Examining, Modeling, and Forecasting Gold Futures Contract Prices

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Abstract

This paper explores both a univariate (ARIMA) and multivariate (VAR) model to explore gold futures contract prices. This research uses the differentiated series of gold futures as the stationary series of gold futures. In conclusion, an ARIMA(0,1,1) model best describes the process of gold futures. This implies a momentum to the price of gold futures. The relations of inflation and volatility on gold futures, with one lag is examined. It is concluded that, on average, a standard deviation increase in inflation increases the change in gold futures prices to be about 4 USD per Troy Ounce, and that, on average, a standard deviation increase in volatility increases gold futures prices by 10 USD per Troy Ounce. The effects of changes in gold itself contribute much more to the changes in gold prices than volatility or inflation, with volatility contributing more than inflation.

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I. Introduction

For this project, I was in studying financial data. I decided to analyze commodities, specifically futures. Part of this is due to the fact that commodity futures are often algorithmically traded with computers, a topic that very much intrigues me. Gold futures specifically, are freer of outside variables like weather, seasonality, politics, etc. This makes gold futures prices a more attractive financial index to explore through the lens of what we have learned in Time Series Econometrics. There is information about the movements of gold future prices through its past movements.

In addition, gold futures are not completely free of external effects. In this paper, we explore the changes in gold futures prices through two external series volatility and inflations. These two series are explored to test two different theories. One is to test gold's use as a hedge of risk. The "risk on risk off" theory states that investors seek less risky assets during times of high volatility, or risk. Gold is viewed as a safer investment, or a hedge. We might therefore expect to see gold futures prices to increase during times of higher volatility due to the increased demand and to fall during times of less volatility. Gold is believed to be an inflation hedge. During times of high inflations, it is likely that gold futures prices should increase due to an increase in demand for inflations hedges.

This paper therefore uses three time series variables. We use the monthly average for all of these variables because our inflation variable is observed monthly and to avoid excessive noise. Observations start March 1990 and go to February 2021. A simple *time* variable is created and used for convenience. The series used are the monthly average of the London Bullion Market Gold Futures Contracts in USD per Troy Ounce, the CBOE volatility index, and changes in the log of the Consumer Price Index less food and energy. (**Table 1)** contains summary statistics of all of the variables and transformed variables.

II. ARIMA Analysis

A. Building a Stationary Series

It ARIMA analysis, it is necessary that our gold futures series is a stationary series. Looking at the graph of gold futures prices **(Figure 2.A.1)**, the series does not appear stationary as it does not tend towards a certain constant. In addition, looking at the autocorrelation function of gold futures **(Figure 2.A.2)**, the auto correlations persist through many, many lags—indicative of a non-stationary series, having a ϕ greater than 1. Performing the Dickey-Fuller test **(Table 2.A.1)** we fail to reject that $\alpha - 1 = 0$ ($\alpha \equiv \phi$), telling us that we do not have a stationary series.

Detrending a linear trend could leave a stationary series. A regression with robust standard errors and a constant, as there is no reason that the gold futures price should've started at zero in March 1990, is used to determine the linear trend **(Table 2.A.2)**. Viewing the linear trend with the gold futures index **(Figure 2.A.4)**, it appears that there could be a linear trend in the series; however, the series does not really tend towards the linear trend; this is also clear in graphing the detrended series, as it does not tend towards zero **(Figure 2.A.5)**. Performing the Dickey-Fuller test with the detrended series **(Table 2.A.3)**, we fail to reject that $\alpha - 1 = 0$, meaning we still do not have a stationary series.

A Hodrick-Prescott Filter could be used to remove a trends and cyclical component of gold futures prices that could be related to general market or commodities trends. Detrending is done with $\lambda = 14400$ as this is monthly data. The trend **(Figure 2.A.6)** and the detrended series **(Figure 2.A.7)** show that gold futures prices tend towards the trend (by definition) and that the detrended series tends towards zero, indicative of a stationary series. Performing a Dickey-Fuller test **(Table 2.A.4)**, we can reject that $\alpha - 1 = 0$, on the left-hand side at a 99% confidence level. Therefore, a stationary series has been detrended with the HP filter.

While a stationary series has been detrended, it could make more sense to differentiate the series, especially as this is financial data. The differentiated series **(Figure 2.A.8)** appears to tend towards zero more strongly than the HP filter. With a Dickey-Fuller test **(Table 2.A.5)** we can reject that $\alpha - 1 = 0$, on the left-hand side at a confidence level much greater than 99%. This means that the changes in gold futures prices is a stationary series. As this is financial data, and differentiating the data provides much less of a worry of overfitting the data like the HP filter, we will continue to work with the detrended, stationary series of gold futures.

B. Choosing an ARIMA Model

Now that we have a stationary series, it is relevant to see what information we can extract from the stationary series. Looking at the autocorrelation function **(Figure 2.B.1)**, it is clear that the first autocorrelation is relevant. But, after that it is hard to tell if any of the other auto correlations are relevant. The fourth and eleventh autocorrelations are outside of the 95% confidence bands; however, this does not necessarily mean there is an important process underlying why those autocorrelations are stronger.

To get an idea of the structure that could be used, let's look at potential AR structures, where the change in gold futures prices depends on the change in gold futures prices from a specified time ago, and therefore persists through continuing observations of the changes in gold futures, though converging to zero. Using the *varsoc* command in Stata **(Table 2.B.1)**, it is clear that a simple AR(1) tells us the most amount of information without adding more noise.

Allowing the *varsoc* command to use up to 24 time period lags, or two years, as this is monthly financial data **(Table 2.B.2)**, shows that an AR(1) is preferred by two information criteria; however, an AR(11) is preferred by two information criteria as well. Of course, explaining any effect that doesn't persist until the 11^{th} lag, or why a change in gold futures prices 11 months ago directly affects the changes in gold futures today would be very difficult.

MA structures should be considered, as well. We consider every combination of a cumulative ARs up to 12 and cumulative MAs up to 12, with and without a constant. It was clear that including a constant added more noise than information, which makes sense looking at the differentiated series **(Figure 2.A.8)**, where it appears that the changes in gold futures revert back to zero. In doing so, each of our information criteria gave us two different recommended structures. AIC recommends an ARMA(5, 5) and BIC recommends an MA(1). Once again, describing structures that do not persist until 5 months after would be difficult. A simple MA(1) structure would make much more sense. The estimated coefficient of the first error term is 0.232 and statistically significant.

Before we continue with an MA(1) structure, it is important to know that our structures were cumulative, meaning that an AR(3) include AR(1), AR(2), and AR(3) terms. It does not seem overly important to test all of these structures to explain why an AR(3) term doesn't exist but an AR(5) one does, doesn't seem very possible. However, it is important to consider what our current model is insinuating. The current model, with a positive MA, implies there is momentum to gold futures prices. If gold prices increase, we can expect them to increase once again, not accounting for noise, or if the changes in gold futures prices is positive, we can expect the change in gold futures prices to remain positive, to a certain extent. Yet, we know by definition, that changes in gold futures prices, is stationary, meaning that it reverts to zero.

Therefore, our current model does not fully account for any correction towards the mean, other than the fact that there exist error terms and that our information of the changes in gold futures past one month becomes irrelevant to predicting the changes in gold prices.

In attempting to add a correction structure to my model, I will test the effect of adding in an MA(3), MA(4), MA(5), or MA(6) term(I already tested the combination of an MA(1) and MA(2) term) by trying to find lower score in the Bayesian Information Criterion. We should also expect the coefficient of the second term to be negative. However, running these models we do not find that adding any of these terms tells us more information than gives us noise.

It is important to note, we could add other terms, and consider the concavity of the gold futures prices, or the second order differentiated series, to add in a mean correction structure to our model. For now, the fact that information is lost past one month and that our model has a lot of white noise, it appears that there is no need to define the structure, the white noise does a significant job in changing the sign of differentiated series of gold futures, which makes our model for gold futures correct. We will therefore use an MA structure to explain the changes in gold futures prices. Checking to make sure that our errors look like white noise **(Figure 2.B.2)**, we do find errors that look like white noise. In conclusion, our MA(1) model of the differentiated series of gold futures, or our ARIMA(0,1,1) model does a good job of explaining gold futures prices.

C. Forecasting

Creating a dynamic forecast for the ARIMA(0,1,1) model will predictively only forecast one month ahead. We create a stationary forecast for the differentiated series of gold futures from April 2009-October 2010 (times periods 230-249) with a dynamic forecast from November

2010-October 2011 (time periods 249-260). Combining this with a 95% confidence interval, we obtain the following forecast **(Figure 2.C.1)**. Our stationary series is what we might expect, with some of the change in gold futures carrying over into the next month. The dynamic forecast contains this same aspect, except it dies off after November 2010 as we no longer feed the model anymore information and we have only incorporated an MA(1) structure. The forecast does capture some of the trend in the differentiates series of gold futures. Nearly all the observations are within the 95% confidence interval.

III. VAR Model for Gold Futures

A. Building the VAR

Here we will study the effects of inflation and market volatility on gold futures, or more specifically, changes in gold futures prices. Once again, changes in the log of consumer price index, less food and energy, is used to estimate inflation and CBOE's volatility index is used to estimate market volatility. **Figure 1** shows a summary statistic of our inflation and volatility. Showing all of these indices on the same graph is clearly not a sufficient way to represent the data, due to differences in scales. **Figures 2.A.8**, **Figures 3.A.1**, and **Figures 3.A.2** show these indices individually through time.

For our vector autocorrelation regressions to work we need all of our variable to be stationary series. We chose the changes in gold futures prices to be stationary. Inflation appears to revert back to a constant. Preforming a Dickey-Fuller **(Table 3.C.1)** test we can reject that $\alpha - 1 = 0$, on the left-hand side at a confidence level greater than 99%. Therefore, inflation is a stationary series, likely with a constant (which the Dickey-Fuller test includes), but this will be taken care of with our VAR. Volatility appears to revert back to a constant to a certain extent.

Performing a Dickey-Fuller test **(Table 3.C.2)** we can reject that $\alpha - 1 = 0$, on the left-hand side at the 99% confidence level. Therefore, our volatility variable is a stationary series, with a constant included. We could likely as an HP filter, to filter our general market trends in the volatility index, providing us with a more stationary series by definition; however, in doing this we would lose information about these longer-term volatility trends and their effects on gold. These trends are important to us, so while we could gain information from the differentiated or HP filtered series of volatility, it makes more sense to work with the original CBOE index series for volatility.

