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25 November 2017

Online at https://mpra.ub.uni-muenchen.de/103721/
MPRA Paper No. 103721, posted 23 Oct 2020 08:52 UTC

What are the drivers of islamic bank deposits ? evidence from Malaysia

Fatimah Osman[1] and Mansur Masih[2]

Abstract

The Islamic banks have had a steady growth particularly since the financial crisis of 2007-2008. It is , therefore, pertinent to ask what the drivers of Islamic bank deposits are. This paper is focused on answering that question. The standard time series techniques are employed for the analysis. Malaysia is taken as a case study. The findings evidenced in the vector error-correction model and Generalized variance decompositions tend to indicate that Islamic bank deposits (SDI) are mainly driven, among others, by the Kuala Lumpur composite index (KLCI), rates of return on Islamic deposits (ROR), base lending rate (BLR) and money supply (M3) These findings have strong implications for the Islamic bank depositors and policy makers.

Keywords: Islamic bank deposits, macroeconomic variables, VECM, VDC, Malaysia

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1. Objective of the study

The purpose of this study is to identify and evaluate the extent of selected economic variables influence on deposits level in the Islamic banking systems in Malaysia. Both long- and short-run relationships between these variables are measured by using advanced time series econometrics. These techniques are co-integration and error correction framework, which are conducted within the vector autoregression framework. By applying econometric techniques, we would like to ascertain determinants such as rates of return (profit) of Islamic bank, rates of base lending rate, Kuala Lumpur composite index, money supply and total Islamic financing have impact on deposits at Islamic banking systems. In most cases, customers of conventional system behave in conformity with the savings behavior theories. In contrast, most of these theories are not applicable to Islamic banking customers. Therefore, there is a possibility that religious belief plays an important role in the banking decisions of Muslim customers.

On the same note, as Islamic customers are sensitive to rewards, they receive from their deposits; rates of returns (profit) of Islamic system must at any time be similar to those of the conventional system. Finally, religious dimension can be considered as an important element to attract more people to deposit their funds in the Islamic banking system.

2. Introduction

The importance of savings has long been recognized in the history of mankind from both religious and economic perspectives. One of the most famous religious stories on savings was foretold during the reign of Joseph as the Prime Minister. In order to overcome the problems of famine owing to a seven-year drought, which had befallen his people, Joseph had successfully introduced a special savings plan on food. From the economic perspective, savings are important because of its direct link to economic growth and prosperity of a country. To date, there is abundance of literature related to savings. This literature can be loosely clustered into several categories such as measuring private savings behaviour of a particular country, the determinants of savings, the effect of monetary and fiscal policies on savings and the relationship between savings and institutional profitability and public policy. Traditional banking business of supplying funds to the economy is still of great importance. For example, most business organizations especially in developing countries are highly dependent on bank loans as a source of capital. Thus, the ability of banks in giving out loans depends very much on their ability of attracting deposits. Unlike, those days where banking was among the most heavily regulated industry, now policies such as the maximum interest rates could be paid on deposits, minimum capital-to-asset ratios, statutory reserve requirements, lending direction, range of products and services offered are no longer strictly imposed by the monetary authority.

The process of financial liberalization has also created a more competitive environment in the banking industry. This forces Islamic banks to compete aggressively for deposits and such competition takes many forms. First, banks are unconstrained in terms of deposit facilities they can offer. Thus, the range of products is much broader than what was previously available. Therefore, customers are free to negotiate any minimum denomination, rates of return and maturity period prior to placing their deposits with a particular financial institution. Second, deposit facilities are now also available at other non-financial institutions. In light of these changes, to remain ahead of its competitors, Islamic banks have to be more sensitive on pricing, products offering and quality of service offered to their customers.

