CENTRAL BANK OF CYPRUS
EUROSYSTEM

WORKING PAPER SERIES

Investing in Gold: Individual Asset Risk in the Long Run

Antonis Michis

June 2014

Working Paper 2014-02

Central Bank of Cyprus Working Papers present work in progress by central bank staff and outside contributors. They are intended to stimulate discussion and critical comment. The opinions expressed in the papers do not necessarily reflect the views of the Central Bank of Cyprus or the Eurosystem

Address
80 Kennedy Avenue
CY-1076 Nicosia, Cyprus

Postal Address
P. O. Box 25529
CY-1395 Nicosia, Cyprus

E-mail
publications@centralbank.gov.cy

Website
http://www.centralbank.gov.cy

Fax
+357 22 378153

Papers in the Working Paper Series may be downloaded from:
http://www.centralbank.gov.cy/nqcontent.cfm?a_id=5755

Investing in gold: individual asset risk in the long run

Antonis Michis[1]

Abstract

This study examines gold's contribution to portfolio risk over different time scales. The analysis is based on wavelet decompositions of the variances and covariances associated with a portfolio that includes gold, stocks, 10-year government bonds and three-month Treasury bills. The results suggest that gold provides the lowest contribution to portfolio risk only when considered over medium- and long-term investment horizons.

Keywords: gold; asset risk; wavelets; covariance

JEL classification: G11; G15

[1] The opinions expressed in this paper are those of the author and do not necessarily reflect the views of the Central Bank of Cyprus or the Eurosystem. The author would like to thank Alex Michaelides, Christos Savva and Panayiotis Theodossiou for helpful comments and suggestions.

Correspondence: Antonis A. Michis, Statistics Department, Central Bank of Cyprus, 80 Kennedy Avenue, P.O.Box 25529, CY-1395, Nicosia, Cyprus. Email: AntonisMichis@centralbank.gov.cy

1. Introduction

Unlike most financial assets used for diversification, gold does not bear a counter-party risk. It is a universally accepted asset that is commonly used as a store of value and is characterized by high liquidity. An important diversification property of gold is its negative correlation with many asset classes commonly used in investment portfolios. This is particularly true for US stocks and portfolios having a large portion of equities.

Technically, gold has been associated with three main properties when used in a portfolio context. First, it reduces negative skewness and the impact of outliers on the distribution of returns, providing a closer approximation to the normal distribution. Second, its diversification properties are not negated during periods of unanticipated inflation. Third, it improves portfolio performance during periods of financial stress (see, Scott-Ram, 2002, p. 137).

In this study, a wavelet analysis is used to obtain time scale decompositions of the variances and covariances associated with a portfolio of assets that includes gold, stocks, 10-year government bonds and three-month treasury bills. The time scale decompositions generated by wavelets permit an evaluation of gold's contribution to portfolio risk over different cycles. The results suggest that gold provides the lowest contribution to portfolio risk and is an effective diversifier only when considered over medium- and long-term investment horizons.

2. Diversification properties and investment horizon

With regard to inflation, gold is known to provide a good hedge only when considered over long periods of time (see, Fraser-Sampson, 2011, p. 169). Over short periods, the price of gold is highly volatile and thus less useful for hedging. Gold is therefore not very appropriate for investors adopting a short-term, strategic approach for quick returns. In contrast, it is highly valuable to investors with a long-term orientation and a passive strategy of holding their assets for long periods of time.

In addition to inflation, gold is also known to provide a good hedge against the US dollar over periods when the value of the dollar weakens (Joy, 2011). Such periods are closely linked with the macroeconomic conditions in the US economy, which are usually associated with business cycles that expand over several months or years. In this case, positions in gold are also more meaningful when considered as medium- to long-term investments. Using copula methods, Reboredo (2013) demonstrated that gold provides both a valuable hedge and a safe haven asset in periods of extreme US dollar movements and effectively reduces risk in currency portfolios.

A number of studies have empirically investigated the diversification properties of gold. Gold's performance as a hedge or safe haven asset varies by asset class and market. For example, Baur and McDermott (2010) showed that gold is a good hedge and a safe haven for stocks from major European countries and the US, but the same is not true for Australia, Canada, Japan and the BRIC countries.

