KIER DISCUSSION PAPER SERIES

KYOTO INSTITUTE
OF
ECONOMIC RESEARCH

Discussion Paper No.765

"Risk Management of Precious Metals"

Michael McAleer

March 2011

KYOTO UNIVERSITY

KYOTO, JAPAN

Risk Management of Precious Metals*

Shawkat Hammoudeh
LeBow College of Business
Drexel University

Farooq Malik
College of Business
University of Southern Mississippi

Michael McAleer
Econometric Institute
Erasmus School of Economics
Erasmus University Rotterdam
and
Tinbergen Institute
The Netherlands
and
Institute of Economic Research
Kyoto University

March 2011

* The third author wishes to acknowledge the Australian Research Council, National Science Council, Taiwan, and the Japan Society for the Promotion of Science.

Abstract

This paper examines volatility and correlation dynamics in price returns of gold, silver, platinum and palladium, and explores the corresponding risk management implications for market risk and hedging. Value-at-Risk (VaR) is used to analyze the downside market risk associated with investments in precious metals, and to design optimal risk management strategies. We compute the VaR for major precious metals using the calibrated RiskMetrics, different GARCH models, and the semi-parametric Filtered Historical Simulation approach. The best approach for estimating VaR based on conditional and unconditional statistical tests is documented. The economic importance of the results is highlighted by assessing the daily capital charges from the estimated VaRs.

Keywords: Precious metals, conditional volatility, risk management, value-at-risk.

JEL Classification: G1

1. Introduction

Financial and commodity markets have been highly volatile in recent years. Volatility brings risk and opportunity to traders and investors, and should therefore be examined. There are many reasons for volatility to occur in commodity markets. Political unrest or extreme weather conditions in commodity producing countries' can cause supply disruptions which can create volatility in commodity prices. Introduction of new financial innovations, such as futures, options, exchange-traded funds (ETFs), and use of precious metal as collateral for trading can affect precious metals volatility. Selling and buying of gold by the International Monetary Fund (IMF) and central banks can also change volatility. Changes in demand for the product of an industry that uses commodities as an input may lead to fluctuations in prices of commodities. Market participants form different expectations of profitable opportunities, perform cross-market hedging across different asset classes, process information at different speeds, and build and draw inventories at different levels. These factors contribute to volatility of commodities over time and across markets.

In addition to policy makers and portfolio managers, manufacturers are also interested in this information because precious metals have important and diversified industrial use in jewelry, medicine, electronic and auto catalytic industries. Quantification of the predictable variations in precious metals' price changes is fundamental in designing sensible risk management strategies. Value-at-risk (VaR) has become an important instrument within financial markets for quantifying and assessing the portfolio market risk associated with financial asset and commodity price movements. There is a cost of inaccurate estimation of the VaR in financial markets which affects efficiency and

accuracy of risk assessments. Widespread evidence suggests that precious metals should be part of a well diversified portfolio. Since the prices of these precious metals have been very volatile, so financial market participants are interested in knowing the downside risk of holding precious metals in their portfolios. The VaR measure directly answers this important question and surprisingly there is no study on the analysis of VaR for precious metals. One of the primary purposes of the paper is to fill this void in the risk management literature.

Specifically, we compute VaR for gold, silver, platinum and palladium using RiskMetrics, the GARCH model (using normal and t-distribution), and the recent Filtered Historical Simulation (FHS) approach. The out-of-sample forecast performance indicates that the GARCH with t- distribution produces a VaR with the most accurate and robust estimates of the actual VaR thresholds for all four precious metals. The unconditional coverage test of Kupiec (1995) and the conditional coverage test of Christoffersen (1998) are used to assess the performance of the various models in regards to VaR, and different risk management strategies based on the empirical results are discussed. The economic importance of the estimation results is highlighted by calculating the capital requirements using different VaR models to assess market risk exposure for all precious metals.

2. Review of Literature

The commodities literature is expanding and gaining importance as a result of the increasingly significant role that commodities play in international financial markets and economies. More ETFs are being created for specific commodities. The most recent promising ETFs have been created for platinum and palladium which suggests that

financial market participants are very interested in these metals. Although the commodities literature is focusing more now on important issues but the coverage remains narrow on commodity risk management, particularly in relation to precious metals like platinum and palladium. In this section, we present a review of existing studies and highlight the economic significance of the relatively sparse literature related to precious metals.