3. RESEARCH METHODOLOGY, RESULTS AND INTERPRETATION

This study employs a time series technique, in particular, cointegration, error correction modelling and variance decomposition, in order to find empirical evidence of the nature of relations between of selected economic variables influence on deposits level in the Islamic banking systems in Malaysia. This method is favoured over the traditional regression method for the following 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, at the expense of committing an arguably even graver mistake. When variables are regressed in their differenced form, the long term trend is effectively removed. Thus, the regression only captures short term, cyclical or seasonal effects. In other words, the regression is 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. 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 endogenous. In other words, with regression, causality is presumed whereas in cointegration, it is empirically proven with the data.

Thirdly, cointegration techniques embrace the dynamic interaction between variables whereas traditional regression methods, by definition, exclude or discriminate against interaction between variables. Economic intuition tells us that the interaction between stock markets is dynamic in nature.

The data obtained were a total of 121 observations which are the monthly numbers of period starting from Month 1 Year 2000 . The source of data was DataStream.

3.1. Testing Stationarity of Variables

We begin our empirical testing by determining the stationarity of the variables used[1]. In order to proceed with the testing of cointegration later, ideally, our variables should be I(1), in that in their original level form, they are non-stationary and in their first differenced form, they are stationary.

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[1] A variable is stationary when its mean, variance and covariance are constant over time.

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

Variable	Test Statistic	Critical Value	Implication
Variables in Level Form			
LSDI	-1.5746	-3.4491	Variable is non-stationary
LBLR	-1.3986	-3.4491	Variable is non-stationary
LROR	-3.2478	-3.4491	Variable is non-stationary
LFIN	-3.2919	-3.4491	Variable is non-stationary
LKLCI	-3.6918 (AIC)	-3.4491	Variable is non-stationary
	-2.8342 (SBC)	-3.4491	Variable is non-stationary
LM3	-2.5096	-3.4491	Variable is non-stationary
Variables in Differenced Form			
DSDI	-8.3939 (AIC)	-2.8868	Variable is stationary
	-9.6341 (SBC)	-2.8868	Variable is stationary
DBLR	-5.3618	-2.8868	Variable is stationary
DROR	-5.2495 (AIC)	-2.8868	Variable is stationary
	-5.8571 (SBC)	-2.8868	Variable is stationary
DFIN	-5.8679 (AIC)	-2.8868	Variable is stationary
	-10.4910 (SBC)	-2.8868	Variable is stationary
DKLCI	-3.5270 (AIC)	-2.8868	Variable is stationary
	-6.8622 (SBC)	-2.8868	Variable is stationary
DM3	-8.3842	-2.8868	Variable is stationary

Relying primarily 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[2]. 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 (for example, this applies to the variable LKLCI, DROR, DFIN and DKLCI as shown in the above table). This is not an issue as in all cases, the implications are consistent.

[2] The null hypothesis for the ADF test is that the variable is non-stationary. In all cases of the variable in level form, the test statistic is lower than the critical value and hence we cannot reject the null. Subsequently, in all cases of the variables in differenced form, the test statistic is higher than the critical value; thus we can reject the null and conclude that the variable is stationary (in its differenced form).

3.2. Determination of the Order of the VAR Model

Proceeding to the next step, i.e. testing the 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 and SBC favours zero lag [3].

	Choice Criteria	
	AIC	SBC
Optimal order	0	0

Based on the results above, considering the lower order of VAR given by AIC and SBC, we address this in the following manner by checking for serial correlation for each variable and obtained the following results.

Variable	Chi-Sq p-value	Implication (at 10%)
DSDI	0.342	There is no serial correlation
DBLR	0.534	There is no serial correlation
DROR	0.001	There is serial correlation
DFIN	0.009	There is serial correlation
DKLCI	0.067	There is serial correlation
DM3	0.032	There is serial correlation

As evident from the above results, there is autocorrelation in 4 out of the 6 variables. Thus, by adopting a lower order, we may encounter the effects of serial correlation.

3.3. Testing Cointegration

[3] Based on highest computed values for AIC and SBC, after stipulating an arbitrary relatively high VAR order of 6.

