Are Gold Bugs Coherent?

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Abstract

We use wavelet models to surface the relationship between gold miners stoc prices and the price of gold. We find that there is little relationship in the short run but some significant and long standing long run relationships. Gold prices appear to lead gold miner stock prices.

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1. Introduction

Significant research suggests that gold, in financial (futures) or physical form, can be a useful diversifier for portfolios. From early work by Sherman (1982) through Jaffe (1989) and to more recent work by Lucey *et al.* (2006) , Hillier *et al.* (2006) and Conover and Jensen (2009) the literature suggests a small, typically less than 5% allocation to gold is beneficial. Gold can be, in the medium to long term, a useful hedge. Gold has also been examined from the perspective of its potential as a safe haven (see inter alia Baur and McDermott (2010), **?**, Joy (2011), Ciner *et al.* (2013), with the general conclusion being that it provides protection to a portfolio from extreme market events. Gold therefore can play a useful role in reducing a portfolio's risk.

Gold is traded in a variety of ways and around the world. The two major centers for gold trading, the London over-the-counter (LOTC) spot market and the New York Mercantile Exchange Futures Market (COMEX), account for approximately 78.0% and 7.7% of the total gold turnover. Murray (2011) The London OTC market for bullion is the largest pool of gold assets, although the most important, from the perspective of setting a gold price, appears to be the New York futures market, COMEX in particular. See Hauptfleich *et al.* (2016). In 2011, estimated daily turnover in the international gold market was 4,000 metric tons, a money volume approximately the same as the daily dollar volume of trade on all of the worlds stock exchanges combined. If we were to consider gold as a currency it would be the fifth largest currency. [1]

Investors wishing to get exposure to gold in other forms can look to gold mining stocks (as well as variety of other approaches - see Batten *et al.* (2015). A complicating factor is that first, there are limited numbers of gold miners, and second in many cases it is impossible to obtain a pure mine substitute, as gold is frequently extracted in conjunction with other minerals. MacDonald and Taylor (1988) provides an early examination, of 20 South African

[1]data on the stock exchanges is from the World Federation of Stock Exchanges , and the currency data is based on BIS data

miners, and finds that there is a statistically significant positive relationship between mine share prices and gold, with asymmetry evident in a greater relationship for higher cost miners. This is also the case in Blose and Shieh (1995), for 23 US miners and for australian miners in Faff and Chan (1998) and for US miners using more recent data, as in Borenstein and Farrell (2007). OConnor *et al.* (2015) however finds that that the gold price leads production costs suggesting that an examination of gold mining companies as alternatives is not a useful path. This finding is in line with the results of Areal *et al.* (2013) who find little benefit from a safe haven perspective of investing in gold mining companies.

Here we examine the relationship between the gold price and the NYSE ARCA Gold Bugs index of gold miner share prices over a 17 year period using wavelet analysis.

2. Methodology

2.1. Continuous Wavelet Transformation

Wavelet multi-scale analysis is a technique appropriate for the estimation of spectral characteristics of a time series. In this paper, we measure the degree of local variability and co-variability between gold (returns) and changes in the Gold Bugs Index using the wavelet power, cross-wavelet coherence and the phase difference. Each of these are displayed in a three dimensional diagram that demonstrates time series information at different frequencies (low and high) and points in time simultaneously. The computational framework adopted for this study is fundamentally based on Torrence and Compo (1998) and Grinsted *et al.* (2004).

The wavelet transform approach is particularly applicable to financial and economic time series and has been widely documented in previous studies (In and Kim, 2006; Gençay *et al.*, 2001; Percival and Walden, 2000). The pioneering work on wavelet multi-scale analysis in finance is documented in Ramsey *et al.* (1995), where they examine the contribution of the wavelet approach in detecting self-similarity in US stock prices, whilst Ramsey and Lampart (1998) study the money, income and expenditure link using the wavelet-based scaling method.

In this study, we apply the continuous wavelet transform and, in particular, wavelet coherency to analyze the phase and the degree of co-movement between changes in the returns of gold miner's stock prices and gold itself. The key innovation of wavelet multi-scale dynamics is detecting the scale-by-scale (or, alternatively, the frequency related) characteristics, thus allowing for separation between the short- and long-term behaviour between common changes in the Gold Bugs Index and the gold price. We specifically utilize the coherence measure, which enables the identification of phase (co-movement) or the anti-phase between oscillations of the series under consideration (Aguiar-Conraria and Soares, 2014; Grinsted *et al.*, 2004).

