Does gold act as an inflation hedge ? Malaysian case

Salleh, Eddee and Masih, Mansur

INCEIF, Malaysia, Business School, Universiti Kuala Lumpur, Kuala Lumpur, Malaysia

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Eddee Salleh[1] and Mansur Masih[2]

Abstract:

Gold is arguably the most popular choice for investment. It has performed well during so many crisis situations such as market decline, currency failure, high inflation, war, and so on. Many studies have looked into the pattern of gold prices (see e.g. Capie, et. al, 2005; Worthington & Pahlavani, 2007; Baur & Lucey, 2010) to recognize the components that impact gold prices. Some of the factors that influence gold prices include inflation, exchange rate, national gold holding, savings and lending interest rate and consumer price index and a country's total reserve. We want to investigate the performance of gold in relation to some of these variables and test whether gold can indeed be considered as a hedge against inflation. The standard time series techniques are used for the analysis and Malaysia is used as a case study. Our findings based on variance decompositions tend to indicate that gold can indeed be considered as a good hedge against inflation. The finding is plausible and intuitive and has a strong policy implication.

Keywords: Gold, inflation hedge, VECM, VDC, Malaysia

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[1] INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia.

2 **Corresponding author**, Senior Professor, UniKL Business School, 50300, Kuala Lumpur, Malaysia.

Email: mansurmasih@unikl.edu.my

1.0 INTRODUCTION

Gold might be the most popular choice for investment. It has performed well during so many crisis situations such as market decline, currency failure, high inflation, war, and so on. Many studies have looked into the pattern of gold prices (see e.g. Capie, et. al, 2005; Worthington & Pahlavani, 2007; Baur & Lucey, 2010) to recognize the components that impact gold prices. Some of the factors that influence gold prices include inflation, exchange rate, national gold holding, savings and lending interest rate and consumer price index and Malaysia total reserve. Just out of curiosity, we add unemployment rate of Malaysia. We just want to see if the price of gold affects the rate of unemployment.

To the best of our knowledge, there is no work that has been done to examine the performance of these factors to gold prices in Malaysia.

We carry out an analysis to study the relationship of gold price towards Malaysia economy by collecting monthly data for 12 years starting from May 2005. Variables that are included in this study will be the National Gold price (NGP), Saving Interest Rate per annum (IRS), Lending Interest Rate per annum (LRS), Malaysia Gold Holding in US Dollar (NGH), Consumer Price Index (CPI), Exchange Rate in US Dollar (EXC), Total Reserve without Gold (TRX) and the Gold Price itself (NGP).

2.0 LITERATURE REVIEW

Many believe that any adjustments in gold price can affect the economy. There are a few businesses in which gold prices have an immediate impact. Most of the time however, gold price reflects financial conditions rather than cause them. Thus this paper will try to find the many ways in which prices tend to respond to changes in the economy.

In general, gold prices have a tendency to reflect changes in the value of the U.S. dollar compared to other foreign currencies. At the point when the dollar is solid, it implies that regardless of the possibility that gold price remains level in dollar terms, gold will be more costly in foreign currency whose monetary forms have declined in esteem. That tends to cut demand and put pressure on gold prices, pushing them down in dollar terms. The inverse is genuine when the dollar debilitates, in light of the fact that falling in foreign-currency make gold more alluring to buy, along these lines raising demand and pushing gold price upward.

Toraman et al. (2011) found high negative correlation between gold prices and US exchange rates. Nguyen et al. (2012) conducted a study on eight countries, viz., Japan, Singapore, UK, Indonesia, Malaysia, the Philippines, Thailand and US, and revealed that Indonesia, Japan, Malaysia and the Philippines markets have relationship with the gold price.

At the point when the economy is solid, resources other than gold have a tendency to perform well. Stocks specifically ascend in esteem, pushing speculation request far from valuable metals and different wares that don't produce any salary. By complexity, when the economy debilitates, interest for stocks and other monetary resources loosens, and that drives more cash toward what are seen to be more steady speculations, for example, money and gold.