Jensen at al. (2002) find that commodity futures substantially enhance portfolio performance for investors, and show that the benefits of adding commodity futures accrue almost exclusively when the Federal Reserve is following a restrictive monetary policy. Overall, their findings indicate that investors should gauge monetary conditions to determine the optimal allocation of commodity futures within a portfolio. Draper et al. (2006) examine the investment role of precious metals in financial markets using daily data for gold, silver and platinum. They show that all three precious metals have low correlations with stock index returns, which suggests that these metals may provide diversification within broad investment portfolios. They also show that all three precious metals have hedging capability for playing the role of safe havens, particularly during periods of abnormal stock market volatility.

Hammoudeh and Yuan (2008) apply univariate GARCH models to investigate the volatility properties of two precious metals, gold and silver, and one base metal, copper. Using the standard GARCH model, they find that gold and silver had almost the same volatility persistence, while the persistence was higher for the pro-cyclical copper. Conover et al. (2009) present new evidence on the benefits of adding precious metals (gold, silver and platinum) to U.S. equity portfolios. They evaluate different weights

(from 5% to 25%) of these metals in a typical portfolio and find that adding a 25% allocation of precious metals in a portfolio consisting of equities substantially improves the portfolio performance. They report that gold relative to platinum and silver has a better stand-alone performance and appears to provide a better hedge against the negative effects of inflationary pressures. They also show that while the benefits of adding precious metals to an investment portfolio varied somewhat over time, they prevailed throughout much of the 34-year period. Chng (2009) examines cross-market trading dynamics in futures contracts written on seemingly unrelated commodities that are consumed by a common industry. He finds such evidence in natural rubber, palladium and gasoline futures markets. The paper offers new insights into how commodity and equity markets relate at an industry level and documents implications for multi-commodity hedging.

Khalifa et al. (2010) suggest that the characterization of return distributions and forecasts of asset-price variability plays a critical role in the analysis of financial markets. They estimate different measures of volatility for gold, silver and copper. They find that the return distributions of the three markets are not normal and the application of financial time sampling techniques is helpful in obtaining a normal distribution. Using the autoregressive distributed lag approach, Sari et al. (2010) examine the co-movements and information transmission among the spot prices of four precious metals (gold, silver, platinum and palladium), oil price, and the US dollar/euro exchange rate. They find evidence of a weak long-run equilibrium relationship, but strong feedbacks in the short-run. They conclude that investors may diversify a portion of the risk by investing in precious metals, oil, and the euro. Hammoudeh et al. (2010) using multivariate GARCH

models examine the conditional volatility and correlation dependence and interdependence of four major precious metals (gold, silver, platinum and palladium), while accounting for geopolitics within a multivariate system. The results indicate significant short-run and long-run dependencies and interdependencies to news and past volatility. The empirical results become more pervasive when exchange rate and federal funds rate are included. Baur and Lucey (2010) examine relations between international stocks, bonds and gold returns to evaluate gold as a hedge and a safe haven. They find that gold is a hedge against stocks, on average, and a safe haven in extreme stock market conditions.

In recent years, the variance (volatility) in prices of precious metals has increased relative to its sample mean. The volatile precious metal price environment requires market risk quantification. VaR has become an essential tool within financial markets for quantifying and assessing portfolio market risk, that is, the risk associated with price movements [see Christoffersen (2009) for a detailed overview of VaR]. VaR determines the maximum loss a portfolio can generate over a certain holding period, with a pre-determined probability value. Therefore, VaR can be used, for instance, to evaluate the performance of portfolio managers by providing risk quantification, together with portfolio returns. Moreover, VaR can help portfolio managers to determine the most suitable risk management strategy for a given situation.

One can estimate VaR using information obtained from univariate or multivariate models. Most studies [see, for example, Giot and Laurent (2004) and Kuester et al. (2006)] analyze VaR forecasting performance for univariate models, while others [see, for example, McAleer and da Veiga (2008a)] have used multivariate models to check for

the impact of volatility spillovers on estimating VaRs. Berkowitz and O'Brien (2002) conclude that a simple univariate model is able to improve the accuracy of portfolio VaR for large US commercial banks. Brooks and Persand (2003) also concluded that there are no gains from using multivariate models while, more recently, McAleer and da Veiga (2008b) found mixed evidence regarding volatility spillovers across financial assets. Christoffersen (2009) argues that univariate models are more appropriate if the purpose is risk measurement as in computing VaR forecasts, while multivariate models are more suitable for risk management as in portfolio selection.