Wavelet multi-resolution analysis decomposes a time series through application of a wavelet $\psi(t)$ which is a function of a time parameter t. The wavelet function provides a balance between localization of time and frequency. Given a time series $f(t)$ expressed over the interval $[-\alpha < t < \alpha]$, the set of wavelet coefficients $W(\tau, \epsilon)$ is given by

$$W(\tau, \epsilon) = \sum_{t=1}^{N} f(t)\, \psi^{*} \left[\frac{t - \tau}{\epsilon} \right] \tag{1}$$

where $[\epsilon > o; -\alpha < \tau < \alpha]$, and the scale associated with the transformation and location of the window are defined by ϵ and τ respectively. ψ^* and $\frac{1}{\epsilon}$ refer to the complex conjugate of the wavelet and the normalization factor respectively. The *Morlet wavelet* , used here, is the product of a sine curve with a Gaussian and given by

$$\psi(t) = \pi^{\frac{1}{4}} \left(e^{i\omega_0 t} - e^{-\frac{\omega_0^2}{2}} \right) e^{\frac{-t^2}{2}} \tag{2}$$

where ω_0 is the wavenumber. For an appropriate choice of the wavenumber ω_0 the Morlet wavelet reduces to

$$\psi(t) = \pi^{\frac{1}{4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}} \tag{3}$$

The cross-wavelet power spectrum is the product of the wavelet coefficients calculated using $W_{\epsilon,\tau}(f,g) = W_{\epsilon,\tau}(f) * W_{\epsilon,\tau}(g)$, where $*$ is defined as a complex conjugate. In common with the conventional, non-spectral measure of covariance, the magnitude of the cross-wavelet power can also be influenced by the variance of each series. In order to ensure a spectral measure of co-movement which is comparable across time series, many studies use the wavelet coherence framework, calculated as the smoothed cross-wavelet spectrum, normalized by the smoothed wavelet power spectra,

$$R^2_{\epsilon,\tau} = \frac{|Q\left(\epsilon^{-1}W_{\epsilon,\tau}(f,g)\right)|^2}{Q\left(|\epsilon^{-1}W_{\epsilon,\tau}(f)\right)|^2 Q\left(|\epsilon^{-1}W_{\epsilon,\tau}(g)\right)|^2} \tag{4}$$

where Q refers to a smoothing operator in both time and scale (Torrence and Compo, 1998). Wavelet coherency is analogous to squared correlation, measuring the co-variation between two series divided by their variation at different scales and points in time. The value of the squared coherency $R^2_{\epsilon,\tau}$ is between zero (low level of synchronization or zero comovement) and one (strong synchronization or perfect co-movement). With this approach, the graphical presentation of the wavelet squared coherence enables us to identify the "region" of co-movement between inflation and gold returns in the time frequency space. The theoretical distribution of wavelet coherency is not known and Monte-Carlo methods are invoked to determine statistical significance (Aguiar-Conraria and Soares, 2014; Torrence and Compo, 1998).

The level of wavelet coherence provides information relating to the synchronization between two time series but does not indicate whether this relationship is positive or negative. To understand the form of synchronization between two time series, the wavelet multi-scale phase is employed. For two time series $f(t)$ and $g(t)$ this is given by

$$\theta_{\epsilon,\tau}\left(f,g\right) = tan^{-1}\left(\frac{\Im\{Q\left(\epsilon^{-1}W_{\epsilon,\tau}(f,g)\right)\}}{\Re\{Q\left(\epsilon^{-1}W_{\epsilon,\tau}(f,g)\right)\}}\right) \tag{5}$$

where $\Im$ and $\Re$ refer to the imaginary and real parts of the wavelet coefficients respectively and Q is the smoothing parameter. The phase arrows indicate the direction of co-movement among the investigated series pairwise. East (west) facing arrows represent in- (out-of-) phase, while north (south) facing arrows indicate that time series two leads (lags) time series one. A north-east (south-east) facing arrow symbolizes that the series are in-phase but that time series two (time series one) leads time series one (time series two). A north-west (south-west) facing arrow signifies that the series are out-of-phase but that time series one (time series two) leads time series two (time series one).

3. Data and Summary Statistics

We use two data series. Our gold price is the closing price each day for COMEX 100oz Gold; the NYSE ARCA Gold Bugs index represents the price of gold mining stocks. All data are daily, from 1/Jan 1998 to 20/Nov 2015, giving in total of 4668 observations. Shown in Figure 1 are the evolution of the two series.

[Figure 1 about here.]

4. Empirical Results

Shown in Figure 2 is the wavelet coherence plot for changes in the two data series. Warmer colours represent stronger coherence. Wavelet coherency analysis allows us to further measure the localized strength of the relationship between the miners and the gold price in both time and period.