With regard to bonds, Baur and Lucey (2010) showed that gold cannot be considered a safe haven for bonds from the US, the UK and Germany. In addition, Agyei-Ampomah et al. (2014) found that gold provides an effective hedge for bonds from countries with debt issues (e.g., Greece and Portugal) but exhibits positive co-movement with UK and German bonds in periods of high market volatility. This finding suggests that investors view high quality bonds and gold as substitutes.

Given the above mentioned cyclical characteristics of gold as an investment asset, it is of interest to examine its contribution to portfolio risk across the cycle. Most studies investigate the diversification properties of gold using actual market- level data. However, such data cannot provide any insight with regard to the diversification properties of gold over different time scales (or cycles). As a result, it is not possible to examine how gold's individual asset risk in the context of a portfolio differs among short-, medium- and long-term cycles. This is an important distinction in the examination of gold as an investment asset.

3. Individual asset risk by time scale

3.1. Wavelet variance and covariance

Square-integrable functions or signals can be decomposed at different time scales using sequences of local basis functions termed father (ϕ) and mother (ψ) wavelets. They are defined as follows (see, Gallegati et. al., 2011):

$$\phi_{j,k} = 2^{-j/2}\phi\left(\frac{t-2^{j}k}{2^{j}}\right) \quad \text{and} \quad \psi_{j,k} = 2^{-j/2}\psi\left(\frac{t-2^{j}k}{2^{j}}\right).$$

A decrease in the value of j reduces the width and doubles the frequency of the mother wavelet, which enables a better representation of the short-term, high-frequency oscillations in the signal. In contrast, the father wavelet is not affected by changes in j. It is designed to represent the smooth trend behavior in the data. Changes in the value of k

shift the location of both the father and mother wavelets, thus enabling better adaptation to the local features of the data.

Using the father and mother wavelets, a multiresolution approximation of a signal χ_t can be formed as follows:

$$\chi_t = \sum_k s_{J,k}\,\phi_{J,k}(t) + \sum_k d_{J,k}\,\psi_{J,k}(t) + .. + \sum_k d_{j,k}\,\psi_{j,k}(t) + ... + \sum_k d_{1,k}\,\psi_{1,k}(t). \qquad (1)$$

The wavelet coefficients in equation (1) are based on the following integrals:

$$s_{J,k} = \int \chi_t\,\phi_{J,k}(t)\,dt \quad \text{and} \quad d_{j,k} = \int \chi_t\,\psi_{j,k}(t)\,dt .$$

The father wavelet coefficients ($s_{J,k}$) capture the low-frequency trend behavior in the signal, and the mother wavelet coefficients ($d_{j,k}$) capture all high-frequency, short-term oscillations from the trend. Therefore, time scales corresponding to higher values of j are associated with long-term cycles in the data, and time scales corresponding to small values of j are associated with short-term cycles in the data.

A wavelet multiresolution analysis can be performed using either a discrete wavelet transform (DWT) or a maximal overlap discrete wavelet transform (MODWT). The DWT provides an orthogonal decomposition of the signal but is associated with two limitations: the sample size must be of dyadic length (a power of 2) and the father and mother wavelet coefficients are not shift-invariant (as a result of the decimation operations they are sensitive to circular shifts).

Although not exactly orthogonal, the MODWT is more efficient than the DWT and is also characterized by the following advantages: (i) for each time scale it generates vectors of wavelet coefficients that have equal length with the actual time series, (ii) it can be used to analyze time series of any length, and (iii) it is translation-invariant; therefore, the wavelet coefficients are not affected by shifts in the signal (see Kim and In, 2010).

In practice, the MODWT is computed with a pyramid algorithm that iteratively filters the time series with a scaling (low-pass) and a wavelet (high-pass) filter to produce the vectors of wavelet coefficients (see, Gencay et. al., 2002, pp. 136-137). When working with monthly time series of length $256 = 2^8$ observations, the generated wavelet coefficients at scale 1 (d_1) capture cyclical variation over durations of 2-4 months. Accordingly, the wavelet coefficients at scales 2 (d_2) and 3 (d_3) capture cyclical variation over durations of 4-8 and 8-16 months, respectively. This is the case up to level 8. For non-dyadic length time series, the data can be padded with the last value of the series to increase the length to the next power of 2, and then perform the MODWT (see, Gencay et al., 2002, p. 144).