In a comparable vein, interest rates additionally associate to the price of gold. Low loan fees and interest rates make it simple to pick gold as a contrasting option. By contrast, high financing costs make bonds substantially more alluring contrasted with non-income-producing delivering resources like gold, and the high borrowings cost for speculators who need to take out credits to purchase the yellow metal additionally make demand for gold go away more rapidly than expected.

According to Ghosh et al. (2004), in the short-run, the variations in real interest rate, gold lease rate, convenience yield, default risk, exchange rate and covariance of gold returns with other assets disturb the equilibrium relationship and generate short-run price volatility.

Inflation threatens the value of financial assets like stocks and bonds, and it therefore makes gold look more attractive as a store of value. Because inflation often accompanies times of economic unrest, many investors look to gold as a safe haven investment for use in times of all sorts of distress, ranging from geopolitical conflict to systemic financial risk. When investors no longer trust currency, it's natural to turn to gold, and that helps push prices up. Obviously, the way that these and different elements tend to move in various bearings in the meantime makes it clear exactly how troublesome it can be to see the relationship between financial conditions and the gold market. In any case, seeing a portion of the apparent basics of how the gold market functions can help you put all the more adequately in the ware. The study of Ghosh et al. (2004), after employing the cointegration regression technique on monthly gold price data ranging from 1976 to 1999, discovered that the price of gold rises over time at the general rate of inflation, and, thus, it is an effective hedge against inflation.

3.0 METHODOLOGY

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 equity markets as alluded to in the introductory paragraphs. This method is favoured over the traditional regression method for the following reasons.

Firstly, 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. 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 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 used here are on monthly basis for 12 years starting May 2005. A total of 128 observations were obtained. The source of data was from International Monetary Fund IMF website.

4.0 EMPIRICAL RESULTS

We begin our empirical testing by determining the stationarity of the variables used1. 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. The differenced form for each variable used is created by taking the difference of their log forms. 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	TEST STATISTIC	CRITICAL VALUE	IMPLICATION
	VARIABLES IN LEVEL FORMS		
LNGP	-1.4250	-3.4452	Non-stationary
LIRS	-1.8181 (AIC)	-3.4452	Non-stationary
	-1.4762 (SBC)	-3.4452	Non-stationary
LNGH	-1.0990	-3.4452	Non-stationary
LUER	-1.6728 (AIC)	-3.4452	Non-stationary
	-.96226 (SBC)	-3.4452	Non-stationary
LCPI	-4.0353	-3.4452	Stationary
LIRL	-1.8365 (AIC)	-3.4452	Non-stationary
	-1.5456 (SBC)	-3.4452	Non-stationary
LEXC	-1.1346	-3.4452	Non-stationary
LTRX	-1.4414	-3.4452	Non-stationary
	VARIABLES IN DIFFERENCED FORMS		
DNGP	-9.8908	-2.8842	Stationary
DIRS	-4.0780 (AIC)	-2.8842	Stationary
	-6.0604 (SBC)	-2.8842	Stationary
DNGH	-11.4009	-2.8842	Stationary
DUER	-5.6966 (AIC)	-2.8842	Stationary
	-10.8500	-2.8842	Stationary
DCPI	-6.2229 (AIC)	-2.8842	Stationary

	-7.4816 (SBC)	-2.8842	Stationary
DIRL	-6.1480 (AIC)	-2.8842	Stationary
	-9.2298 (SBC)	-2.8842	Stationary
DEXC	-7.8596	-2.8842	Stationary
DTRX	-6.9818	-2.8842	Stationary

From the above results, we found out that LCPI is stationary. In order to rectify this, we will run the Philips-Perron test to see if the results change.