Several issues are evident. Recalling that the vertical axis denotes days we can see that increased coherence between the two series is much more common in periods greater than one week. To the extent that there is a relationship between gold mining and gold prices it seems them to be a lagged relationship, taking at least a week for a changes to filter through. Second, most arrows are eastward facing, suggesting a broad in-phase relationship, indicating that the two variables are comoving positively. We do see some periods of anti-phase. At the lower frequency one in particular corresponds to the May-July 2012 period (around 3800 obs) and this is notable as also being a rare period of strong coherence at the lower frequency, around 5 days. At higher frequencies, over 1000 (or four years) we see strong and consistent coherence, with north-east facing arrows strongly suggesting that it is the gold price that leads miners stock prices, as would be expected as mine costs tend to lag behind price changes, as in OConnor *et al.* (2015). There are very few instances of strong coherence where we find a south-east arrow, which would suggest miners rarely lead the gold price. One instance in the medium frequency, of around 100 days, is evident from approximately Feb 2013 through the end of August 2013. This corresponds to a period of very rapidly declining gold prices, from circa. $1600 to $1200 in June. Though gold prices made a short lived recovery to $1400 by August, miners share prices fell continuously during this period, as eben with the rise the gold price was lower than the All-in Cost of producing gold in 2013 at $1741 (GFMS Gold Survey, 2015). Another period of south east arrows occurs between 2008 and 2010 at a year long frequency (between observations 2500 and 3200), of about 250 days. It is evident that we have reasonable coherence at the higher, longer frequencies. Examining the low frequency dynamics, for periods of 1-4 days, we see very few periods of extended coherence. A few regions are evident on close inspection but with very few exceptions they are short lived. We find some coherence in the periods August 2002-March 2003, September 2003-December 2003, April 2007-February 2008, April 2009-November 2010 with the other times being very shortlived. This implies that other factors dominate gold miners share prices over short periods, with gold acting as the long run determinant. A final feature is a quite distinct band of lack of coherence, extending from the start up to approx May 2012, at the higher frequency of approx 4 weeks. There is another, more broken but still evident band of lack of coherence, at approx 1 year frequency, quite strong to end 2004, recommencing in early 2005 and petering out in late 2008. However, if we look at the middle frequencies as a whole, from approx 1 month to 1 year the general rule is that at some or all of these frequencies we see rather more a lack of than a presence of coherence.

[Figure 2 about here.]

5. Conclusions

The period under examination in this paper covers the bottoming of the gold price at just over $250 in 1999 through to its nominal high at $1879 in 2011. This paper finds that gold prices in general lead the NYSE ARCA Gold Bugs index of gold miner share prices when we look at periods of 1 year or greater. This fits well with recent studies, such as OConnor *et al.* (2015), who have found that gold prices also lead gold mine production costs. Both sets of results imply that miners do particularly well in in a rising price environment as the gap between costs and prices widens in their favor, and vice versa. However as it is gold that leads the relationship the ability of gold miners stocks to provide the diversification or safe haven benefits that have been attributed to gold , by studies such as Baur and Lucey (2010), is again called into question.

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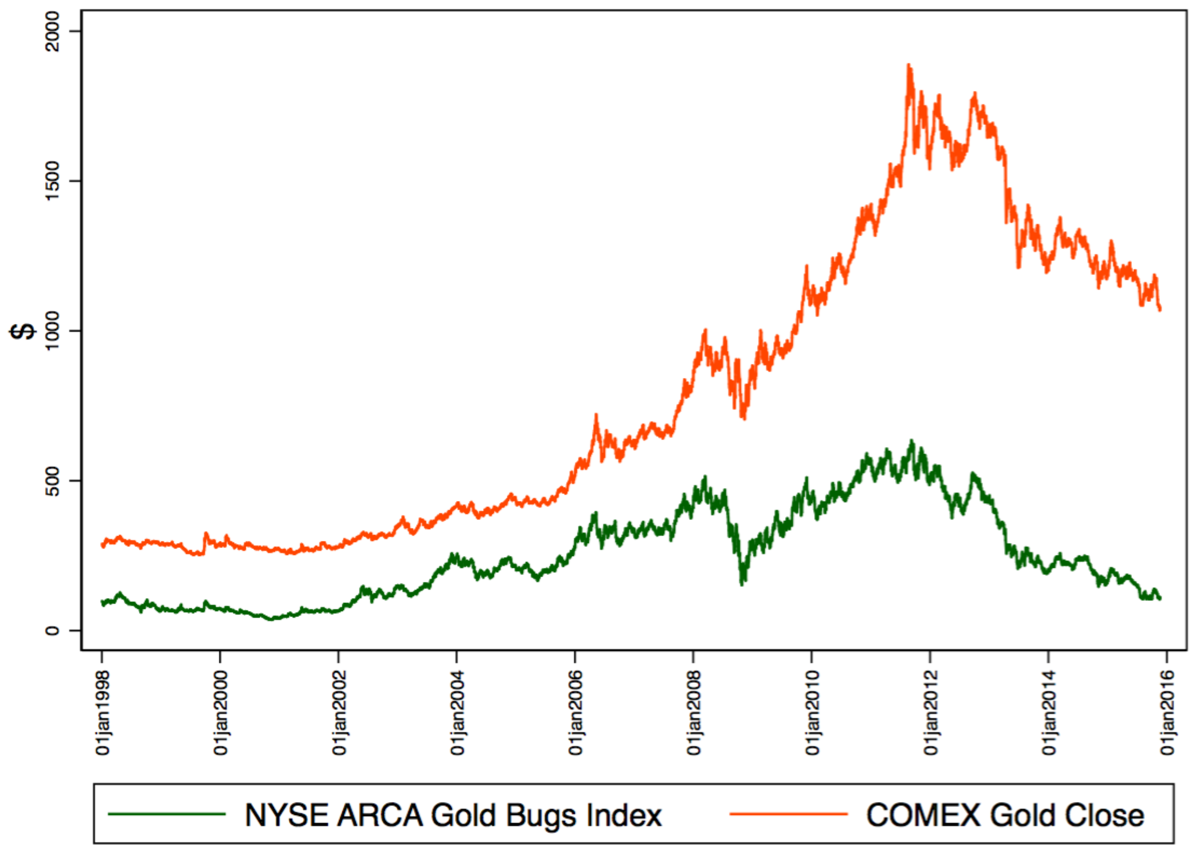

