Does financial development lead or lag economic growth ? Malaysian evidence

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Abstract: The relationship between the financial development and economic growth is a never ending debate, especially in the literature of financial economics. Even though some papers have provided empirical and theoretical results, the dynamism of finance and economic growth which changes over time does not lead us to a conclusive answer. Here we are trying to shed some light on the causality that exists between these two indicators, which is also our issue. Does the financial development lead economic growth or the other way around? Using the standard times series techniques, we hope to clarify this issue further. This paper is focusing on Malaysia, a gap that we try to fill in since there are not many papers discussing it particularly in the Malaysian context. The results that we have found is that economic growth and financial development are theoretically related as evidenced in their being cointegrated and that economic growth leads (rather than lags) the financial development. The implication of this is that in the Malaysian context, further attention should be given to raising economic growth in order to enhance financial development.

Keywords: Lead-lag, finance, growth, VECM, VDC, Malaysia

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INTRODUCTION: MOTIVATION OF THE STUDY

This paper will try to attempt to see the relationship between financial development and economic growth. Going further, it seeks to find empirical evidence about the causality of these two. Finally, this paper will try to shed the light on which one that influence most between the financial development and economic growth. In short, three research question can be asked:

1. Is there any theoretical relationship between financial development and economic growth?
2. If there is any, what is the direction of causality? Does financial development cause economic growth or the other way around?
3. If causality direction is evidenced, what is the policy implication?

Looking at the questions posed above, this seems to have very interesting discussion and the debate about it is still ongoing. Using Malaysia as a case study, this paper hopes to shed some lights about this issue. This topic is interesting in the sense of financial globalization that was happening around the world lately.

The paper will adopt time series technique in order to address this issue, due to several reasons that will be explained in the methodology. The rest of this papers are as follows. We will be discussing the theoretical framework that follows this issue next, and also will be looking at discussion of previous research. The methodology of time series techniques will be explained after that, followed by the results and the discussion of the findings. Finally, the limitations and conclusion of the study will be explored on the last part of the paper.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The role that is being played by financial sector has received attention lately. The recognition of a significant relationship between financial development and economic growth dates back to the year 1912. However, the relationship remains to be discussed still even these days.

Some of the research documented positive relationship between financial development and economic growth. There are findings that argued that these two are not related somehow and independent. Another angle of the studies finds that both financial development and economic growth are mutually causal i.e, they have bidirectional causality.

Reviewing earlier studies on the finance-nexus growth conducted either in emerging or advanced economics, researchers hold different views on the existence and the direction of causalities between these two. Earlier studies on this issue documented mixed and inconclusive findings, particularly due to various reasons. Examining the finance-growth nexus by adopting different methods, sets of data, and samples of study may lead to different results.

Before the financial crisis occurs, seems that the development of financial sector is happening at a very fast pace. This in turn see the expansion of the economic world, along with the liberalization. But the crash of the financial sector also brings the world economic down as those two have a relationship. And the question is who started the expansion? Is it economic growth promote financial development in the first place?

The implications that this paper hopes to bring is it helps to shed more evidence about the ongoing debate about financial development and economic growth. This in turn will help the policy makers about what action should be taken if they know the causality and thus promoting better environment of economic of the country.

RESEARCH METHODOLOGY, RESULTS AND INTERPRETATION

This study is using a time series technique, mainly by cointegration, error correction modelling and variance decomposition, in order to find empirical evidence of the nature of relations between financial development and the economic growth. This method is being used over the traditional regression method for the several reasons.

Firstly, most finance variables are non-stationary. This means that performing ordinary regression on the variables will render the results misleading, as statistical tests like t-ratios and F statistics are not statistically valid when applied to non-stationary variables. Performing regressions on the differenced form of these variables will solve one problem but then it will expose the danger of committing an arguably even graver mistake. When variables are regressed in their differenced form, the long term trend is effectively removed. Here, the regression method only captures short term, cyclical or seasonal effects. In other words, it does not really testing long term (theoretical) relationships.

Secondly, in traditional regression, the endogeneity and exogeneity of variables is pre-determined by the researcher, usually on the basis of prevailing or a priori theories. However, in this case, as we are dealing with a relatively nascent sector, there is notable absence of established theories. Cointegration techniques are advantageous in that it does not presume variable endogeneity and exogeneity. In the final analysis, the data will determine which variables are in fact exogenous, and which are exogenous. In other words, with regression, causality is presumed earlier whereas in cointegration, it is empirically proven and backed up with the results of data.