Using the wavelet coefficients generated by the MODWT, the wavelet variance of a stationary process (χ_t), at time scale λ_j, can be estimated as follows (see, Percival and Walden, 2000, p. 306):

$$\sigma_{\chi}^{2}(\lambda_j) = \frac{1}{\tilde{T}_j} \sum_{t=L_j-1}^{T-1} (d_{j,t}^{\chi})^2 \ . \qquad (2)$$

The variances generated by the wavelet coefficients at each time scale effectively capture the variance of the actual time series. As before, $d^{\chi}_{j,t}$ represents the scale λ_j wavelet coefficients of the process generated by the MODWT. $L_j = (2^j - 1)(L+1) + 1$ is the length of the wavelet filter used to generate the scale λ_j wavelet coefficients and $\tilde{T}_j = T - L_j + 1$ refers to the number of coefficients unaffected by the boundary. Consequently, the coefficients that make use of the periodic boundary conditions are not included in the variance estimator.

Similarly, the wavelet covariance estimator decomposes the covariance between two stationary processes (χ_t and y_t) into different time scales as follows:

$$\sigma_{\chi,y}(\lambda_j) = \frac{1}{\tilde{T}_j} \sum_{t=L_j-1}^{T-1} d^{\chi}_{j,t} d^{y}_{j,t} \, . \tag{3}$$

In this case, coefficients that make use of the periodic boundary conditions are also not included in the estimator. These wavelet variance and covariance estimators were used by Gencay et al. (2005) to estimate the systematic risk (beta) of stocks and by Kim and In (2010) to analyze optimal portfolio allocation by time scale.

3.2. Individual asset risk

In this subsection, the expressions for the wavelet variance and covariance reported in equations (2) and (3) above are used in the context of the mean-variance portfolio framework to obtain estimates of the risk associated with a single asset (e.g., gold). To see this, consider a portfolio of N risky assets. The variance of the portfolio is equal to the sum of all possible weighted covariances associated with the returns (r) of the N risky assets:

$$V(r) = \sum_{i=1}^{N} \sum_{h=1}^{N} w_i w_h \sigma_{ih} .$$

To evaluate the contribution of a single risky asset to total portfolio risk, Copeland et al. (2005, p. 139) suggested calculating the partial derivative of the portfolio variance with respect to the weight of the asset (w_i is the percentage invested in the i -th risky asset) as follows:

$$\frac{\partial V(r)}{\partial w_i} = 2 w_i \sigma_i^2 + 2 \sum_{h=1}^{N} w_h \sigma_{ih} . \tag{4}$$

Using the partial derivative in (4) and the expressions for the wavelet variance and covariance in (2) and (3), the risk associated with asset i , at time scale λ_j , can be estimated as follows:

$$risk(i, \lambda_j) = 2 w_i \sigma_i^2 (\lambda_j) + 2 \sum_{h=1}^{N} w_h \sigma_{ih} (\lambda_j) . \tag{5}$$

In the next section, expression (5) is used in the context of a portfolio of assets to calculate the risk associated with each class of assets.

4. Results and discussion

In this section, an equally weighted portfolio is considered that includes gold, stocks, 10-year government bonds and three-month Treasury bills (T-bills). The data consist of monthly returns for the period of September 1991 to December 2012. Three major economies are represented in the asset classes of the portfolio: Germany, the UK and the US. The data for gold returns were obtained from the World Gold Council. For the other asset classes the data were obtained from the OECD statistical database. Summary statistics of the returns associated with each asset class are included in Table 1.

Table 1 Summary statistics of returns

	Germany			UK			US			
	Stocks	**Bonds**	**T-bills**	**Stocks**	**Bonds**	**T-bills**	**Stocks**	**Bonds**	**T-bills**	**Gold**
Mean	0.467	4.696	3.637	0.390	5.483	4.910	0.584	4.926	3.460	0.713
St. Dev	4.907	1.651	2.207	3.648	1.923	2.397	3.702	1.501	2.105	4.526
Min	-20.857	1.240	0.190	-18.182	1.640	0.500	-22.486	1.530	0.190	-17.383
Max	13.855	8.500	9.880	10.475	9.770	10.780	12.652	7.960	6.730	17.347

The returns of the ten asset classes included in Table 1 were analyzed with the MODWT using a Daubechies least asymmetric wavelet filter of length 8. This filter was also used by Gencay et al. (2005) and Kim and In (2010) to analyze similar data, and provided good resolutions of the data used in this study. Following the wavelet transform, all possible wavelet variances and covariances between the ten asset classes were estimated for eight time scales using the estimators in equations (2) and (3). The estimates were then incorporated into expression (5) to calculate the individual risk associated with each asset class by time scale. The results are presented in Table 2.