Figure 1: **Gold Bugs Index and Gold Close**
NYSE ARCA Gold Bugs Index vs COMEX 100oz Gold Futures Contract Close 1998 to 2015.

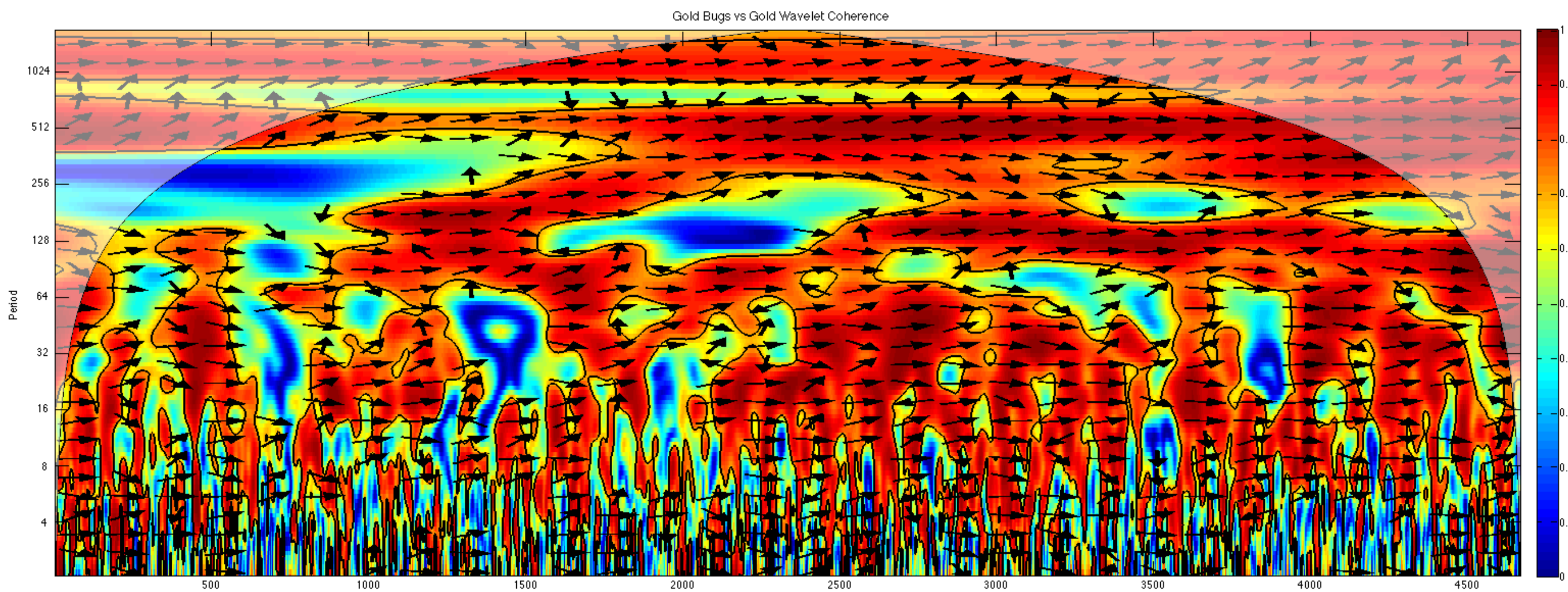

Figure 2: **Wavelet Coherence Plot**
Wavelet Coherence Plot between NYSE ARCA Gold Bugs Index and COMEX Gold 1998 to 2015.