We have ascertained that the variables are I(1) and determined the optimal VAR order as 0, we are ready to test for cointegration. As depicted in the table below, the maximal Eigenvalue indicates there is one cointegrating vector, Trace indicates two cointegrating vectors where else AIC reported 5 cointegrating vectors, SBC with zero cointegrating vector and HQC with four cointegrating vectors, respectively [4].

Criteria	Number of cointegrating vectors
Maximal Eigenvalue	1
Trace	2
AIC	5
SBC	0
HQC	4

We believe that there is one cointegrating vector within the above variables to the Malaysian banking systems as these variable are intertwined with one another. Based on the above statistical result as well as our belief and knowledge, for the purpose of this study, we **shall assume that there is one cointegrating vector**, or relationship.

3.4. Long Run Structural Modelling (LRSM)

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 KLCI Index, we initially obtained the results in the following table.

Calculating the t-ratios manually, we found three variables to be significant – SDI, ROR and FIN.

[4] In the case of Maximal Eigenvalue and Trace, the test statistic for null of r = 0 is greater than the 95% critical value whereas for other null hypotheses, statistic is less than the critical values. For AIC, SBC and HQC, the number of cointegrating vectors is obtained by locating the highest numbers.

Variable	Coefficient	Standard Error	t-ratio	Implication
LSDI	-5.6734	1.5959	-3.555	**Variable is significant**
LBLR	-0.43961	0.33158	-1.326	Variable is insignificant
LROR	-0.7985	0.18349	-4.352	**Variable is significant**
LFIN	3.593	1.2002	2.994	**Variable is significant**
LKLCI	-	-	-	
LM3	-5.7649	2.9415	-1.96	Variable is insignificant

These initial results were generally expected. However, we were curious as to why the M3 index found to be insignificant. Driven by that curiosity, 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 contradicted with the earlier findings that only SDI, ROR and FIN were significant, as detailed in the table below. We could see that, based on the table shown below that actually, SDI, BLR, FIN and M3 are actually significant.

Variable	Chi-Sq p-value	Implication
LSDI	0.000	**Variable is significant**
LBLR	0.000	**Variable is significant**
LROR	0.965	Variable is insignificant
LFIN	0.008	**Variable is significant**
LKLCI	-	-
LM3	0.052	**Variable is significant**

When we made the over-identifying restrictions all at once, that is, testing the null hypothesis that BLR and M3 were all insignificant, the null hypothesis is rejected, or in other words, that set of restrictions is incorrect. This observation confirmed our earlier thoughts, that M3 was actually a significant variable, despite its earlier computed t-ratio of less than two. **We are more inclined to believe that M3 is a significant variable.**

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

$$\begin{array}{c} KLCI - 5.67\,SDI - 0.44BLR + 3.59FIN - 5.76M3 \rightarrow I(0) \\ (1.60) \quad (0.33) \quad (1.20) \quad (2.94) \end{array}$$

3.5. Vector Error Correction Model (VECM)

From our analysis so far, we have established that at least five indices are cointegrated to a significant degree – KLCI, SDI, BLR, FIN and M3. However, the cointegrating equation reveals nothing about causality, that is, which index is the leading variable and which is the lagging variable. Information on direction of Granger-causation can be particularly useful for depositors. By knowing which variable is exogenous and endogenous, depositors can better forecast expected results of their deposits over a certain period of times.

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.

As to what that has been explained in the principles used in Granger-causality, we determine the extent to which the change in one variable is caused by another variable in a previous period will reflect the causality of that variable. By examining the error correction term, e_{t-1}, for each variable, and checking whether it is significant, we found that **there are two exogenous variables, ROR and KLCI**, as depicted in the table below. The other variables were found to be endogenous.

Variable	ECM(-1) t-ratio p-value	Implication
LSDI	0.000	Variable is endogenous
LBLR	0.070	Variable is endogenous
LROR	0.901	**Variable is exogenous**
LFIN	0.000	Variable is endogenous
LKLCI	0.672	**Variable is exogenous**
LM3	0.036	Variable is endogenous

Translated from the above, the index that would be of interest to depositors would be the ROR and KLCI. These indices, being the exogenous variables, would receive market shocks and transmit the effects of those shocks to other indices. A depositor who is interested to make a deposit or further deposits, would be interested to monitor movements in the ROR and KLCI as changes to these indices are likely to affect his judgement or timing to deposit.