It is also necessary to define an AR structure of the differentiated series of gold. It is not typical to include MA structures in multivariate analysis because of the mathematical simplicity of VARs. Using the *varsoc* command, as used above, two information criteria tell us to choose an AR(1), while the other two tell us to choose an AR(11). Once again, explaining any effect that doesn't persist until the 11th lag, or why a change in gold futures prices 11 months ago directly affects the changes in gold futures today would be very difficult. An AR(1) makes much more sense and this is what we will use. While this may seem unsettling since an MA(1) made more sense in our univariate model, auto-regressing the changes in gold futures **(Table 3.A.3)**, it is clear that the coefficient on the lagged term is statistically significant. Also, the autocorrelations of the errors look like white noise **(Figures 3.A.3)** so we can feel comfortable working with an AR(1) model for our VAR with one lag. This also makes sense since inflation and volatility would not contemporaneously affect changes in gold futures prices, as there is no clear mutual process working between the variables. Finally, it makes sense for the following impulse response functions to work with inflation being the most exogenous variable, then volatility, with of course, changes in gold futures prices being the most endogenous variable. This makes sense as inflation is a much more macroeconomic characteristic, and volatility pertains to financial markets, which of course depend on macroeconomically trends. The coefficients from our VAR model can be found in **Table 3.A.4**.

B. Impulse Response Functions

Looking at the coefficients of the VAR model are not very informative due to the interconnectivity of the variables in the model. It makes much more sense to look at the impulse response function to interpret the results. **Figure 3.B.1** shows these impulse response functions; however, they are graphed on the same axes making it very hard to tell the response of gold. This can be fixed by graphing the impulse variables changes in gold futures prices, on their own graphs **(Figure 3.B.2, Figure 3.B.3, Figure 3.B.4)**. Before trying to interpret these results, it is important to note that a one-unit shock in the CBOE volatility index and a one-unit shock in the changes in the log of the Consumer Price Index have very different meanings. These shocks are all weighted by the variance of each of these series. This can be fixed by orthogonalizing the impulse response functions **(Figure 3.B.5, Figure 3.B.6, Figure 3.B.7)**. Here we provide a one standard deviation shock to our impulse variables and observe the effect of the changes in gold futures prices (in USD per troy ounce). Once again, there is an easier way to view the response of gold futures to shocks in our impulse variables. We could cumulate these responses so that we can know the effect on gold futures prices through time from one standard deviation shock in volatility, inflation, and gold futures itself, one month ago.

Looking at our cumulative, orthogonalized impulse response functions **(Figure 3.B.8, Figure 3.B.9, Figure 3.B.10)**, the effects from our shocks in volatility and inflation are not statistically significant from zero. At first, this may appear disheartening; however, it is important that we are working in the realm of financial indices. These effects, on average, still hold valuable information, even if sometimes our conclusions result in a loss of profit.

Looking at a one standard deviation shock in inflation, we see that changes in gold futures cumulatively increase, on average, to about 4 USD per Troy Ounce. This would, on average, have an even greater effect on the actual price of gold futures. This, therefore, does, on average, support the theory that gold is used as an inflation hedge. When inflation is higher, gold future prices on average increase in price, likely due from the large demand for gold futures to retain the value of the asset when fiat money becomes worth less.

On average, a one standard deviation shock in the CBOE volatility index, results in a cumulative increase in gold futures prices to about 10 USD per Troy Ounce. This fits the "risk on risk off" theory. In times of higher volatility, implying higher risk associated with assets in general, people buy up gold, likely due to its less volatile nature as to not take on too much risk.

The results from a one-unit shock in the changes in the price of gold futures are statistically significant from zero. This is expected as our coefficient of our lagged term was statistically significant from zero. The structure is also predictable as the shock slowly no longer provides any more information, dying off towards a cumulated constant. A one-unit shock in the change in gold futures results in, on average, a 40 USD per Troy Ounce increase in the change of gold futures itself over time.

Looking at the Cholesky variance decomposition of our model **(Table 3.B.1)** it is clear the past changes in gold futures explains much more about changes in gold futures than inflation and volatility. This is determined from its large contribution to the variance in changes in gold prices compared to inflation and volatility. Finally, to check the robustness of our conclusions, we should switch the order of the exogeneity of volatility and inflation. Doing so gives extremely similar results **(Figure 3.B.11, Figure 3.B.12)**

IV. Conclusion

In conclusion, when defining a univariate model for gold futures prices, it was necessary to first create a stationary series. Using an HP filter and differentiating both gave stationary series; however, due to the nature of financial data, it made more sense to work with the differentiated series of gold futures. The ARIMA model that made the most sense for gold futures was an ARIMA(0,1,1). The coefficient on the MA term was positive, meaning that the change in gold prices persists through the next month, implying momentum to gold futures prices. Forecasting this model, with some portion stationary and another dynamic, it is clear that forecast captures some of the trend of the changes in gold futures; however, there is a lot of variance in our estimates, with a large 95% confidence interval. Nonetheless, nearly all of the observations are within the 95% confidence interval.

Looking at the effect of inflation and volatility on the changes in gold futures, we find positive correlations with each. Cumulative, orthogonalized shocks are best for viewing the effects of these series. A shock in volatility has a larger effect, with a one standard deviation shock resulting in a cumulative shock in the change in gold futures of 10 USD per Troy Ounce, as compared to a cumulative shock of 4 USD per Troy Ounce with inflation. A one standard deviation shock in gold futures has the greatest effect of a cumulative shock of 40 USD per Troy Ounce. Therefore, on average, gold is used as both an inflation and volatility hedge. These results are all consistent with the estimated contribution of each series to the changes in gold futures derived from the Cholesky variance decomposition.

These results tell us a lot about not just gold futures contract prices, but also analyzing financial data, VARs, and univariate models. The ARIMA model acted as a sort of momentum model, which is one of the most common tactics in algorithmic trading, the other being mean reversion/correction. This likely implies that if we were trading these futures, we would likely want to stick to these established trading models. It was clear, with the VAR variance decomposition, that the gold series itself gave significantly more information that other variables like volatility and inflation. When considering financial data models, many are univariate models likely for this reason. Financial data is very volatile and unpredictable. In the case of gold futures, it probably makes more sense to stick with a univariate model.

V. Figures and Tables

Table 1

Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
gold	372	781.088	502.393	256.198	1971.17
dgold	371	3.828	33.424	-112.755	190.974
vol	372	19.485	7.778	10.125	62.639
cpi	372	202.631	37.678	133.5	270.299
dlncpi	371	.002	.001	-.004	.006
ar1 errors	371	.013	32.701	-120.13	179.656
gold hp	372	0	61.671	-168.197	261.998
gold wo lintrend	372	0	246.889	-350.239	704.559
arma0 1 errors	371	3.076	32.651	-112.663	182.173