4.1 Philips-Perron

VARIABLES	TEST STATISTIC	CRITICAL VALUE	IMPLICATION
	VARIABLES IN LEVEL FORMS		
LNGP	-2.6502	-2.8832	Non-stationary
LIRS	-1.7351	-2.8832	Non-stationary
LNGH	-1.1868	-2.8832	Non-stationary
LUER	-1.3632	-2.8832	Non-stationary
LCPI	-1.2799	-2.8832	Non-stationary
LIRL	-.86171	-2.8832	Non-stationary
LEXC	-1.2512	-2.8832	Non-stationary
LTRX	-1.9260	-2.8832	Non-stationary
	VARIABLES IN DIFFERENCED FORMS		
DNGP		-2.8842	Stationary
DIRS		-2.8842	Stationary
		-2.8842	Stationary
DNGH		-2.8842	Stationary
DUER		-2.8842	Stationary
		-2.8842	Stationary
DCPI		-2.8842	Stationary
	-7.4816 (SBC)	-2.8842	Stationary
DIRL	-6.1480 (AIC)	-2.8842	Stationary
	-9.2298 (SBC)	-2.8842	Stationary
DEXC	-7.8596	-2.8842	Stationary
DTRX	-6.9818	-2.8842	Stationary

The above table shows the results of Philips-Perron test. The results shows that LCPI now is at non-stationary which is different from the ADF test. This may be due to heteroscedasticity issue. Between PP and ADF, PP is more robust as compared to ADF. With that, we will use the PP test result and proceed to the next steps.

4.2 Determination of Order of the VAR Model

Before proceeding with test of integration, 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 OF CRITERIA	
	AIC	SBC
OPTIMAL ORDER	1 (at 2242.60)	0 (at 2224.40)

Given this apparent conflict between recommendation of AIC and SBC, we address this n 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%)
DNGP	0.309	There is no serial correlation
DIRS	0.001	There is serial correlation
DNGH	0.375	There is no serial correlation
DUER	0.085	There is serial correlation
DCPI	0.095	There is serial correlation
DIRL	0.607	There is no serial correlation
DEXC	0.158	There is no serial correlation
DTRX	0.298	There is no serial correlation

As evident from the above results, there is autocorrelation in 3 out of the 8 variables. Even though this results differ from the VAR test we did earlier, we will maintained the number of lags of 1 as computed by the system; VAR.

4.3 Testing Cointegration

Once we have established that the variables are I (1) and determined the optimal VAR order as 1, we are ready to test for cointegrating. As depicted in the table below, the Maximal Eigenvalue, Trace, HQC, AIC and SBC, all indicates 8 cointegrating vector.

CRITERIA	NO OF COINTERGRATING VECTORS
Maximal Eigenvalue	1
Trace	1
AIC	r = 6 (2376.5)
SBC	r = 0 (2337.1)
HQC	r = 2 (2347.9)

We are inclined to believe that there is one cointegrating vector as intuition as well as familiarity the variables are typically “connected” or “integrated”. 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.

4.4 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 of national gold holding, results in the following table . Calculating the t-ratios manually, we found only 1 variable (indices) to be significant – NGP.

VARIABLES	COEFFICIENT	STANDARD ERROR	T-STAT	IMPLICATION
LCPI	38.9647	25.3781	1.535	Variable is insignificant
LEXC	1.5824	3.2724	0.484	Variable is insignificant
LIRL	-1.5683	5.4381	0.288	Variable is insignificant
LIRS	0.58908	2.5285	0.233	Variable is insignificant
LNGH	-	-	-	-
LNGP	-3.0731	1.4202	-2.163	Variable is significant
LTRX	0.83844	1.3422	0.625	Variable is insignificant
LUER	-0.28023	0.59382	0.472	Variable is insignificant

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

LNGH = -3.0731LNGP

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 however defer from our previous results. After the over identification being done, now the variables of CPI becomes significant, while NGP maintained to be significant after more than 30000 iterations.

VARIABLES	CHI-SQUARE P VALUE	IMPLICATIONS
LCPI	**0.001**	Variable is significant
LEXC	**0.555**	Variable is insignificant
LIRL	**0.732**	Variable is insignificant
LIRS	**0.791**	Variable is insignificant
LNGP	-	-
LTRX	**0.608**	Variable is insignificant
LUER	**0.669**	Variable is insignificant
LNGH	**0.005**	Variable is significant

Interestingly, when we made the over-identifying restrictions all at once, that is, testing the null hypothesis that EXC, IRL, IRS, TRX and UER and were all insignificant, the null hypothesis is rejected, or in other words, that set of restrictions is incorrect.