The shaded areas indicate the minimum values (lowest contributions to risk) by time scale. Gold provides the lowest contribution to portfolio risk in time scales 5-8 (negative values indicate reduction of risk). These time scales are associated with cyclical movements of length 32-256 months and are therefore more relevant to investors with a medium- to long-term orientation. With regard to time scales 1-4 that are associated with cyclical movements of length 2-32 months, the lowest contribution to risk is provided by US Treasury bills. Gold's contribution to risk in time scale 1 (cycles of length 2-4 months) is similar to stocks, and in time scales 2 and 3, exceeds that of bonds.

Table 2 Individual asset risk by time scale

Time	Germany			UK			US			
Scale	Stocks	Bonds	T-bills	Stocks	Bonds	T-bills	Stocks	Bonds	T-bills	Gold
1	3.678	0.042	0.040	3.095	0.037	0.021	2.849	0.043	**-0.010**	3.179
2	2.643	0.071	0.083	2.081	0.064	0.064	2.129	0.041	**0.022**	1.101
3	1.621	0.073	0.081	1.015	0.064	0.074	1.171	0.056	**0.020**	0.263
4	0.947	0.250	0.198	0.548	0.268	0.274	0.740	0.230	**0.132**	0.246
5	0.455	0.484	0.578	0.379	0.565	0.633	0.501	0.450	0.352	**-0.023**
6	0.303	0.566	1.075	0.166	0.696	1.274	0.043	0.579	1.022	**-0.098**
7	0.472	0.966	0.764	0.397	1.229	1.185	0.425	0.929	1.100	**-0.536**
8	0.191	0.653	0.511	0.189	0.764	0.717	0.234	0.629	0.691	**-0.537**

The shaded areas indicate minimum values.

Furthermore, the results in time scales 5-8 suggest that stocks are less risky when considered over long time horizons. This finding is consistent with the study of Kim and In (2010), who suggest the allocation of greater weighting to stocks as the investment horizon lengthens, due to the mean reverting property that characterizes stock returns (see Barberis, 2000).

The results for gold confirm the findings presented in Section 2. The price of gold is highly volatile in the short term and therefore entails a high contribution to portfolio risk when considered over short-term investment horizons. Therefore, it is not appropriate for investors adopting a short-term, strategic approach to investments. In the long term, gold is very useful for hedging due to its negative correlation with the other asset classes and effectively reduces portfolio risk. Therefore, it is highly valuable to investors with a long-term orientation.

References

Agyei-Ampomah, S., Gounopoulos, D., Mazouz, K., 2014. Does gold offer a better protection against losses in sovereign debt bonds than other metals? Journal of Banking and Finance, 40, 507-521.

Barberis, N., 2000. Investing for the long-run when returns are predictable. Journal of Finance, 55, 225-264.

Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review, 45, 217–229.

Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. Journal of Banking and Finance, 34, 1886–1898.

Copeland, T., Weston, J., Shastri, K., 2004. Financial Theory and Corporate Policy, fourth ed. Pearson Addison Wesley, Mass.

Fraser-Sampson, G., 2010. Alternative assets: investments for a post-crisis world. John Wiley and Sons, Chichester, UK.

Gallegati, M., Gallegati, M., Ramsey, J.B., Semmler, W., 2011. The US Wage Phillips Curve across Frequencies and over Time. Oxford Bulletin of Economics and Statistics, 73, 489-508.

Gencay, R., Selcuk, F., Whitcher, B., 2005. Multiscale systematic risk. Journal of International Money and Finance, 24, 55-70.

Gencay, R., Selcuk, F., Whitcher B., 2002. An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Academic Press, New York.

Joy, M., 2011. Gold and the US dollar: hedge or heaven? Finance Research Letters, 8, 120-131.

Kim, S., In, F., 2010. Portfolio allocation and the investment horizon: a multiscaling approach. Quantitative Finance, 10, 443-453.

Percival, D.B., Walden, A.T., 2000. Wavelet Methods for Time Series Analysis. Cambridge University Press, Cambridge.

Reboredo, J.C., 2013. Is gold a safe haven of a hedge for the US dollar? Implications for risk management. Journal of Banking and Finance 37, 2665-2676.

Scott-Ram, R., 2002. Investing in gold and precious metals, in: Jobman, D.R., (Ed.), The Handbook of Alternative Assets, New York, John Wiley and Sons.