Figure 2.A.1

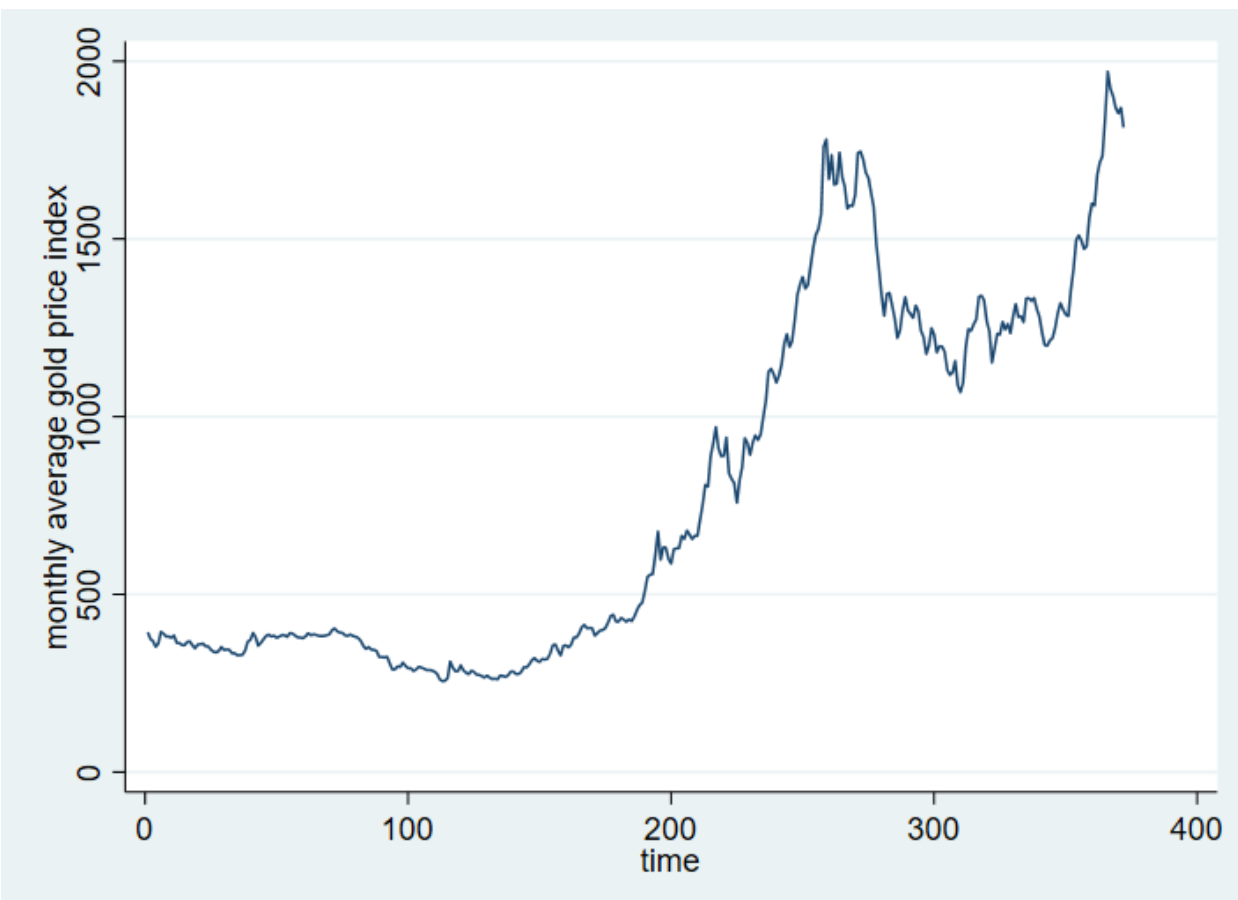

Figure 2.A.2

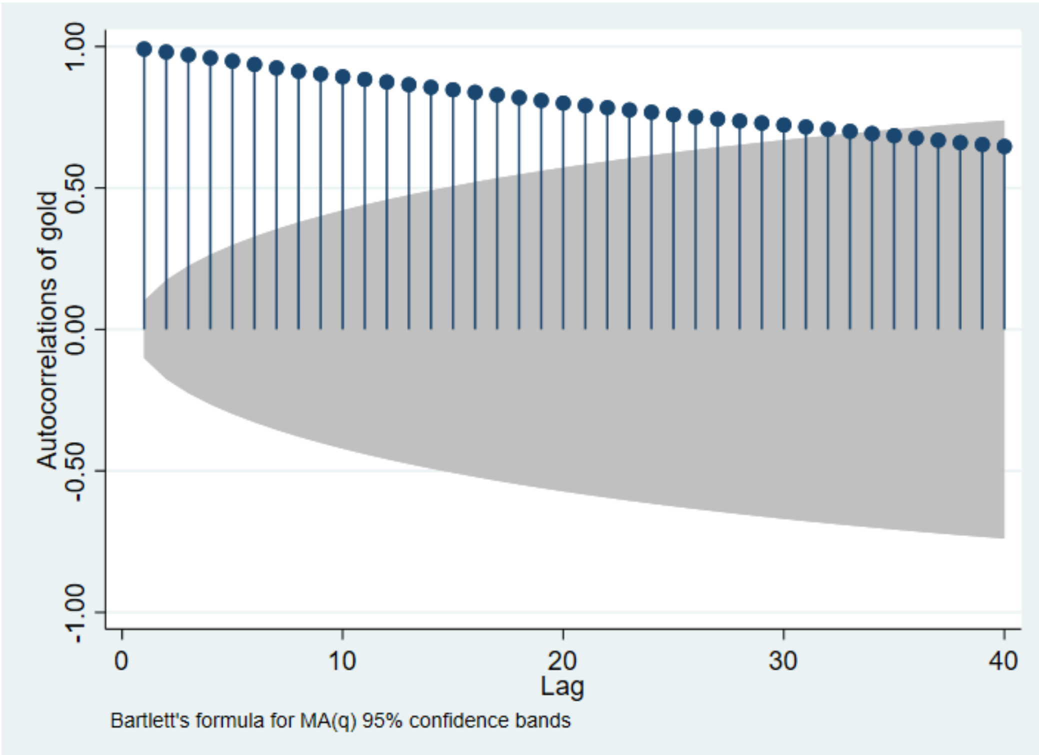

Table 2.A.1

Dickey-Fuller test for unit root Number of obs = 371

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		---------- Interpolated Dickey-Fuller ---------		
Z(t)	0.786	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Table 2.A.2

Linear regression

gold	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]
time	4.069	.108	37.65	0	3.856	4.282
Constant	22.222	22.735	0.98	.329	-22.484	66.929

Mean dependent var	781.088	SD dependent var	502.393
R-squared	0.758	Number of obs	372.000
F-test	1417.274	Prob > F	0.000
Akaike crit. (AIC)	5157.340	Bayesian crit. (BIC)	5165.178

Figure 2.A.4

Figure 2.A.5

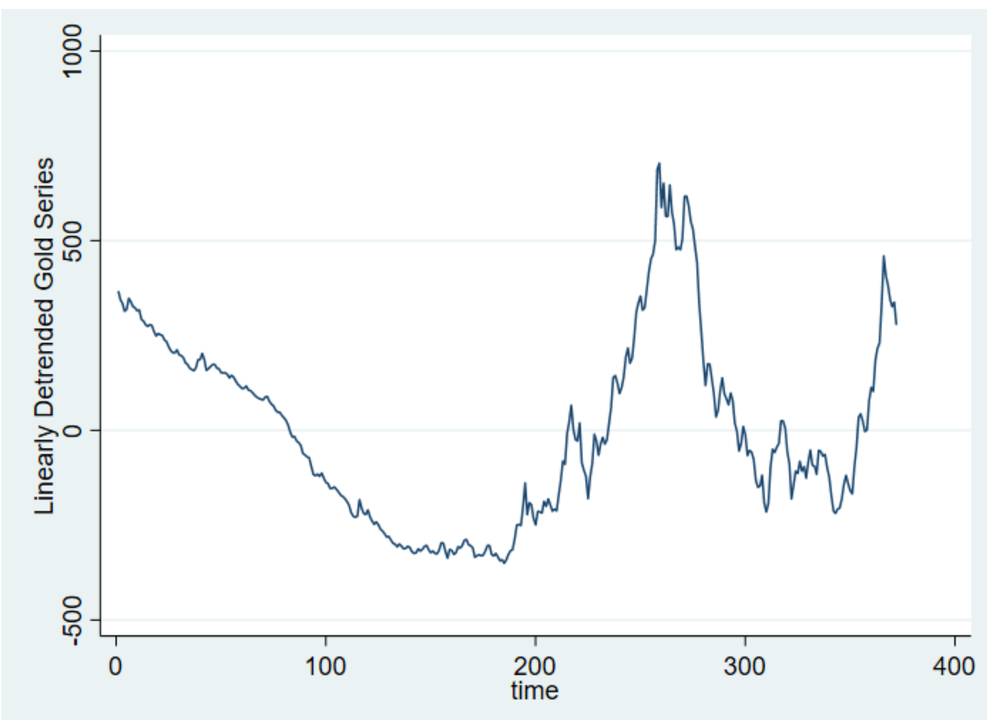

Table 2.A.3

Dickey-Fuller test for unit root Number of obs = 371

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		---------- Interpolated Dickey-Fuller ---------		
Z(t)	-1.487	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Figure 2.A.6

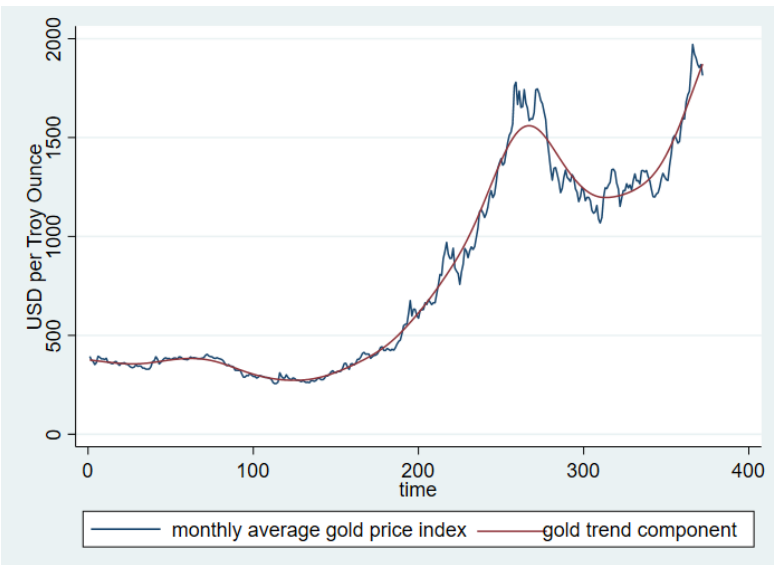

Figure 2.A.7

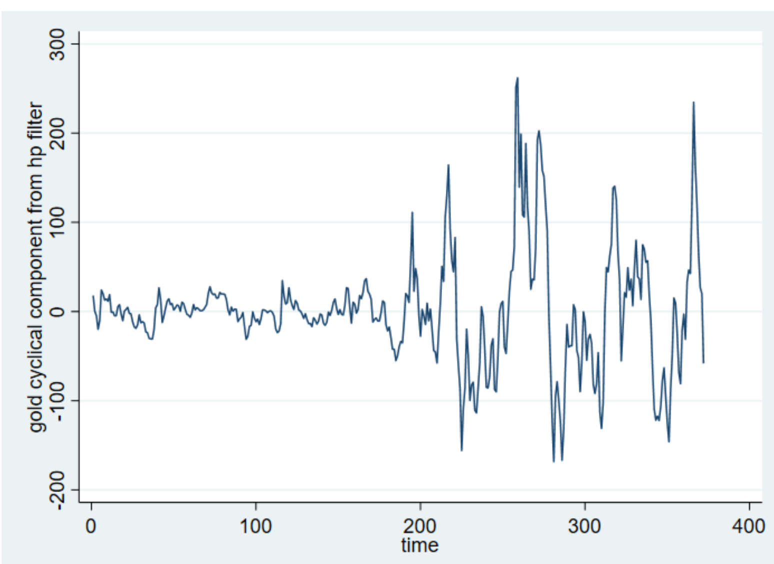

Table 2.A.4

Dickey-Fuller test for unit root Number of obs = 371

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.113	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Figure 2.A.8

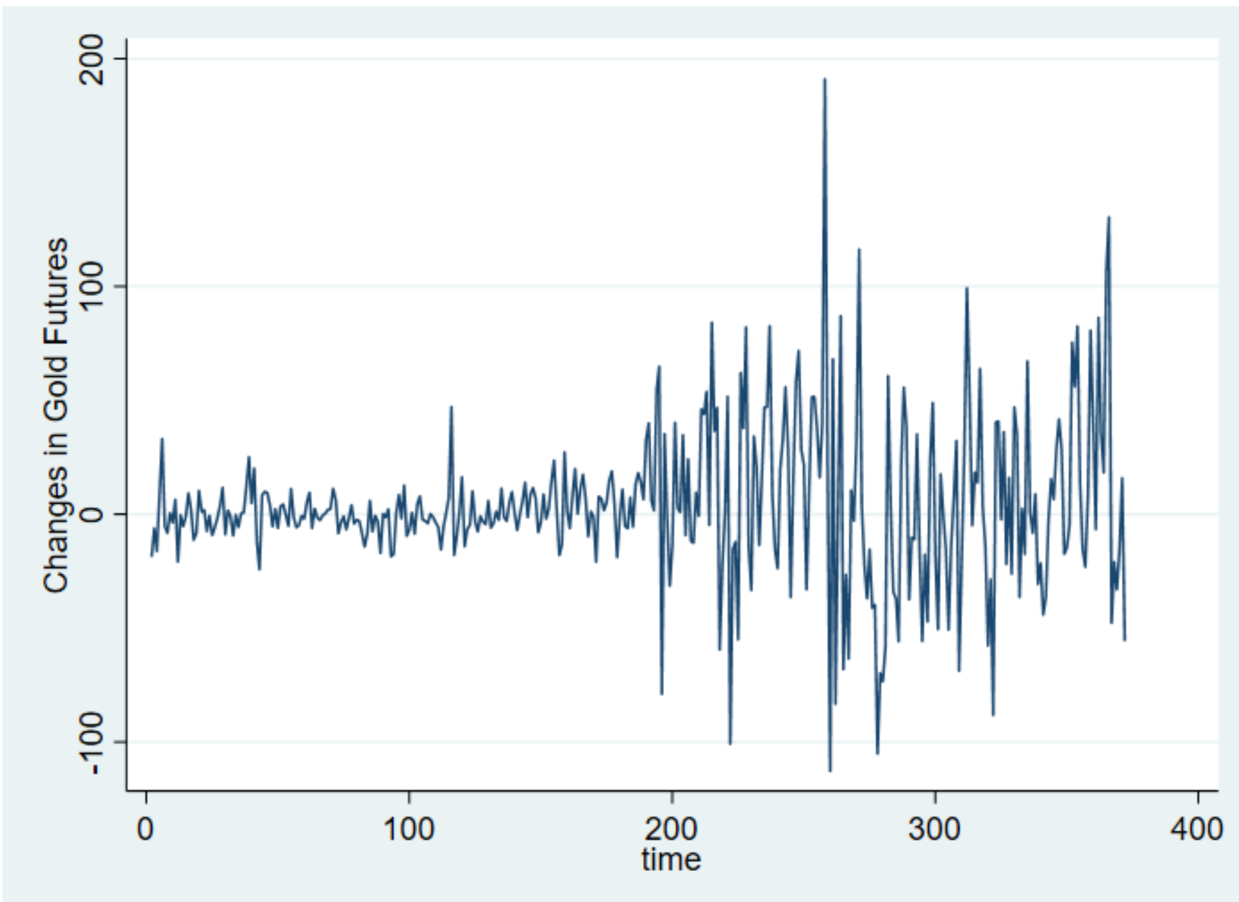

Table 2.A.5

Dickey-Fuller test for unit root Number of obs = 371

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-15.477	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Figure 2.B.1