4.5 VECM

From our analysis thus far, we have established that at least 3 indices are co-integrated to a significant degree – NGP, NGH and CPI (over-identification results). 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 for investors. By knowing which variable is exogenous and endogenous, investors can better forecast or predict expected results of their investment. Typically, an investor would be interested to know which index is the exogenous variable to monitor the movement of other variables.

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 there are 3 exogenous variables, NGP, IRL and IRS, as depicted in the table below. The other variables were found to be endogenous .

VARIABLES	ECM(-1) t-ratio p-value	IMPLICATIONS
LNGP	**0.340**	Variable is exogenous
LIRS	**0.482**	Variable is exogenous
LUER	**0.044**	Variable is endogenous
LCPI	**0.025**	Variable is endogenous
LIRL	**0.226**	Variable is exogenous
LEXC	**0.000**	Variable is endogenous
LTRX	**0.000**	Variable is endogenous
LNGH	**0.028**	Variable is endogenous

The implication of this result is that, the variables of interest would be the NGP, IRS and IRL. These variables, being the exogenous variables, would receive market shocks and transmit the effects other variables. Perhaps, to the policy maker, government or economist, would be interested to monitor movements of these variable, as any changes to these 3 variables are likely to affect other variables.

In addition, the VECM produces a statistic that may be of interest of this information user. The coefficient of et-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 imbalance corrected in each period.

4.6 VDC

Whilst we have established that NGP, IRS and IRL are the exogenous index, we have not been able to say anything about the relative erogeneity of these variables and the endogeneity of the remaining variable. In other words, of all the exogenous and endogenous variables, which are the most laggard variables 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 and 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 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

Orthogonalized Forecast at Horizon = 48 (months)

	LCPI	LEXC	LIRL	LIRS	LNGH	LNGP	LTRX	LUER
CPI	**63.95%**	**0.46%**	**0.009%**	**0.30%**	**12.84%**	**19.83%**	**1.77%**	**0.85%**
EXC	**31.42%**	**44.29%**	**0.006%**	**0.21%**	**8.76%**	**13.50%**	**1.21%**	**0.58%**
IRL	**7.42%**	**3.42%**	**84.54%**	**0.039%**	**1.66%**	**2.57%**	**0.23%**	**0.11%**
IRS	**4.64%**	**1.02%**	**16.11%**	**76.62%**	**0.58%**	**0.90%**	**0.08%**	**0.038%**
NGH	**28.24%**	**1.17%**	**0.65%**	**0.17%**	**58.54%**	**9.92%**	**0.88%**	**0.43%**
NGP	**4.63%**	**7.92%**	**0.031%**	**0.78%**	**0.10%**	**86.37%**	**0.12%**	**0.058%**
TRX	**39.78%**	**6.04%**	**0.0007%**	**0.023%**	**15.92%**	**26.57%**	**10.79%**	**0.87%**
UER	**12.55%**	**0.011%**	**0.70%**	**0.62%**	**1.10%**	**10.90%**	**0.036%**	**74.09%**

Orthogonalized Forecast at Horizon = 60 (months)

	LCPI	LEXC	LIRL	LIRS	LNGH	LNGP	LTRX	LUER
CPI	**61.42%**	**0.49%**	**0.01%**	**0.32%**	**13.74%**	**21.21%**	**1.89%**	**0.91%**
EXC	**32.02%**	**43.20%**	**0.006%**	**0.21%**	**8.94%**	**13.81%**	**1.23%**	**0.59%**
IRL	**7.72%**	**3.38%**	**84.08%**	**0.041%**	**1.73%**	**2.68%**	**0.24%**	**0.11%**
IRS	**4.79%**	**1.00%**	**16.06%**	**76.45%**	**0.61%**	**0.95%**	**0.08%**	**0.04%**
NGH	**29.35%**	**1.18%**	**0.64%**	**0.17%**	**56.90%**	**10.37%**	**0.92%**	**0.44%**
NGP	**4.78%**	**7.88%**	**0.03%**	**0.78%**	**0.08%**	**86.25%**	**0.12%**	**0.06%**
TRX	**40.30%**	**5.90%**	**0.00%**	**0.02%**	**16.05%**	**26.75%**	**10.10%**	**0.88%**
UER	**12.99%**	**0.00%**	**0.69%**	**0.62%**	**1.16%**	**11.17%**	**0.031%**	**73.31%**

