(Y^{t+1}|Y^t, Z^t) = E[g(Y_{t+1} - f_1(X^t, Z^t))]$
- The expected value of the prediction error given Y^t and X^t
  $R(Y^{t+1}|X^t, Y^t, Z^t) = E[g(Y_{t+1} - f_2(X^t, Y^t, Z^t))]$

In both models, the functions f(.) and f(.) are chosen to minimize the expected value of the loss function. In most cases, these functions are retrieved with linear and, possibly, with nonlinear regressions, neural networks etc. Typical forms for g(.) are the l1- or l2-norms.

Different kinds of entropies Joint Entropy: Given a coupled system (X,Y), where $P_y(y)$ is the pdf of the random variable Y and $P_{X,Y}$ is the joint pdf between X and Y, the joint entropy between X and Y is given by the following:

$$H(X,Y) = -\sum_{x \epsilon X} \sum_{y \epsilon Y} P_{X,Y}(x,y) log P_{X,Y}(x,y)$$

Conditional Entropy: The conditional entropy is defined by:

$$H(Y|X) = H(X,Y) - H(X)$$

We can interpret $H(Y|X)$ as the uncertainty of Y given a realisation of X

Transfer entropy can be used to computer Granger-causality. Since its introduction (Schreiber 2000), Transfer Entropy has been recognized as an important tool in the analysis of causal relationships in nonlinear systems (Hlavackovaschindler et al. 2007).The transfer entropy can be defined as the difference between the conditional entropies. Transfer entropy detects directional and dynamical information (Montalto 2014) while not assuming any particular functional form to describe interactions among systems.

Formally,

$$TE(XY|Z) = H(Y^F|Y^P, Z^P) - H(Y^F|X^P, Y^P, Z^P)$$

Transfer entropy is an asymmetric measure, that is, $TE(XY) \neq TE(YX)$. The net information flow is defined as:

$$\hat{TE}_{XY} = TE(XY) - TE(YX)$$

The Link Between Granger-causality and Transfer Entropy

It has been shown (Barnett, Barrett, and Seth 2009) that linear G-causality and Transfer Entropy are equivalent if all processes are jointly Gaussian. This result provides a direct mapping between the Transfer Entropy and the linear G-causality implemented in the standard VAR framework. Hence, it is possible to estimate the transfer entropy both in its general form and with its equivalent form for linear G-causality.

Why is correlation not enough?

Certainly, no one is privy to the age old adage ”Correlation does not imply causation”. While the saying is common enough, rarely is the full gravity behind it understood completely.

Let us take a look at the Pearson Correlation coefficient to demonstrate our point. The Pearson’s Correlation Coefficient is given by:

$$\rho_{X,Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\rho_X \rho_Y}$$

Here, μ denotes the mean value of the respective random variables X and Y.

The range of the correlation coefficient lies from -1 to 1, where a $\rho_{X,Y}$ value of 1 indicates strong positive correlation, while -1 indicates strong negative correlation. A value of 0 indicates no correlation among the two random variables.

While the correlation coefficient seems sufficient enough to detect relationships between two variables, it rarely is. The prime reason being that it barely tells us anything about the direction of the relationship between the variables .i.e. the dependent variable viz-a-viz the independent variable. This has led to misinformed hypothesis and incorrect studies, and it will be difficult to establish relationships between two random variables without a proper understanding of causal theory.

Reichenbach's common cause principle

The common cause principle establishes a relation between probability and causality. In essence, the principle says that given some correlation between two random variables X and Y, either one causes the other, or there exists another random variable Z which causes both X and Y.

The claim proposed by the common cause principle has been well established and proved (**?**).

Dataset

Two different but related datasets were used for the analysis. One was St. Louis dataset and the other was the World Bank dataset for indicators. The Transfer Entropy test was used for all combinations of Y and X on the dataset, both intra-country as well as inter-country. Interpolation was also done on the individual datasets. Various techniques such as MinMax Scaler, Standard Scaler, log of values, along with vanilla TE techniques.

Empirical Analysis

Two techniques were used to check for causality in the datasets viz. Transfer entropy (TE) and Granger causality. Moreover, several scaling techniques were combined with Transfer Entropy calculation to obtain robust results. The different scaling techniques used in the research were:

- MinMax Scaler on both X and Y
- Standard Scaler on both X and Y
- Log on only X
- Log on only Y
- Log on both X and Y
- No Scaling on either X or Y

After scaling the factors appropriately, the transfer entropy was calculated and using a threshold of TE>1.0, the appropriate time series pairs from each scaling were selected. To further increase the robustness of our results, only pairs with T.E>1.0 in a minimum of three of the six scaling techniques were selected. No pairs with TE>1.0 were observed for Log on both X and Y. Tables 1 and 2 outline the results of the experiments. No pairs were found with TE>1.0 for five scaling techniques.