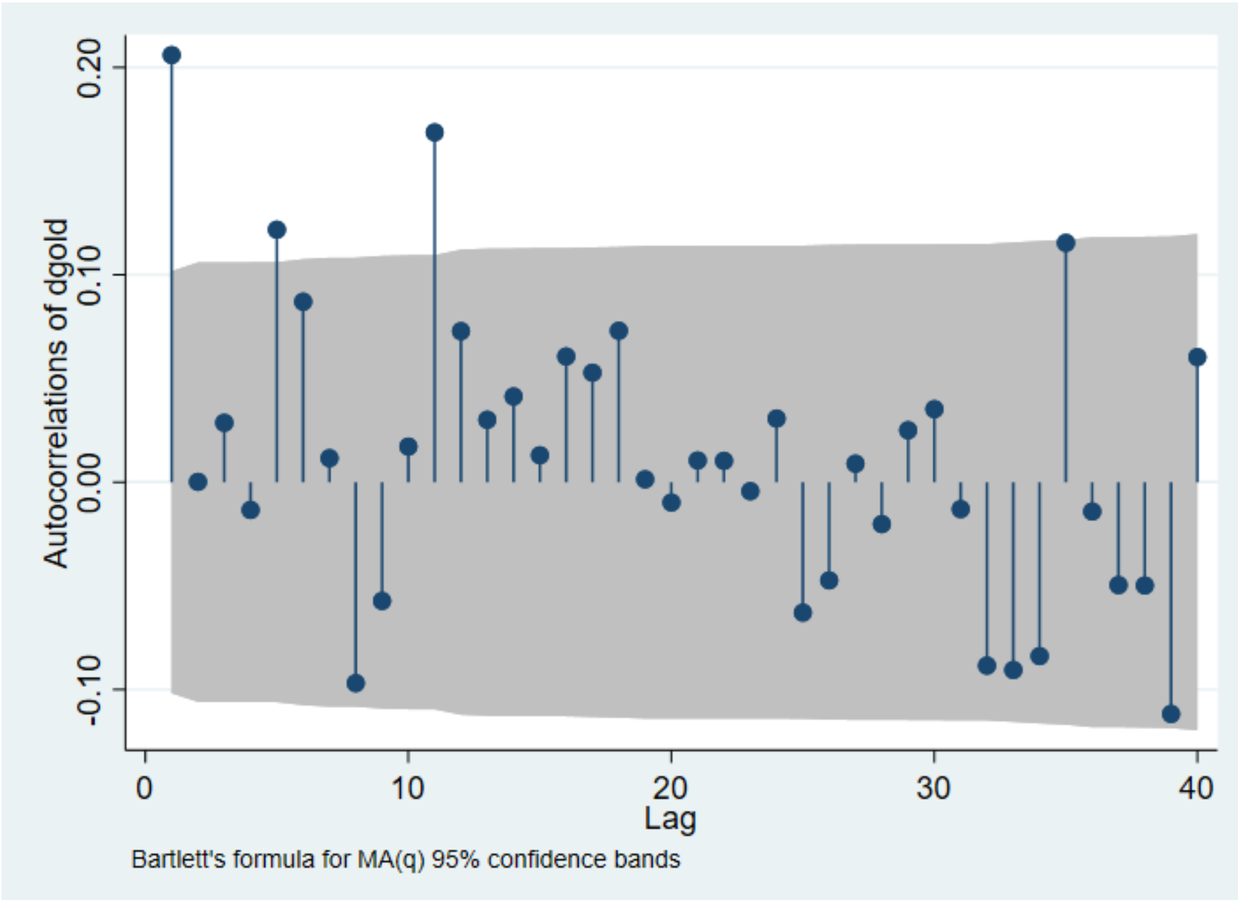

Table 2.B.1

Selection-order criteria
Sample: 6 - 372 Number of obs = 367

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1809.680				1129.570	9.867	9.872	9.878
1	-1801.680	16.008*	1	0.000	1087.27*	9.8293*	9.83775*	
2	-1801.290	0.775	1	0.379	1090.900	9.833	9.845	
3	-1800.970	0.632	1	0.427	1094.970	9.836	9.853	
4	-1800.820	0.304	1	0.581	1100.050	9.841	9.862	

Endogenous: dgold
Exogenous: _cons

Table 2.B.2

Sample: 26 - 372 Number of obs = 347

lag	LL	LR	df	p	FPE	AIC	HQIC
0	-1719.630	1187.160	9.917	9.922	9.928		
1	-1712.050	15.174	1	0.000	1142.940	9.879	9.88807*
2	-1711.690	0.710	1	0.400	1147.200	9.883	9.896
3	-1711.400	0.587	1	0.444	1151.880	9.887	9.905
4	-1711.250	0.296	1	0.586	1157.550	9.892	9.914
5	-1707.870	6.753	1	0.009	1141.800	9.878	9.905
6	-1707.690	0.374	1	0.541	1147.170	9.883	9.914
7	-1707.660	0.051	1	0.822	1153.630	9.889	9.924
8	-1705.120	5.090	1	0.024	1143.410	9.880	9.919
9	-1705.070	0.091	1	0.763	1149.720	9.885	9.929
10	-1705.040	0.064	1	0.800	1156.160	9.891	9.939
11	-1699.970	10.14*	1	0.001	1129.36*	9.86726*	9.920
12	-1699.960	0.009	1	0.925	1135.870	9.873	9.930
13	-1699.530	0.873	1	0.350	1139.580	9.876	9.938
14	-1699.250	0.554	1	0.457	1144.350	9.880	9.947
15	-1699.220	0.063	1	0.801	1150.760	9.886	9.957
16	-1699.210	0.025	1	0.874	1157.350	9.892	9.967
17	-1699.190	0.038	1	0.845	1163.930	9.897	9.977
18	-1698.490	1.393	1	0.238	1165.980	9.899	9.983
19	-1698.480	0.023	1	0.880	1172.670	9.905	9.993
20	-1698.480	0.002	1	0.966	1179.460	9.911	10.003
21	-1698.480	0.000	1	0.992	1186.310	9.916	10.014
22	-1698.470	0.021	1	0.885	1193.120	9.922	10.024
23	-1698.350	0.236	1	0.627	1199.240	9.927	10.033
24	-1698.030	0.633	1	0.426	1204	9.931	10.041