Thirdly, cointegration techniques embrace the dynamic interaction between variables whereas traditional regression methods, by definition, exclude or discriminate against interaction between variables.

The data used here are yearly data for 51 years starting from 1961. A total of 51 observations were obtained and the source of data was DataStream.

TESTING STATIONARITY OF THE VARIABLES

To begin with, we will start our empirical testing by determining the stationarity of the variables used. Ideally, our variables should be I(1), meaning that in their original level form, they are non-stationary and in their first differenced form, they are stationary. This in turn enables us to proceed to the testing of the cointegration later on.

The differenced form for each variable used is created by taking the difference of their log forms. For example, DGDP = LGDP – LGDPt-1. We then conducted the Augmented Dickey-Fuller (ADF) test on each variable (in both level and differenced form). The table below summarizes the results

Variables in Level Form			
Variable	Test Statistic	Critical Value	Implication
LGROSSFIX	-2.1380	- 3.5112	Variable is non-stationary
LGDPCAP	-2.1821	- 3.5112	Variable is non-stationary
LCPI	-1.7158	- 3.5112	Variable is non-stationary
LGDP	-1.5362	- 3.5112	Variable is non-stationary
LBANK	-2.0391	- 3.5112	Variable is non-stationary
Variables in Differenced Form			
DGROSSFIX	-4.4199	-2.9287	Variable is stationary
DGDPCAP	-5.1096	-2.9287	Variable is stationary
DCPI	-3.8423	-2.9287	Variable is stationary
DGDP	-3.7602	-2.9287	Variable is stationary
DBANK	-5.2763	-2.9287	Variable is stationary

Using on the AIC and SBC criteria, the conclusion that can be made from the above results is that all the variables we are using for this analysis are I(1), and thus we may proceed with testing of cointegration. Note that in determining which test statistic to compare with the 95% critical value for the ADF statistic, we have selected the ADF regression order based on the highest computed value for AIC and SBC. In some instances, AIC and SBC give different orders and in that case, we have taken different orders and compared both. This is not an issue as in this test cases as all the implications are consistent.

DETERMINATION OF ORDER OF THE VAR MODEL

Before proceeding with test of cointegration, we need to first determine the order of the vector auto regression (VAR), that is, the number of lags to be used. As per the table below, results show that AIC recommends order of 1 whereas SBC favours zero lag

	Choice Criteria	
	AIC	SBC
Optimal Order	1	0

If the recommendation of the AIC and SBC are the same, we can easily take the figure that has been given. However, because of the conflict between recommendation of AIC and SBC, we address this in the following manner. First we checked for serial correlation for each variable and obtained the following results.

Variable	Chi-Square p-value	Implication (at 10%)
DGROSSFIX	0.402	There is no serial correlation
DGDPCAP	0.771	There is no serial correlation
DCPI	0.019	There is serial correlation
DGDP	0.471	There is no serial correlation
DBANK	0.364	There is no serial correlation

The decision of taking the VAR order is to address the problem of autocorrelation. Here we find that only one autocorrelation that exists, and since we had a short observation, the higher order of VAR seems suitable to be used as the order of VAR. By the way, apparently the order of 1 is too minimal to capture the effect that might show off later. Considering the trade-off of lower and higher orders, we decided to choose the VAR order of 2.

3.3. TESTING COINTEGRATION

When we have established that the variables are indeed I(1) and determined the optimal VAR order as 2, we are ready to test for cointegration. As seen in the table below, the maximal Eigenvalue, Trace and HQC indicate that there is one cointegrating vector whereas according to AIC and SBC, there are 5 and zero cointegrating vectors, respectively.

Criteria	Number of cointegrating vectors
Maximum Eigenvalue	1
Trace	1
AIC	5
SBC	0

In our understanding, we can believe that there is one cointegrating vector as intuition as well as the indication that the variable will move together in the long term. Based on the above statistical result as well as our insight, for the purpose of this study, we shall assume that there is one cointegrating vector, or relationship.