To further verify our results, Granger causality was used. As a first step, it was determined whether the time series is stationary or not using the Augmented Dickey Fuller test and KPSS test. All non-stationary series were converted to stationary time series by using differencing. The series were then tested for co-integration using Johansen's methodology. Finally, the series were tested for Granger causality. Null hypothesis for all the X, Y pairs were rejected as the p- value was less than the chosen significance level of 0.05 for all pairs in at least one of the lags.

Intra country analysis for India

The relationship of India's GDP with several key economic indicators was analysed using a multi-variate linear regression model. The independent variables used were 'Stocks traded', 'Industry', 'Repo Rate', 'Capital Formulation' and 'NSE'. Mathematically, the model can be represented as:

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 \quad (1)$$

where Y = GDP(India) , X_1 = Stocks traded (India), X_2 = value added by industry (India), X_3 = Repo Rate, X_4 = Capital formulation and X_5 = NSE index.

The model had an adjusted R^2 value of 0.975 and the F statistic was found to be significant. Only the coefficient for 'value added by industry (India)' was found to be significant. Table 3 shows the results of the regression,and 4 shows the 99% confidence interval. It can be seen from table 3 that the stocks traded in India do not have a significant impact on India's GDP. Thus, it can be established that there is no correlation between the stocks traded in India, and India's GDP.

Results and Discussion

Several TE Values were found to be greater than 1, indicating good causation among values. Table 1 indicates that there exists a bi-directional causal relationship between the stock markets of India and China. Moreover, the GDP of Japan plays a role in moving the stock market in India. Both these results can be expected by the geographical proximity of India to the Asian countries, and massive imports and exports that India engages in with the Asian countries. A unidirectional causal relationship was also observed from Japan's GDP to Japan's industry sector. Given Japan's huge investments in the industry sector, and Japan's tendency to allows consume indigenously, it is expected that periods of economic boom lead to increased value of Japan's industry.

Tables 1 and 2 indicate that economic growth in the United States affects the stock market of both India as well as China. Moreover, economic growth in the United Kingdom also affects the stock market of India. This can be explained by an outbreak of positive sentiments in the Indian stock market on observing economic growth in the developed nations. Expectations can be formed on greater foreign investment in the country, greater exports, increased job opportunities by multinational corporations. and more companies setting up their manufacturing base in India.

Table 1. Features where T.E.>1 for a minimum of three scaling techniques

X	Y
'China', 'Stocks traded, total value (current US$)'	'India', 'Stocks traded, total value (% of GDP)'
'Japan', 'GDP per capita (constant 2010 US$)'	'Japan', 'Industry (including construction), value added (current US$)'
'United States', 'GDP per capita (constant 2010 US$)'	'China', 'Stocks traded, total value (current US$)'
'Japan', 'GDP per capita (constant 2010 US$)'	'India', 'Stocks traded, total value (current US$)'
'India', 'Stocks traded, total value (current US$)'	'China', 'Stocks traded, total value (current US$)'

Table 2. Features where T.E.>1 for a minimum of four scaling techniques

X	Y
'United States', 'GDP per capita (constant 2010 US$)'	'India', 'Stocks traded, total value (current US$)'
'United Kingdom', 'GDP per capita (constant 2010 US$)'	'India', 'Stocks traded, total value (current US$)'

Table 3. Regression results for India's GDP

Variable	**Coefficient**	**Std. Error**	**t value**	**P > | t |**
constant	1.421e+12	8.92e+11	1.593	0.146
India,Stocks Traded (% of GDP)	5.51e+08	2.1e+09	0.262	0.799
India,Industry,value added(current US$)	2.8303	0.354	7.987	0.000
Repo Rate	2.197e+10	3.93e+10	0.559	0.590
Capital Formulation	-4.336e+10	2.58e+10	-1.678	0.128
NSE	4.421e+07	3.2e+07	1.383	0.200

Table 4. Confidence intervals for regression results for India's GDP

Variable Name	**Confidence Interval**
Constant	[-1.478568e+12,4.321201e+12]
India,Stocks Traded (% of GDP)	[-6.286278e+09,7.388282e+09]
India,Industry,value added(current US$)	[1.678686e+00,3.981865e+00]
Repo Rate	[-1.057914e+11,1.497261e+11]
Capital Formulation	[-1.273712e+11,4.064442e+10]
NSE	[-5.967670e+07,1.480971e+08]

Thus, positive expectations and sentiments lead to growth in the Indian (and similarly China) stock market as well.

Conclusion

The study shows that not only do causal relationships exist between the stock market and economic growth of one country, but several causal relationships also exist between the stock market of one country and the economic growth of another. It was also observed that these causal relationships could exist in any direction, or even be bi-directional (such as China, Stocks traded and India, Stocks traded). The study highlights the importance of studying the impact relationships between the stock market and growth not just within the country, but also on a global scale, to take into account all the factors that influence the stock market and the GDP in today's time. Transfer Entropy combined with different Scaling techniques can be an important tool for the same.

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