Figure 2.B.2

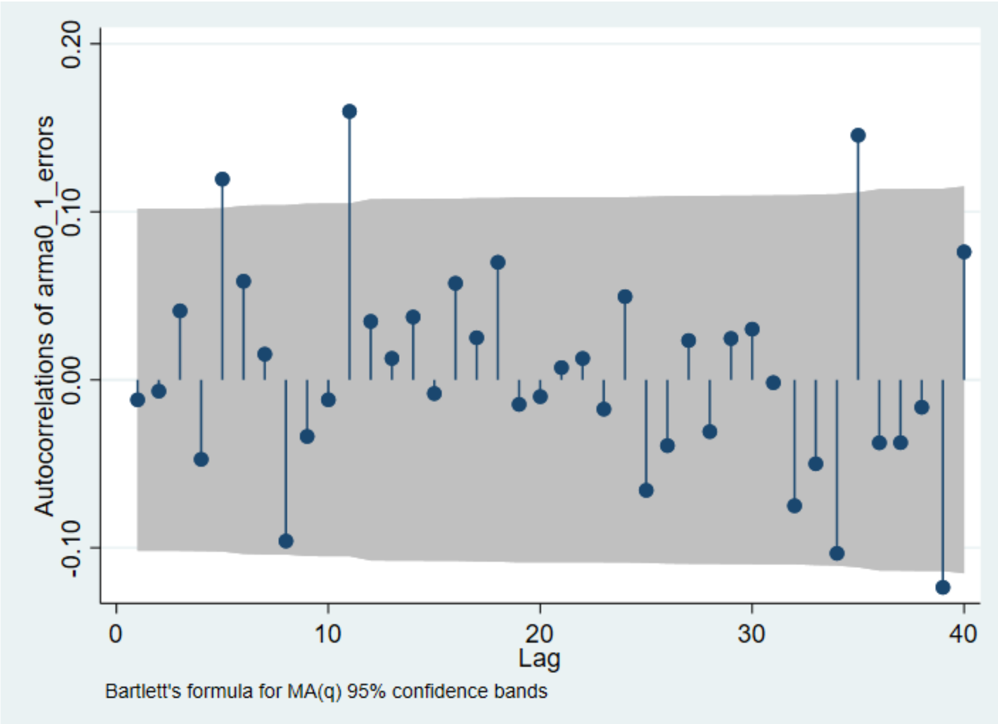

Figure 2.C.1

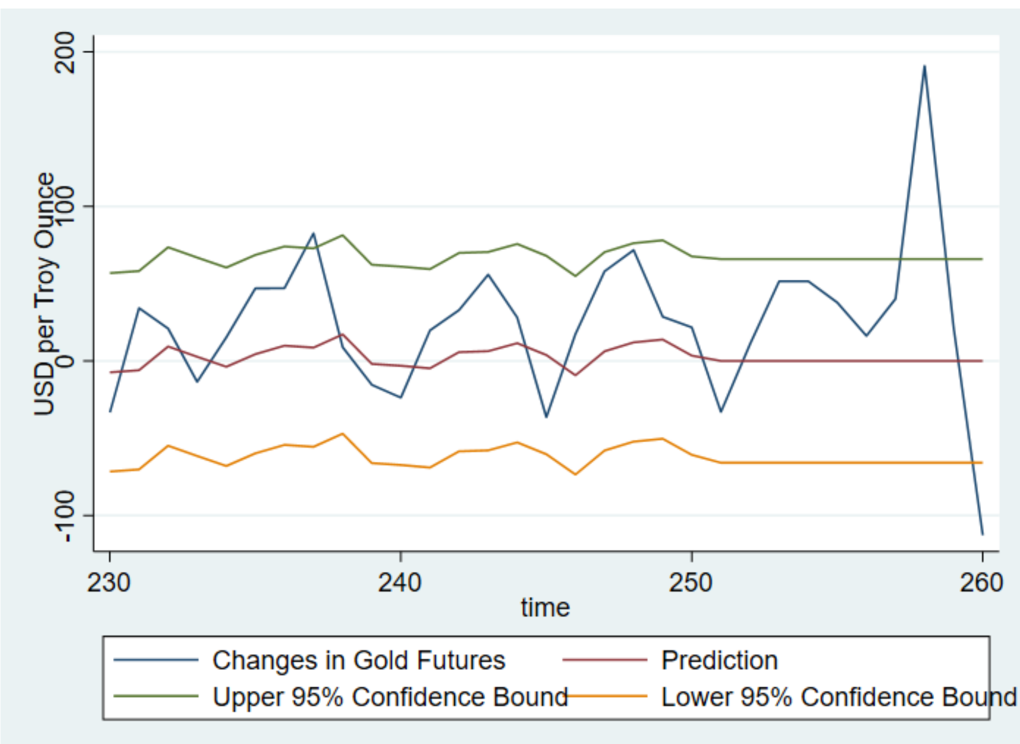

Figure 3.A.1

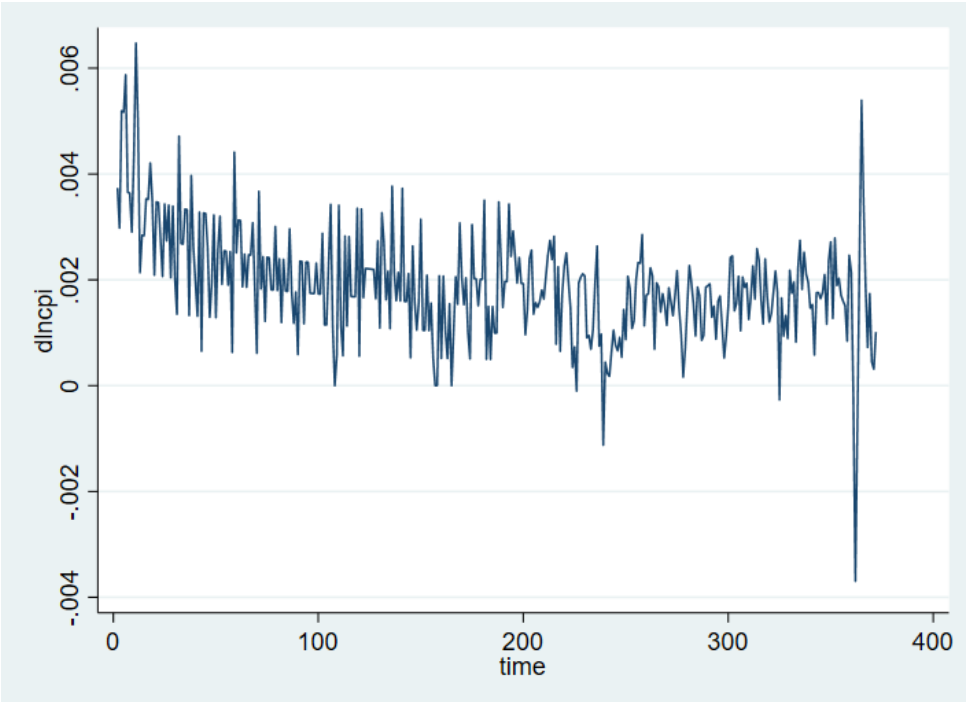

Figure 3.A.2

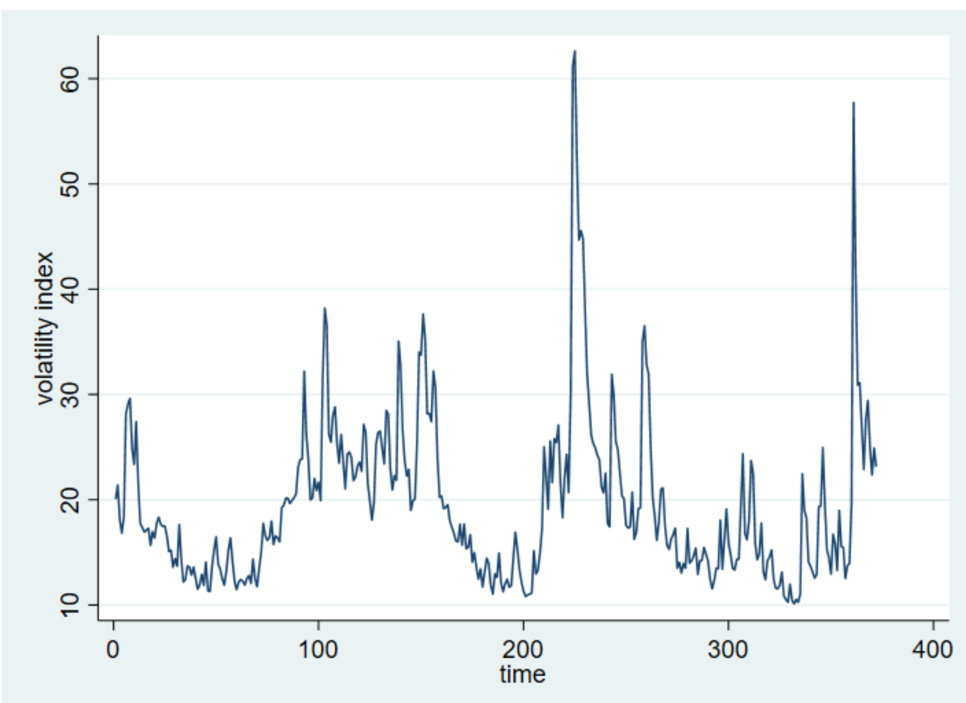

Table 3.A.1

Dickey-Fuller test for unit root		Number of obs =	371	
	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.379	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Table 3.A.2

Dickey-Fuller test for unit root		Number of obs =	371	
	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-12.553	-3.450	-2.875	-2.570

MacKinnon approximate p-value for Z(t) = 0.9914

Table 3.A.3

ARIMA regression

dgold	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	3.77	2.24	1.68	.092	-.621	8.16	
L.ar	.207	.036	5.74	0	.137	.278	
Constant	32.658	.693	47.10	0	31.299	34.017	

Mean dependent var	3.828	SD dependent var	33.424
Number of obs	371.000	Chi-square	32.929
Prob > chi2	.	Akaike crit. (AIC)	3645.520

Figure 3.A.4

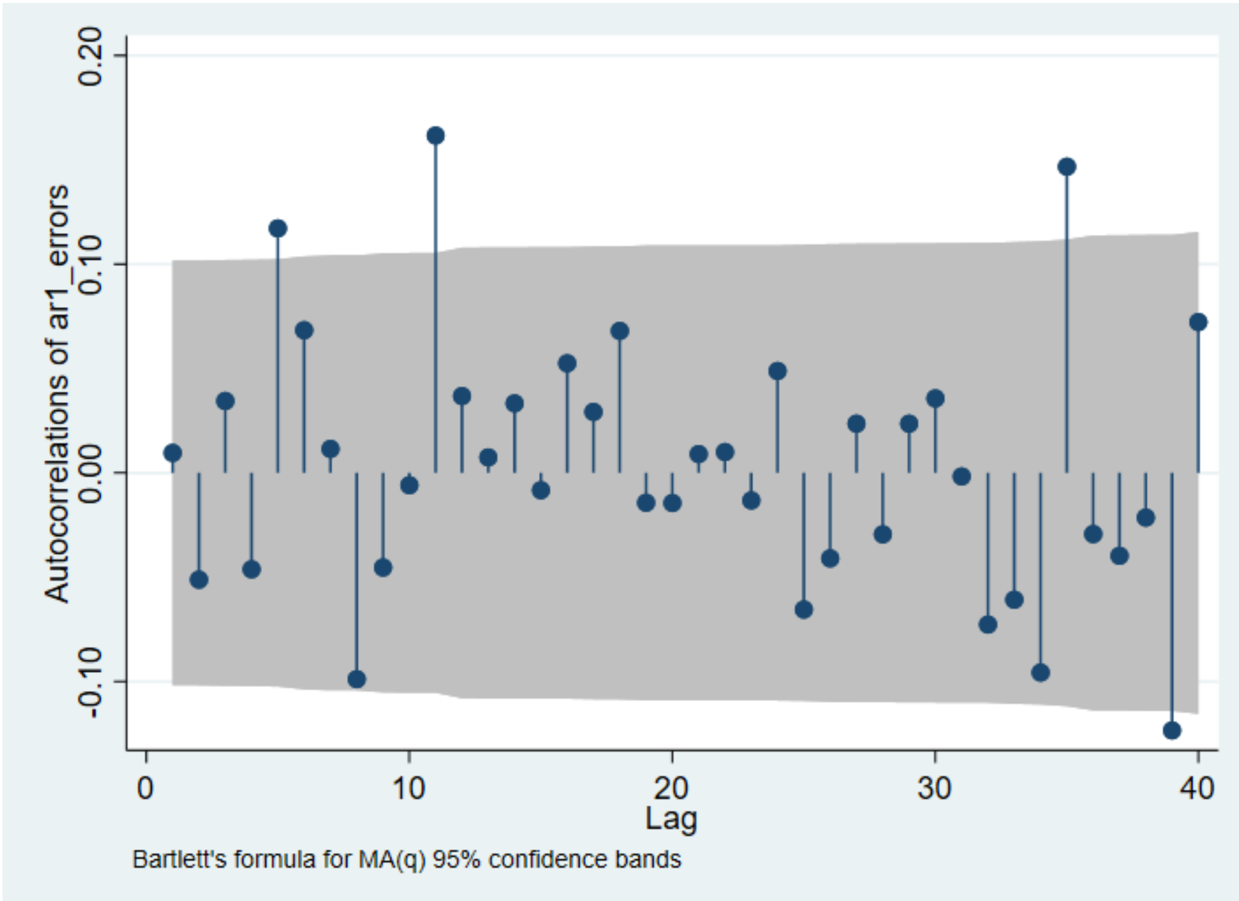
Autocorrelations of ar1_errors
0.20
0.10
0.00
-0.10
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands

Table 3.A.4

Vector autoregression
Sample: 3 - 372 Number of obs = 370
Log likelihood = -805.2757 AIC = 4.417706
FPE = .0166404 HQIC = 4.468122
Det(Sigma_ml) = .0155952 SBIC = 4.544631

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dgold	4	32.7781	0.0475	18.44128	0.0004
dlncpi	4	.000958	0.1772	79.70191	0.0000
vol	4	4.06019	0.7311	1006.01	0.0000

	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
dgold						
dgold						
L1.	0.200	0.051	3.890	0.000	0.099	0.300
dlncpi						
L1.	857.320	1633.120	0.520	0.600	-2343.537	4058.177
vol						
L1.	0.290	0.222	1.310	0.191	-0.145	0.726
_cons	-4.192	5.974	-0.700	0.483	-15.901	7.517
dlncpi						
dgold						
L1.	0.000	0.000	0.260	0.798	-0.000	0.000
dlncpi						
L1.	0.383	0.048	8.030	0.000	0.290	0.477
vol						
L1.	-0.000	0.000	-2.450	0.014	-0.000	-0.000
_cons	0.001	0.000	8.440	0.000	0.001	0.002
vol						
dgold						
L1.	0.002	0.006	0.380	0.707	-0.010	0.015
dlncpi						
L1.	290.966	202.293	1.440	0.150	-105.521	687.453
vol						
L1.	0.860	0.028	31.230	0.000	0.806	0.914
_cons	2.171	0.740	2.930	0.003	0.721	3.621