Statistically explained, the above results indicate that the variables we have chosen, in some combination, result in a stationary error term. The economic interpretation, in our view, is that the 5 indices are theoretically related, in that they tend to move together, in the long term. In other words, the 5 indices are cointegrated, that is, their relations to one another is not merely spurious or by chance.

This conclusion has an important implication for the policy makers. Given that the financial development or economic growth are cointegrated, this in turn provides crucial information to the policy makers for drafting policies that will result in extent of effectiveness of short run monetary and fiscal policies.

LONG RUN STRUCTURAL MODELLING

Next, we attempt to quantify this apparent theoretical relationship among the indices. We do this in order to compare our statistical findings with theoretical (or intuitive) expectations. Relying on the Long Run Structural Modelling (LRSM) component of Microfit, and normalizing our variable (index) of interest, the LGDP, we initially obtained the results in the following table.

Since the main focus of this article was to identify the direction of causality between the GDP per capita (GDPCAP) and the financial development variable (GRFIX), we first imposed a normalizing restriction of unity on the GDP variable at the 'exact identifying' stage. Calculating the t-ratios manually, we found three variables (indices) to be significant – GDPCAP, CPI and GRFIX.

Variable	Coefficient	Standard Error	T-Ratio	Implication
LGDP	-Normalize-			
LGDPCAP	-35.8087	7.8534	-4.5597	Variable is significant
LCPI	87.2509	24.6836	3.535	Variable is significant
LGRFIX	19.8179	5.1787	3.827	Variable is significant
LBANK	-1.3428	3.7102	-0.36	Variable is insignificant

Just to be ensure, we decided to verify the significance of the variables by subjecting the estimates to over-identifying restrictions. We did this for all the variables (making one over-identifying restriction at a time) and the results confirmed earlier findings that only GDPCAP, CPI and GRFIX were significant, as detailed in the table below. In other words, the set of restriction was correct.

Variable	Chi-Square P-Value	Implication
LGDP	-Normalize-	
LGDPCAP	0.000	Variable is significant
LCPI	0.002	Variable is significant
LGROSSFIX	0.002	Variable is significant
LBANK	0.715	Variable is insignificant

From the above analysis, we arrive at the following cointegrating equation (numbers in parentheses are standard deviations):

LGDP – 19.82LGRFIX + 87.25LCPI – 3508087LGDPCAP

VECTOR ERROR CORRECTION MODEL

From our analysis thus far, we have established that at least four variables are cointegrated to a significant degree. However, the cointegrating equation reveals nothing about causality, that is, which index is the leading variable and which is the laggard variable. Information on direction of Granger-causation can be particularly useful to the policy makers. For instance, by knowing which variable is exogenous and endogenous, they can know which policy they have to alter in order to promote growth within the economic environment.

In light of this, the next part of our analysis involves the Vector Error Correction Model (VECM). Here, in addition to decomposing the change in each variable to short-term and long-term components, we are able to ascertain which variables are in fact exogenous and which are endogenous. The principle in action here is that of Granger-causality, a form of temporal causality where we determine the extent to which the change in one variable is caused by another variable in a previous period. By examining the error correction term, et-1, for each variable, and checking whether it is significant, we found that GRFIX is an endogenous variable, as depicted in the table below.

Variable	ECM(-1) t-ratio p-value	Implication
LGRFIX	0.000	Variable is endogenous
LCPI	0.400	Variable is exogenous
LBANK	0.152	Variable is exogenous
LGDP	0.350	Variable is exogenous
LGDPCAP	0.833	Variable is exogenous

VARIANCE DECOMPOSITION MODEL (VDC)

Whilst we have established that the LGRFIX is the endogenous variable, we have not been able to say anything about the relative exogeneity of the remaining indices. In other words, of the remaining variables, which is the most laggard variable compared to others, or, the least laggard? As the VECM is not able to assist us in this regard, we turn our attention to variance decomposition (VDC). Relative exogeneity can be ascertained in the following way. VDC decomposes the variance of forecast error of each variable into proportions attributable to shocks from each variable in the system, including its own. The most exogenous variable is thus the variable whose variation is explained mostly by its own past variations.