In addition, the VECM produces a statistic that may be of interest to depositors. The coefficient of e_{t-1} tells us how long it will take to get back to long term equilibrium if that variable is shocked. The coefficient represents proportion of imbalances corrected in each period.

For instance, in the case of the M3 index, the coefficient is 0.017. This implies that, when there is a shock applied to this index, it would take, on average, 1.7 week for the index to get back into equilibrium with the other indices.

3.6. Variance Decompositions (VDC)

Whilst we have established that the ROR and KLCI are the exogenous variables, we have not been able to say anything about the relative endogeneity of the remaining indices. In other words, of the remaining indices, 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 endogeneity 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 least endogenous 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:

Forecast at Horizon = 25

	SDI	BLR	ROR	FIN	KLCI	M3
SDI	1.96%	2.01%	2.73%	2.24%	15.14%	34.36%
BLR	45.50%	0.76%	2.57%	32.80%	59.75%	56.25%
ROR	10.00%	37.80%	22.50%	13.06%	24.23%	11.50%
FIN	1.25%	1.38%	64.39%	0.16%	17.63%	72.60%
KLCI	35.87%	0.11%	3.50%	0.12%	0.93%	19.89%
ME	21.00%	49.90%	1.40%	45.10%	99.10%	0.17%

Forecast at Horizon = 50

	SDI	BLR	ROR	FIN	KLCI	M3
SDI	1.96%	2.01%	2.73%	2.24%	15.14%	34.36%
BLR	45.50%	0.76%	2.57%	32.80%	59.75%	56.25%
ROR	10.00%	37.80%	22.50%	13.06%	24.23%	11.50%
FIN	1.25%	1.38%	64.39%	0.16%	17.63%	72.60%
KLCI	35.87%	0.11%	3.50%	0.12%	0.93%	19.89%
ME	21.00%	49.90%	1.40%	45.10%	99.10%	0.17%

For the above two tables, 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:

No.	Index
1	ROR
2	SDI
3	KLCI
4	BLR
5	M3
6	FIN

The data above is not in sync with the data obtained from the VECM analysis. We found that ROR and KLCI were the exogenous variables, and yet, in the VDC, though ROR is the first in its rank of relative exogeneity, KLCO is only third in rank.

To further understand this result, we need to recognize the importance of two limitations of orthogonalized VDCs. 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.

We decided to test on Generalized VDCs, which assume indifference 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 = 2

	SDI	BLR	ROR	FIN	KLCI	M3
SDI	52.51%	8.59%	9.64%	23.53%	0.96%	4.77%
BLR	3.38%	83.34%	0.85%	1.52%	2.83%	8.07%
ROR	1.09%	1.28%	90.62%	4.33%	4.33%	2.52%
FIN	28.24%	4.46%	0.76%	16.91%	16.91%	6.54%
KLCI	3.57%	0.55%	0.11%	91.78%	91.78%	3.60%
M3	11.92%	6.38%	0.12%	3.57%	3.57%	77.32%

Forecast at Horizon = 5

	SDI	BLR	ROR	FIN	KLCI	M3
SDI	61.16%	0.77%	1.10%	29.75%	1.17%	6.06%
BLR	26.60%	63.03%	0.66%	1.20%	2.25%	6.26%
ROR	0.69%	0.83%	55.58%	0.10%	27.06%	15.75%
FIN	29.07%	4.76%	0.79%	40.77%	17.69%	6.92%
KLCI	0.34%	0.58%	0.11%	0.36%	94.79%	3.81%
ME	12.53%	6.11%	0.10%	0.73%	3.85%	76.69%

We can now decipher the rank of the variable by relative exogeneity, as depicted in the table below.