Figure 3.B.1

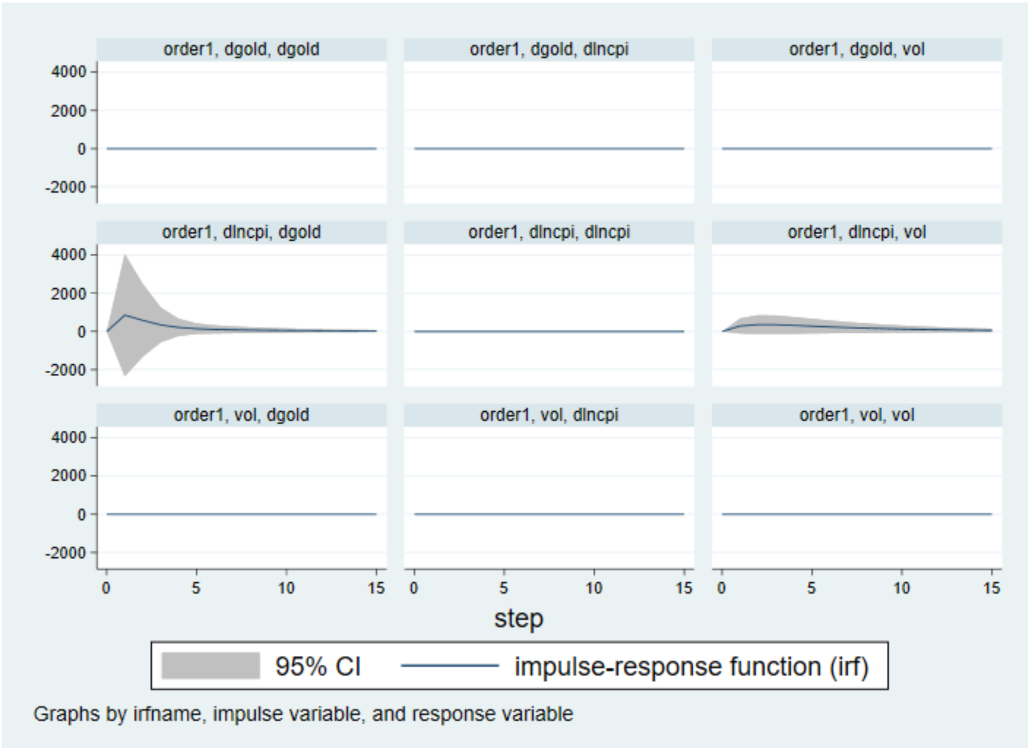

Figure 3.B.2

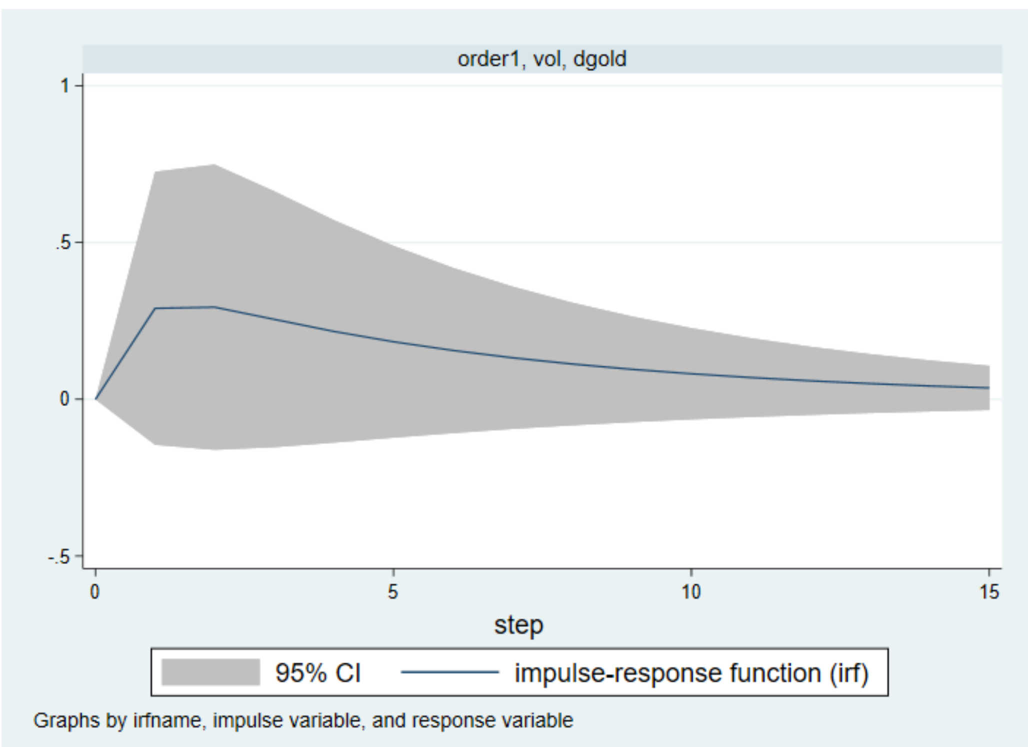

Figure 3.B.3

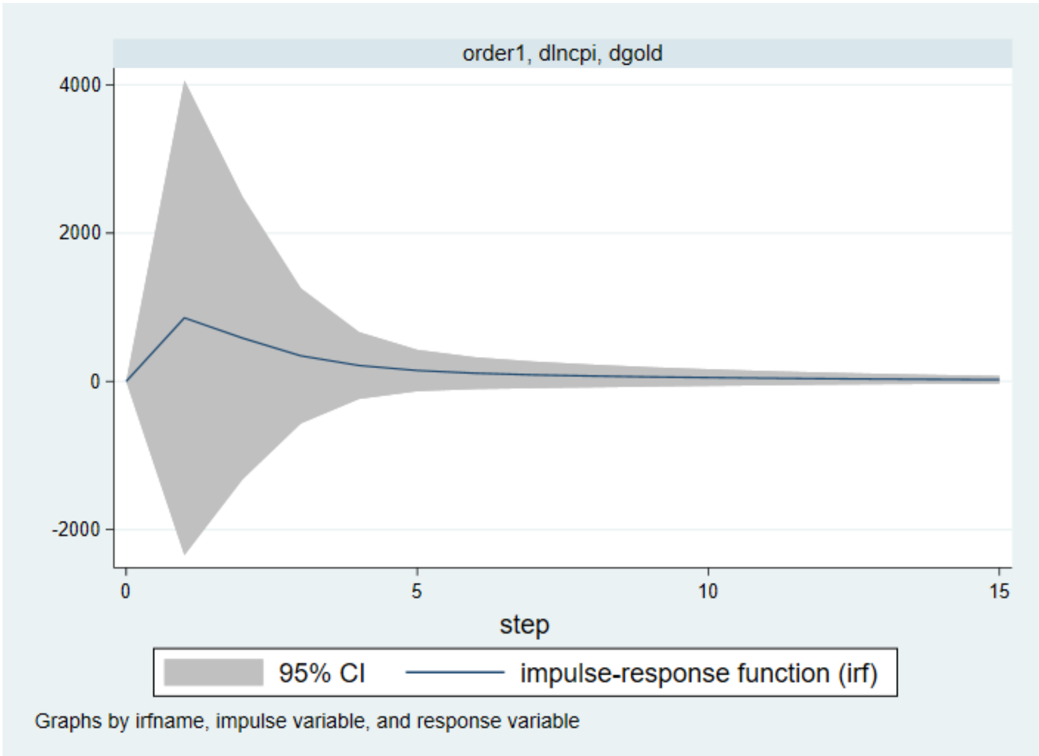

Figure 3.B.4

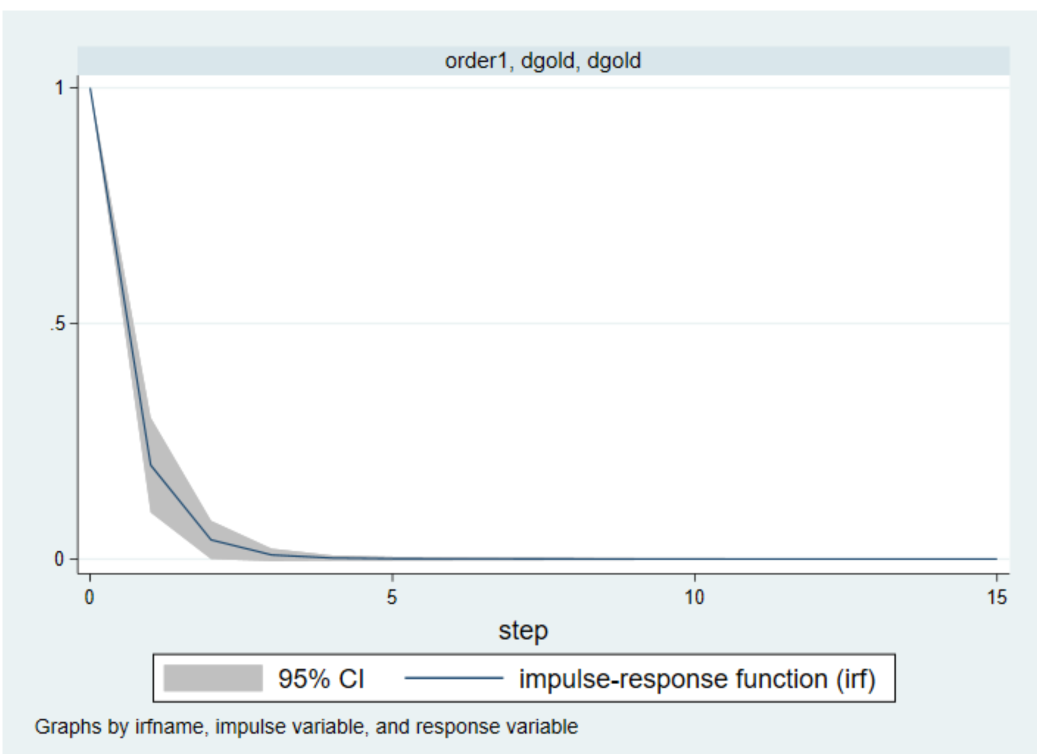

Figure 3.B.5

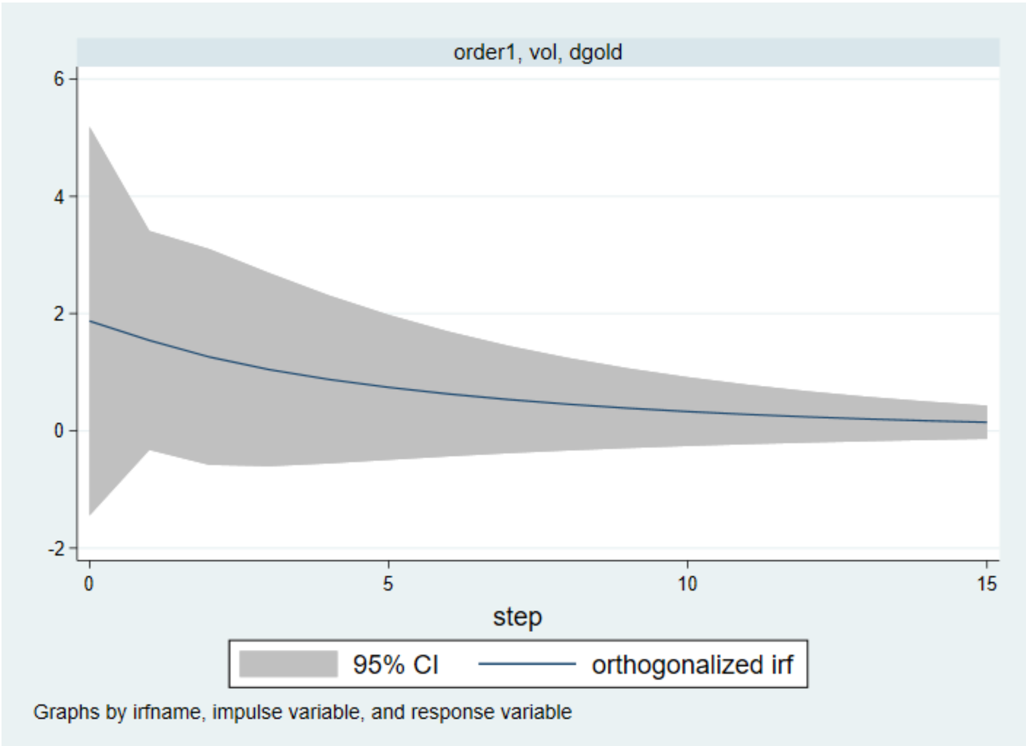

Figure 3.B.6

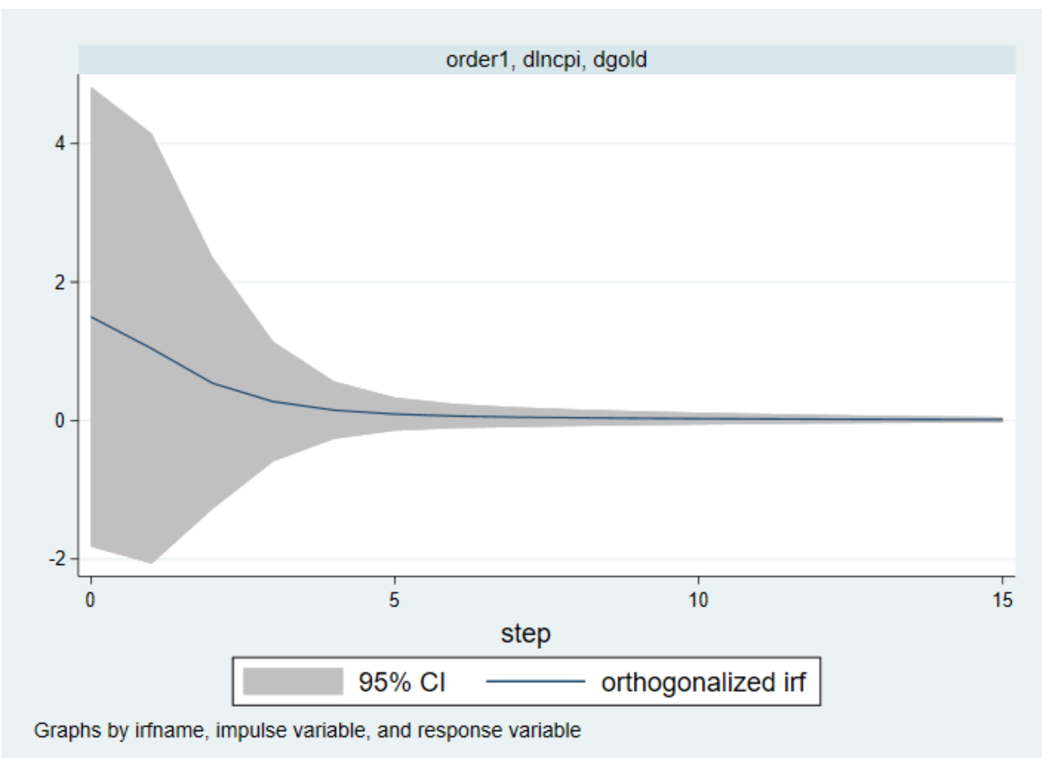

Figure 3.B.7

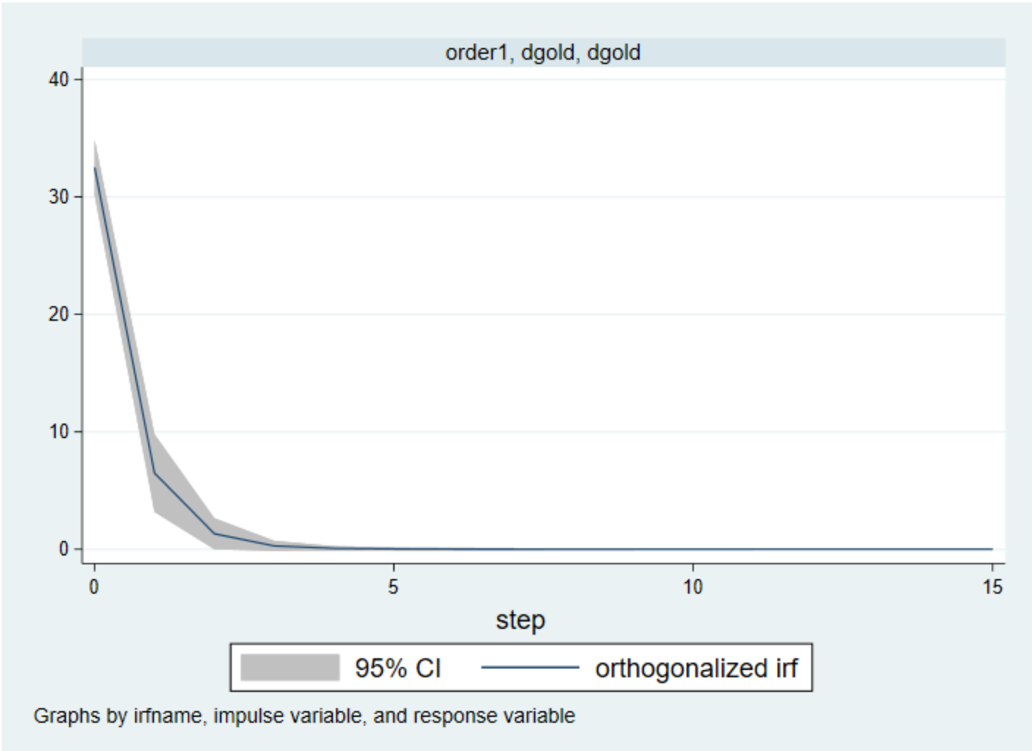

Figure 3.B.8

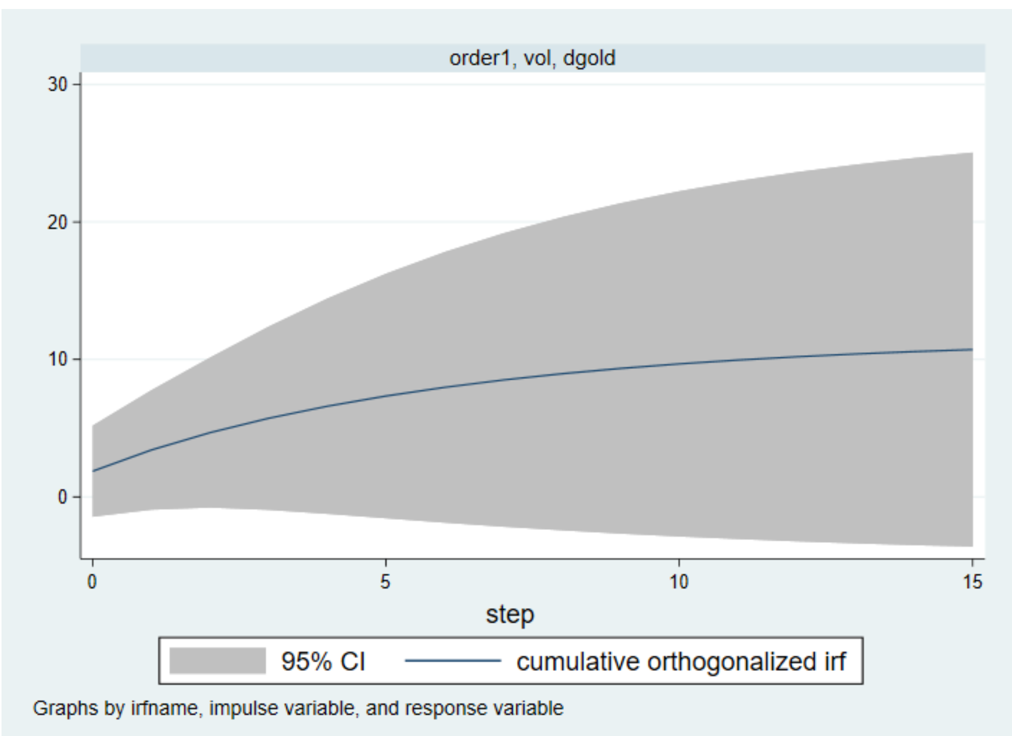

Figure 3.B.9

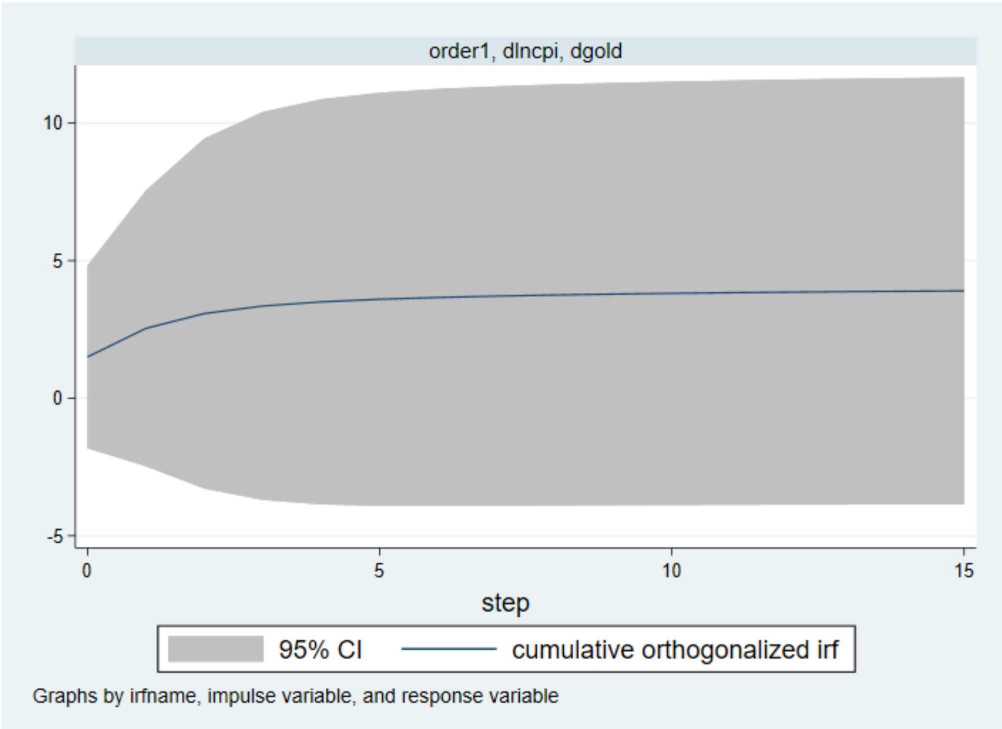

Figure 3.B.10

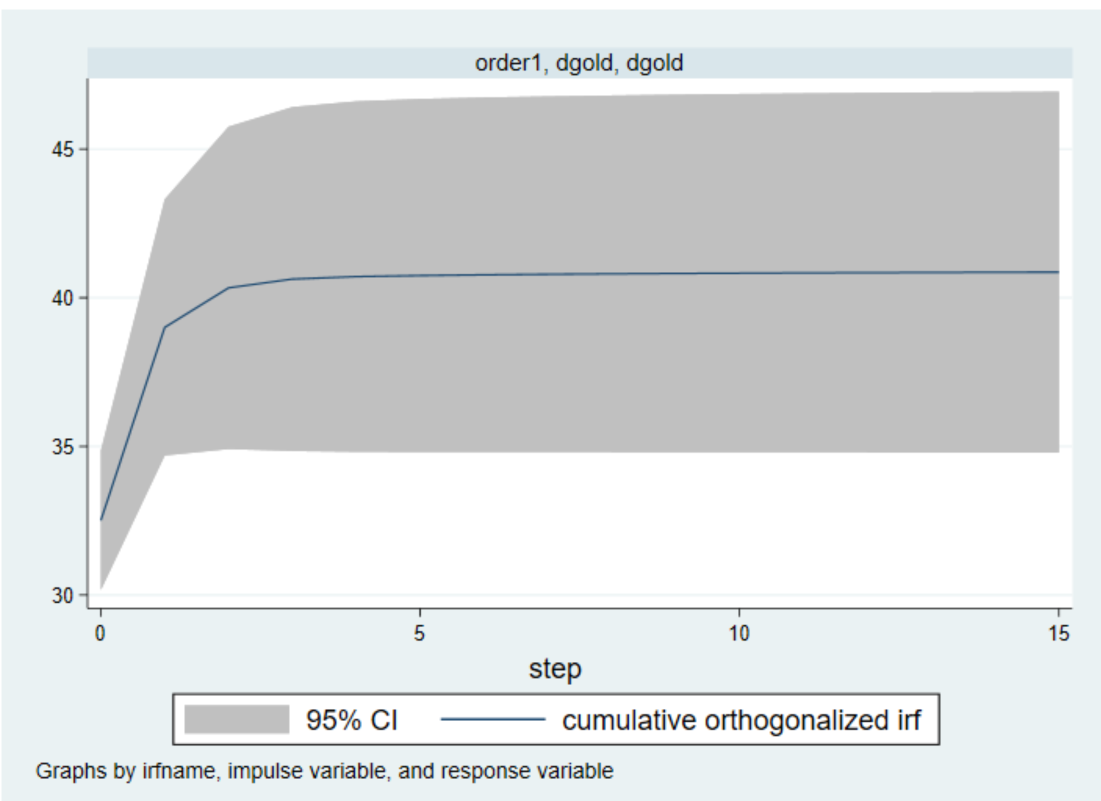

Table 3.B.1

	(3)		
step	Upper	fevd	Lower
0	0	0	0
1	0.018	0.002	-0.007
2	0.009	0.003	-0.009
3	0.008	0.003	-0.009
4	0.011	0.003	-0.010
5	0.013	0.003	-0.010
6	0.015	0.003	-0.010
7	0.016	0.003	-0.010
8	0.017	0.003	-0.010
9	0.018	0.003	-0.010
10	0.018	0.003	-0.010
11	0.019	0.003	-0.010
12	0.019	0.003	-0.010
13	0.019	0.003	-0.010
14	0.019	0.003	-0.010
15	0.019	0.003	-0.010