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:

NO	VARIABLE	% 48 month	% 60 month
1	NGP	86.37	86.25
2	IRL	84.54	84.08
3	IRS	76.62	76.45
4	UER	74.09	73.31
5	CPI	63.95	61.42
6	NGH	58.54	56.90
7	EXC	44.29	43.20
8	TRX	10.79	10.10

Our results from VDC confirmed that our VECM analysis where NGP, IRL and IRS are exogenous. From the table above, we can see that all the 3 variables are ranked at the top 3 of VDC test. Also, the remaining of the variables which are endogenous are ranked at the same level in the 42 and 60 months respectively.

However, we should take note of two important 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. The generated numbers are dependent upon the ordering of variables in the VAR. Typically, the first variable would report the highest percentage and thus would likely to be specified as the most exogenous variable. For the limitations given above, we decided to test on Generalized VDC just to make sure.

Generalized Forecast at Horizon = 48 (months)

	LCPI	LEXC	LIRL	LIRS	LNGH	LNGP	LTRX	LUER
LCPI	**63.95%**	**0.17%**	**0.15%**	**0.001%**	**16.35%**	**12.99%**	**0.099%**	**0.71%**
LEXC	**31.42%**	**47.18%**	**1.37%**	**0.053%**	**4.60%**	**29.12%**	**3.02%**	**0.29%**
LIRL	**7.42%**	**0.30%**	**89.87%**	**19.60%**	**3.82%**	**0.63%**	**1.29%**	**1.70%**
LIRS	**4.64%**	**0.85%**	**17.84%**	**96.50%**	**0.94%**	**1.57%**	**2.60%**	**1.34%**
LNGH	**28.24%**	**1.67%**	**0.64%**	**0.14%**	**65.45%**	**20.64%**	**0.88%**	**2.85%**
LNGP	**4.63%**	**8.40%**	**0.49%**	**3.14%**	**0.33%**	**95.92%**	**2.90%**	**1.47%**
LTRX	**39.78%**	**7.31%**	**0.086%**	**0.104%**	**11.24%**	**29.26%**	**19.94%**	**1.60%**
LUER	**12.55%**	**0.028%**	**0.93%**	**1.79%**	**0.72%**	**10.24%**	**0.044%**	**78.00%**

Generalized Forecast at Horizon = 60 (months)

	LCPI	LEXC	LIRL	LIRS	LNGH	LNGP	LTRX	LUER
LCPI	**61.42%**	**0.19%**	**0.15%**	**0.090%**	**17.32%**	**13.99%**	**0.088%**	**0.77%**
LEXC	**32.02%**	**46.10%**	**1.32%**	**0.048%**	**4.74%**	**29.33%**	**2.88%**	**0.30%**
LIRL	**7.72%**	**2.98%**	**89.41%**	**19.52%**	**3.94%**	**0.67%**	**1.30%**	**1.72%**
LIRS	**4.80%**	**0.84%**	**17.80%**	**96.31%**	**0.98%**	**1.63%**	**2.60%**	**1.35%**
LNGH	**29.35%**	**1.71%**	**0.63%**	**0.15%**	**63.90%**	**21.28%**	**0.89%**	**2.90%**
LNGP	**4.78%**	**8.36%**	**0.48%**	**0.32%**	**0.29%**	**95.75%**	**2.86%**	**1.47%**
LTRX	**40.30%**	**7.18%**	**0.078%**	**0.10%**	**11.34%**	**29.38%**	**19.92%**	**1.64%**
LUER	**12.99%**	**0.029%**	**0.93%**	**1.81%**	**0.76%**	**10.53%**	**0.039%**	**77.20%**