VaR has become a standard measure of downside market risk and is widely used by financial intermediaries and banks [see Basel Committee on Banking Supervision, (1988, 1995, 1996); Perignon and Smith (2010)], equity markets [McAleer and da Veiga (2008a, b), McAleer (2009), McAleer et al. (2009, 2010)], energy markets [see Cabedo and Moya (2003)], among others. As mentioned above, despite the importance of precious metals and their volatile nature, there is no study of VaR using precious metals. One of the primary purposes of our paper is to fill this void in the literature.

3. Estimating and Forecasting Value-at-Risk

In this section, we explicitly define VaR followed by description of different methods that we use to estimate VaR for precious metals.

3.1. Defining Value-at-Risk

Let the asset return process be denoted by

$$R_t = \mu_t + \varepsilon_t \tag{1}$$

where $\varepsilon_t \mid \mathrm{I}_{t-1} \sim (0, h_t)$, I_{t-1} is the information set at time t-1 and h_t is the variance at time t. The VaR measure with coverage probability, *p*, is defined as the conditional quantile, $VaR_{t|t-1}(p)$, where

$$Pr\,(R_t \le VaR_{t|t-1}(\mathrm{p}) \mid \mathrm{I}_{t-1}) = \mathrm{p} \qquad (2)$$

This means the proportion of exceptions, or days when the actual loss exceeds the 99% VaR, is at most 1%. The conditionality of the VaR measure is important. Throughout the paper, we will assume that $\mu_t = 0$, so that $R_t = \varepsilon_t$. This is a reasonable assumption for daily data and is consistent with the literature [see Christoffersen (2009)]. However, volatility is presumed to be time-varying. The probability, *p*, is taken with respect to the distribution function of the portfolio returns, conditional on the information set at t-1. Throughout the paper, we focus on the portfolio VaR with the coverage probability *p* = 1%, which is consistently used in the literature for computing risk exposure [see Basel Committee on Banking Supervision (1988, 1995, 1996)]. Based on the evidence from our review of the literature, we use only univariate models in the empirical analysis.[1]

There are many ways of specifying univariate volatility to capture VaR. This paper uses the following four specifications of volatility.[2]

[1] We also estimated multivariate GARCH models incorporating all precious metals using different parameterizations. The empirical results are not reported for the sake of brevity but are available on request.

[2] All VaR calculations reported in the paper are calculated with the help of files which were graciously provided by Peter Christoffersen. We also calculated VaR with the historical simulation approach, which is a naive method but is still popular among banks and financial institutions [see Perignon and Smith (2010)]. The empirical results are not reported but are available on request.

3.2. RiskMetrics

Under the J.P. Morgan's (1996) RiskMetrics approach, the variance is calibrated using the following Integrated GARCH model:

$$h_t = (1-\lambda)\varepsilon_{t-1}^2 + \lambda h_{t-1} \tag{3}$$

where λ is set to 0.94 for daily data and assuming that the standardized residuals are normally distributed, the VaR measure is given by

$$VaR^{RM}{}_{t|t-1}(\mathrm{p}) = Z_p\sqrt{h_t} \tag{4}$$

where Z_p denotes the p-th percentile of a standard normal variable.

3.3. GARCH

In the Gaussian GARCH(1,1) model of Bollerslev (1986) the conditional variance evolves as:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{5}$$

Where assuming all parameters are positive, the one-step ahead conditional quantile with coverage probability, *p*, is given as

$$VaR^{GARCH}{}_{t|t-1}(\mathrm{p}) = Z_p\sqrt{h_t} \tag{6}$$

where the forecast of h_t is obtained from Eq. (5).

3.4. GARCH with t distribution

The normality assumption can produce VaR estimates that are inappropriate measures of the true risk, thus we also estimate VaR thresholds assuming a t-distribution given as:

$$VaR^{GARCH-T}{}_{t|t-1}(\mathrm{p}) = T_p(\hat{v}_t).\sqrt{\frac{\hat{v}_t - 2}{\hat{v}_t}}.\sqrt{h_t} \tag{7}$$

where $T_p(\hat{v}_t)$ denotes the p-th percentile of a student t random variable with $\hat{v}_t$ degrees of freedom, and h_t is the forecast obtained from the GARCH model.

3.5. GARCH - Filtered Historical Simulation (FHS)

In GARCH-FHS method, a parametric GARCH model is initially filtered which generates a sequence of standardized returns, $\hat{z}_t = R_t / \sqrt{\hat{h}_t}$, where $\hat{h}_t$ denotes the in-sample fitted conditional volatility estimate from the GARCH model. VaR is then estimated as:

$$VaR^{GARCH-FHS}{}_{t|t-1}(\mathrm{p}) = \hat{Z}_p \sqrt{\hat{h}_t} \tag{8}$$

where $\hat{Z}_p$ is the empirical p-th percentile of the fitted standardized returns, $\hat{Z}_t$, over the previous 250 trading days [see Christoffersen (2009), Barone-Adesi et al. (1999, 2002) for further details].