No.	Variable Relative Exogeneity	
	At Horizon = 25	At Horizon = 50
1	KLCI	KLCI
2	ROR	M3
3	BLR	BLR
4	M3	SDI
5	SDI	ROR
6	FIN	FIN

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

- The Generalized VDCs confirm the results of the VECM that KLCI is the most exogenous variable.

- The relative rank in exogeneity is somewhat different as time passes. Between 25 weeks and 50 weeks, there are a few changes change in the ranking, for example :
  ROR ranked 2nd at week 25 as compared to M3 ranked 2nd at week 50;
  M3 ranked 4th at week 25 as compared to SDI being ranked 4th at week 50; and
  SDI rank at 5th at week 25 as compared ROR being ranked at 5th at week 50.

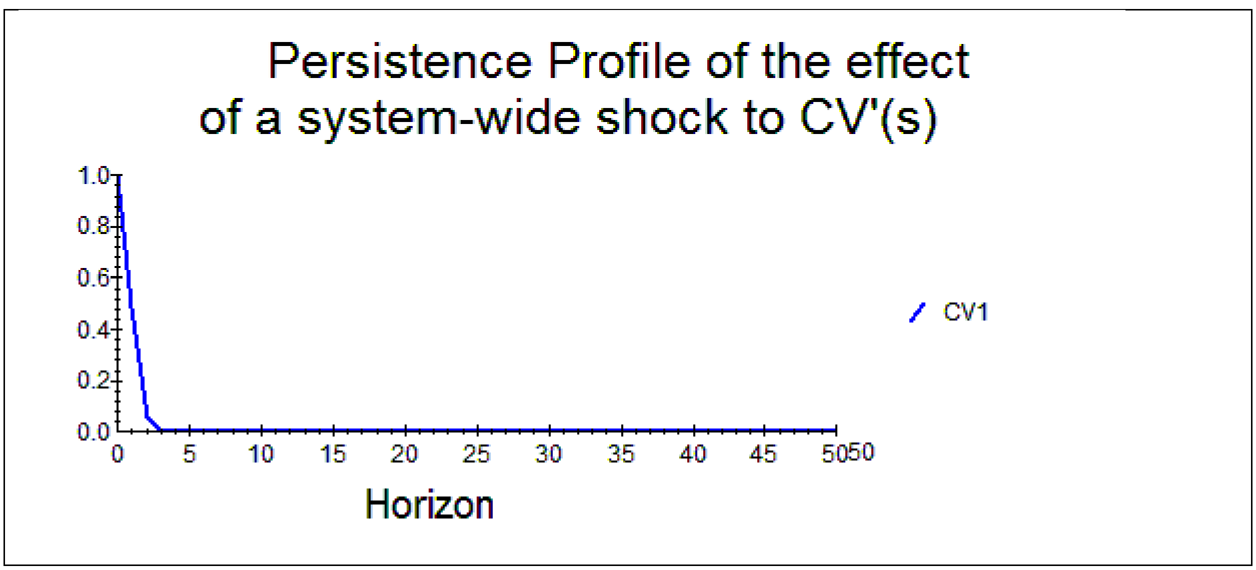
- The difference in exogeneity between the variable is not substantial. For example, in the horizon of 25 weeks, only 1.16% differences between the most exogenous variable, i.e. KLCI and the 2nd most exogenous, i.e. ROR but the difference between the most exogenous and the least exogenous (or most endogenous) variable is very substantial, charting a difference of 73.71 %.

3.7. 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.

3.8. Persistence Profile

The persistence profile reflected the situation when the entire cointegrating 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 cointegrating equation of this study.



4. CONCLUSIONS

In conclusion, we could conclude the followings based on the evidence reflected throughout the entire analysis, that we could confirm that certain variables do have its impact in determining the rate of Islamic deposits in the Malaysian banking system.

Variables such as KLCI index, Rate of Return, the Money Supply as well as the Base Lending Rate have quite substantial bearing on influencing the depositors. Last but not the least, there is a possibility that religious belief might have played an important role in the banking decisions of Muslim customers.

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