	(6)			(9)		
step	fevd	Lower	Upper	fevd	Lower	Upper
0	0	0	0	0	0	0
1	0.003	-0.008	0.015	0.995	0.980	1.010
2	0.005	-0.009	0.019	0.992	0.973	1.010
3	0.007	-0.009	0.023	0.990	0.969	1.011
4	0.008	-0.010	0.026	0.989	0.967	1.011
5	0.008	-0.011	0.028	0.988	0.965	1.012
6	0.009	-0.012	0.030	0.988	0.963	1.012
7	0.009	-0.012	0.031	0.987	0.962	1.013
8	0.009	-0.013	0.032	0.987	0.961	1.013
9	0.010	-0.013	0.032	0.987	0.961	1.013
10	0.010	-0.013	0.033	0.987	0.960	1.013
11	0.010	-0.013	0.033	0.987	0.960	1.013
12	0.010	-0.014	0.034	0.987	0.960	1.014
13	0.010	-0.014	0.034	0.987	0.960	1.014
14	0.010	-0.014	0.034	0.987	0.960	1.014
15	0.010	-0.014	0.034	0.987	0.959	1.014

95% lower and upper bounds reported
(3) irfname = order1, impulse = dlncpi, and response = dgold
(6) irfname = order1, impulse = vol, and response = dgold
(9) irfname = order1, impulse = dgold, and response = dgold

Figure 3.B.11

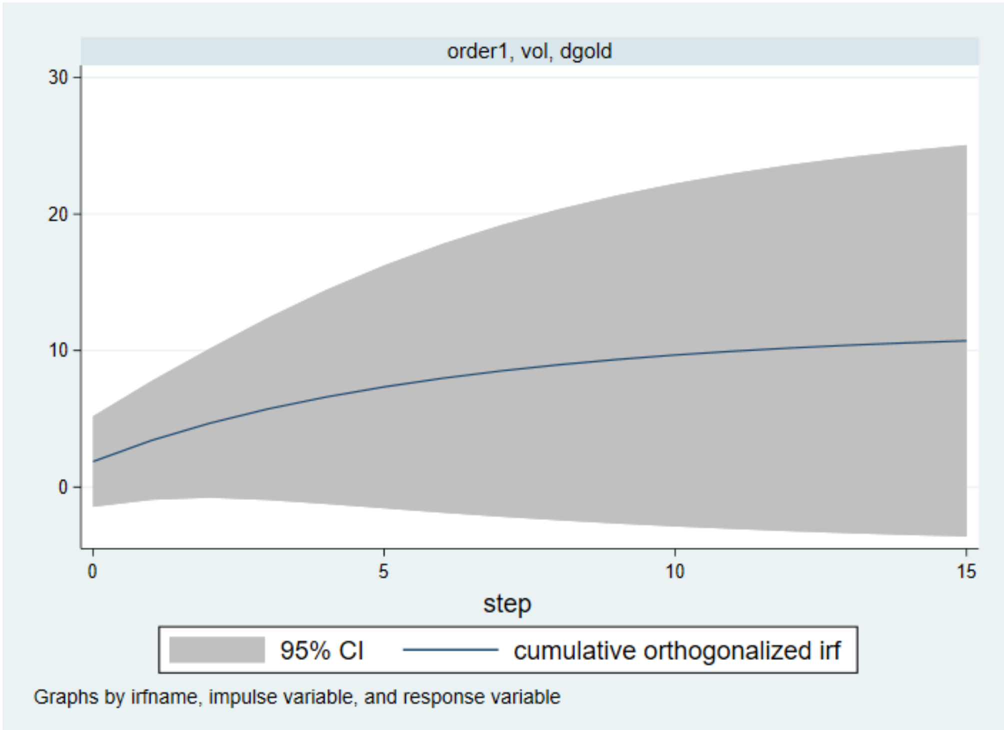

Figure 3.B.12