4. Data

We used daily returns based on closing spot prices for the four precious metals (gold, silver, platinum, and palladium) for the period January 4, 1995 to November 12, 2009. Our sample period is particularly interesting to study since it includes the financial crisis of 2008-09. All precious metals are traded at COMEX in New York, and their prices are measured in US dollars per troy ounce. The descriptive statistics are given in Table 1, which shows that palladium has the highest standard deviation, while gold has

the lowest. The Jarque-Bera statistic indicates that all series are not normally distributed. All series also have high kurtosis, which implies that a GARCH-type model is appropriate.

These statistics show that the seemingly close precious metals can be quite different. The low volatility of the gold price is consistent with the fact that gold has an important monetary component, and is not used frequently in exchange market interventions. Silver is more commodity-driven than gold as its monetary element has been gradually phased out. However, the two precious metals are closely related. Silver outperforms gold when the market is up and does worse when the market is down. In terms of contemporaneous correlations (not reported but available on request), the correlation between platinum and palladium returns is positive and is the highest among all the pairs of precious metals, followed by the correlation between gold and silver returns.

5. Empirical Results

In this section, we provide empirical results for the out-of-sample VaR forecasts followed by the results of the unconditional and conditional coverage tests.

5.1. Out-of-Sample VaR Forecasting

In order to assess the out-of-sample performance of the VaR measures, we proceed as follows: A 10-year rolling sample, starting from January 4, 1995, is used to estimate the VaR measures and a 1-year holdout sample (year subsequent to the estimation) is used to evaluate the performance. Specifically, the first rolling (estimation)

sample includes the returns for the years 1995 to 2004 and the first holdout sample includes the returns for the year 2005. Next, the estimated sample is rolled forward by removing the returns for the year 1995 and adding the returns for the year 2005. Consequently, the new holdout sample includes the returns for the year 2006. The procedure continues through to the end of the sample. As the precious metals price returns span the period January 4, 1995 to November 12, 2009, the 10-year rolling estimation procedure yields a total holdout sample of 5 individual years. As mentioned before, this sample period includes the 2008-2009 global financial crises and a method which can predict accurately during this financial turmoil will be indispensable.

The results for the out-of-sample VaR for the one-day ahead forecast at the 1% level for the four estimation methods for the four previous metals are provided in Figure 1. The estimated VaR for the hold-out period 2005-2009 was volatile for all four precious metals, with palladium having the highest VaR volatility. One thing which clearly stands out is the high variance and corresponding VaR for all precious metals during the late 2008 financial crisis period.[3] As the financial markets were in turmoil and risk was rising, financial market participants were investing heavily in safe treasuries and precious metals (gold in particular) which contributed to high volatility. Figure 1 also shows the relatively positive returns of gold during that time period.

We also note the high VaR in 2006 for all precious metals, particularly for silver.[4] Silver return and its corresponding VaR experienced a spike in April 2006 as the first

[3] Precious metals' prices in 2008 were also volatile because of power shortages and labor strikes in South Africa, the world's second largest gold producer and the first largest platinum producer. (see http://www.forbes.com/feeds/afx/2008/02/11/afx4638217.html)

[4] There was also extreme volatility in 2006. Value of demand for gold in dollars terms hit a record in that period. Demand in 2007 was much like in 2006, with steady in the first eight months before seeing a sharp

ETF for silver was launched on the American Stock Exchange.[5] Meanwhile, palladium had a huge negative return in June 2006 largely attributed to the correction in the market fueled by earlier speculation that palladium may also have its own ETF, which materialized at the end of 2009.

The VaR results of the different approaches for all precious metals show that the VaR based on GARCH-t gives a fairly conservative VaR and the VaR based on RiskMetrics gives the most aggressive. We conclude that when the volatility of return is low like the early part of our forecasting sample, one can use any method since all give similar results. However, when markets experience high volatility, like during the 2008 financial crisis, then VaR estimates among different models diverge considerably, underscoring the importance of a conservative method like GARCH-t.[6]

5.2. Unconditional Coverage Test

This test checks the percentage of violations (i.e. actual loss exceeds predicted loss) against what is expected under the null, namely 1%. The null hypothesis is that the proportion of exceptions, or days when the actual loss is greater than the 99% VaR, equals 1%. In a sample of T daily VaRs at the 99% confidence level, we check whether we observe $0.01 \times T$ exceptions. A rejection of the null hypothesis means that the model