Variable Relativity		
48 Months (%)		**60 Months (%)**
IRS (96.50)		IRS (96.31)
NGP (95.92)		NGP (95.75)
IRL (89.87)		IRL (89.41)
UER (78.00)		UER (77.20)
NGH (65.45)		NGH (63.90)
CPI (63.95)		CPI (61.41)
EXC (47.18)		EXC (46.10)
TRX (19.94)		TRX (19.92)

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

i. The Generalized VDCs confirm the results of the VECM in that IRS is the most exogenous variable.

ii. The relative rank in exogeneity is somewhat stable for all the variables as time passes.

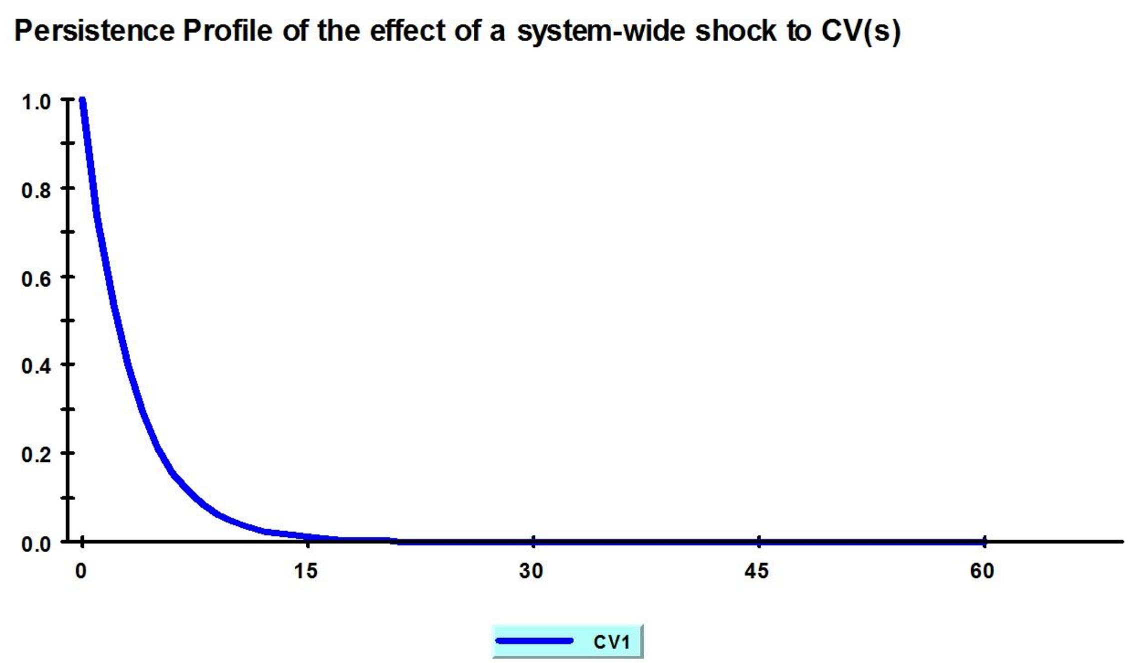
iii. The difference in in percentage of each and every variables is small over the time.

4.7 IRF

The impulse response functions (IRFs) essentially produce the same information as the VDCs, except that they can be presented in graphical form. For the sake of completeness, we have done the various graphs of IRFs and confirmed their consistency with VDC.

4.8 Persistence Profile

The persistence profile illustrates 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.



The chart indicates that it would take approximately 15 months for the cointegrating relationship to return to equilibrium following a system-wide shock.

4.0 CONCLUSION

We have modelled gold prices in Malaysia and shown it to have a long term relationship with government's gold holding and Consumer Price Index. Gold acts as a good inflation hedge as it moves in the same direction as CPI. In the long run too, gold seems to very stable and at the same time CPI follows the same direction. Perhaps, Malaysian government should buy and keep the gold to control the inflation rate in the long run as indicated in this paper.

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