We started out applying orthogonalized VDCs and obtained the following results

FORCAST AT HORIZON 25 YEARS

	LGRFIX	LCPI	LBANK	LGDP	LGDPCAP
LGRFIX	51.92	5.48	64.65	23.93	18.60
LCPI	2.34	73.51	1.37	4.77	18.01
LBANK	12.61	4.65	62.93	6.59	13.22
LGDP	2.78	8.40	0.70	78.77	9.35
LGDPCAP	19.83	9.24	2.79	1.71	66.44

FORCAST AT HORIZON 50 YEARS

For the above two tables, rows read as the percentage of the variance of forecast error of each variable into proportions attributable to shocks from other variables (in columns), including its own. The columns read as the percentage in which that variable contributes to other variables in explaining observed changes. The diagonal line of the matrix (highlighted) represents the relative exogeneity. According to these results, the ranking of indices by degree of exogeneity (extent to which variation is explained by its own past variations) is as per the table below:

	LGRFIX	LCPI	LBANK	LGDP	LGDPCAP
LGRFIX	51.01	5.79	36.64	25.57	18.49
LCPI	2.40	73.03	1.41	4.84	18.32
LBANK	12.21	4.79	62.33	6.89	13.78
LGDP	3.07	9.21	0.48	77.61	9.63
LGDPCAP	19.92	9.20	2.81	1.47	66.33

No.	Variable Relative Exogeneity	
	At Horizon = 25 years	At Horizon = 50 years
1	LGDP	LGDP
2	LCPI	LCPI
3	LGDPCAP	LGDPCAP
4	LBANK	LBANK
5	LGRFIX	LGRFIX

The results are somewhat fitting considering the LGRFIX is ranked the lowest considering it is endogenous factor as has been tested in the VECM before. However, the orthogonalized VDC's has its limitations. Firstly it assumes that when a particular variable is shocked, all other variables are "switched off". Secondly and more importantly, orthogonalized VDCs do not produce a unique solution. The generated numbers are dependent upon the ordering of variables in the VAR. To experiment with the extent to which this is true (that orthogonalized VDCs are "biased" by the ordering of variables), we switched GRFIX, which appears first, with GDPCAP which appears last, and rerun the orthogonalized VDC. The result confirmed our suspicion. For forecast horizon of 26 weeks, for GDPCAP, the percentage of variation explained by its own past jumped from 66 % to 98 %.

With this in mind, we decided to use instead on Generalized VDCs, which are invariant to the ordering of variables. In interpreting the numbers generated by the Generalized VDCs, we need to perform additional computations. This is because the numbers do not add up to 1.0 as in the case of orthogonalized VDCs. For a given variable, at a specified horizon, we total up the numbers of the given row and we then divide the number for that variable (representing magnitude of variance explained by its own past) by the computed total. In this way, the numbers in a row will now add up to 1.0 or 100%. The tables below show the result.

FORECAST AT HORIZON 25 YEARS

	LGRFIX	LCPI	LBANK	LGDP	LGDPCAP
LGRFIX	43.46	12.35	4.68	23.00	16.49
LCPI	1.88	51.90	8.11	8.85	37.21
LBANK	12.54	8.13	66.19	12.43	0.74
LGDP	3.04	6.65	0.989	80.57	8.76
LGDPCAP	14.27	2.81	9.83	2.23	70.86

FORECAST AT HORIZON 50 YEARS

	LGRFIX	LCPI	LBANK	LGDP	LGDPCAP
LGRFIX	43.02	12.89	4.39	23.83	15.88
LCPI	1.92	51.29	8.3	0.898	37.64
LBANK	12.27	8.40	65.73	13.00	0.58
LGDP	3.43	7.40	0.89	80.00	8.30
LGDPCAP	14.31	2.78	9.80	2.31	70.78

GENERALIZED RANKING OF INDICES BY DEGREE OF EXOGENEITY

No.	Variable Relative Exogeneity	
	At Horizon = 25 years	At Horizon = 50 years
1	LGDP	LGDP
2	LGDPCAP	LGDPCAP
3	LBANK	LBANK
4	LCPI	LCPI
5	LGRFIX	LGRFIX

From the above results, we can make the following key observations:

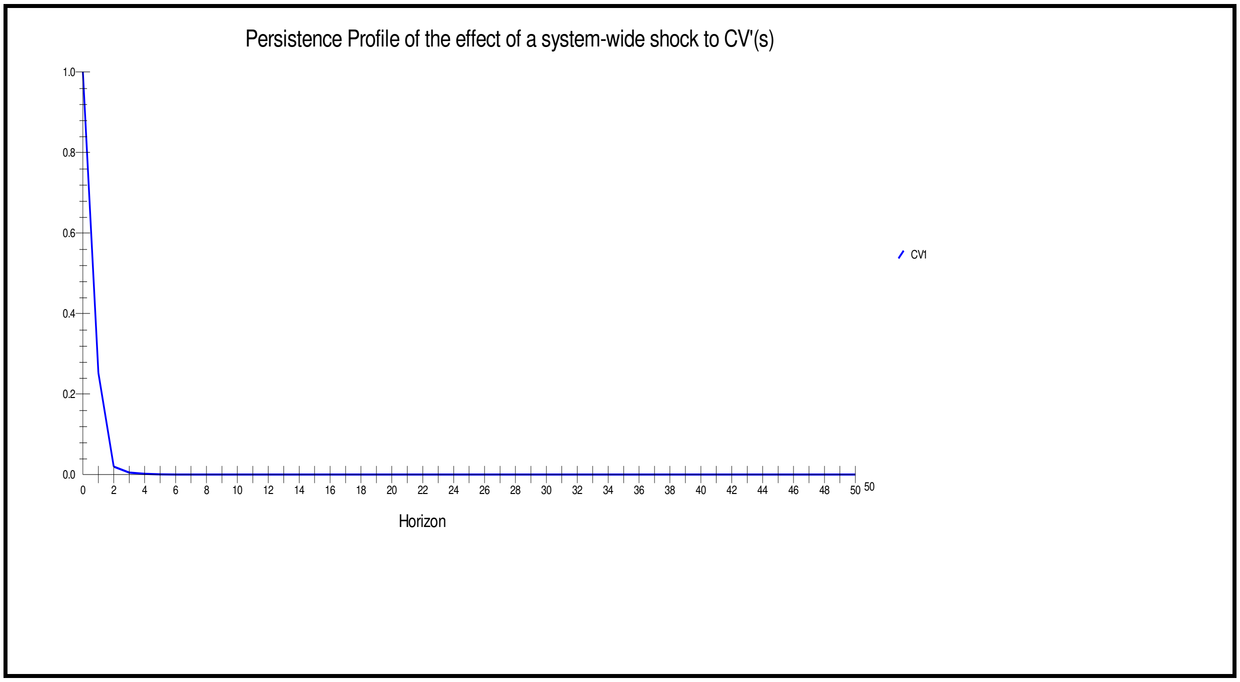
- The Generalized VDCs confirm the results of the VECM in that GDP is the most exogenous variable and the finance variables are endogenous (i.e.,dependent).
- The relative rank in exogeneity is somewhat stable as time passes. Between 26 weeks and 52 weeks, nothing changes in the order of it.

IMPULSE RESPONSE FUNCTIONS (IRF)

The impulse response functions (IRFs) essentially produce the same information as the VDCs, except that they can be presented in graphical form.

PERSISTENCE PROFILE

The persistence profile illustrates the situation when the entire co-integrating equation is shocked, and indicates the time it would take for the relationship to get back to equilibrium. Here the effect of a system-wide shock on the long-run relations is the focus (instead of variable-specific shocks as in the case of IRFs). The chart below shows the persistence profile for the co-integrating equation of this study.



The chart indicates that it would take approximately 5 years for the co-integrating relationship to return to equilibrium following a system-wide shock.

CONCLUSION

In conclusion, we revisit the earlier questions posed at the beginning of the paper. Based on the quantitative analysis, we found the answers to be:

1) There is a theoretical relationship between financial development and economic growth, as evidenced in their being cointegrated.

2) The financial development has been driven by economic growth, and not the other way around.

3) The policy implication is that more attention should be focused on raising the rate of economic growth in order to enhance financial development in countries like Malaysia.

LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

The following are some conceivable limitations of this study and hence presents opportunities for future research:

Other variables can be taken to represent economic growth and also financial development. As for example, there are many definitions of financial development such as the ratio of broad money to base money, bank deposits to nominal GDP and private sector credit to nominal GDP.

The theoretical foundations and framework of this study leave something to be desired. Underlying theory is crucial or otherwise studies such as this may be criticized as being purely exercises of number crunching or statistical data mining.

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