---

turn and experiencing some extreme bouts of volatility in the final quarter. (see http://www.resourceinvestor.com/News/2008/2/Pages/Gold-Demand-Can-t-Escape-High-Prices-and.aspx)

[5] See http://www.forbes.com/feeds/afx/2006/04/30/afx2708906.html

[6] The literature on the use of VaR in connection with the recent financial crisis has expanded considerably. A detailed analysis of evaluating our GARCH-t model on data from commercial banks during the financial crisis is beyond the scope of the current paper but is an excellent avenue for future research. Interested readers can read an article on VaR at http://www.nytimes.com/2009/01/04/magazine/04risk-t.html which is written for general audience while Smith and Perignon (2010) provide a more rigorous analysis on VaR.

is not adequate. We employ the Likelihood Ratio test of Kupiec (1995), known as the unconditional coverage test, as follows:

$$LR_{UC} = -2\ln\left\{(1-p)^{T-X}\, p^{x}\right\} + 2\ln\left\{(1-\hat{p})^{T-X}\,(\hat{p})^{X}\right\} \tag{9}$$

where p = 0.01 is the target exception rate, $\hat{p}$ the sample proportion of exceptions, X is the total number of exceptions, T is the total number of observations, and LR is asymptotically distributed as chi-square with one degree of freedom.

The results are presented in Table 2, which shows that the RiskMetrics and GARCH models perform poorly while GARCH-FHS does well, and GARCH-t performs the best as it does not fail the unconditional test for any of the four metals.

5.3. Conditional Coverage Test

The LR_{UC} given in the previous equation is an unconditional test statistic as it simply counts violations over the entire period. However, in the presence of volatility clustering, the VaR models that ignore mean-volatility dynamics may have the correct unconditional coverage, but at any given time, they may have incorrect conditional coverage. In such cases, the LR_{UC} test will be of limited use as it will classify inaccurate VaR estimates as "acceptably accurate".

The conditional coverage test developed by Christoffersen (1998) inspects serial independence of VaR estimates. For a given VaR estimate, the indicator variable, I_t, is constructed such I_t is 1 if a violation occurs, and I_t is 0 if no violation occurs. Christoffersen (1998) proposes the following likelihood ratio test statistic for the null hypothesis of serial independence against the alternative of first-order Markov dependence:

$$LR_{IND} = 2\left[n_{00}\ln(\Pi_{00}/(1-\Pi)) + n_{01}\ln((1-\Pi_{00})/\Pi) + n_{10}\ln(\Pi_{10}/(1-\Pi)) + n_{11}\ln((1-\Pi_{10}/\Pi)\right] \quad (10)$$

where n_{ij} is the number of observations with value i followed by j, $\Pi_{00} = n_{00}/(n_{00}+n_{01})$, $\Pi_{10} = n_{10}/(n_{10}+n_{11})$, and $\Pi = (n_{01}+n_{11})/N$, respectively. The LR_{IND} statistic has an asymptotic chi-square distribution with one degree of freedom. In essence, Christoffersen (1998) argues that violations should be independent and identically distributed over time.

However, what we really care about is simultaneously testing if the VaR violations are independent and the average number of violations is also correct. We can test jointly for independence and correct coverage using the conditional coverage test. The joint test (LR_{CC}) of conditional coverage can be calculated by simply summing the two individual tests for unconditional coverage and independence [see Christoffersen (2003) for details].

The results for both LR_{IND} and LR_{CC} are presented in Table 2. The LR_{IND} test shows that RiskMetrics and GARCH produce an inadequate VaR in the case of platinum as the evidence indicates that the violations are not independent. Focusing on LR_{CC}, we see that RiskMetrics fails this important test for all metals, GARCH fails for all metals except palladium, GARCH-FHS fails only for gold, and GARCH-t does not fail for any metal. Overall, our results indicate that the GARCH-t model not only performs the best on average but also its violations are independent. This is quite remarkable, given the fact that the sample period includes the global financial crisis, where one might expect repeated violations.

6. Calculating Daily Capital Charges Based on VaR Forecasts

The aim in this subsection is to compare the statistical results obtained above with the requirements established by the current regulatory framework set by the Basel II Accord. Under the framework of Basel II, the VaR estimates of the banks must be reported to the domestic regulatory authority. These estimates are used to compute the amount of regulatory capital requirements in order to monitor and control a financial institution's market risk exposure, and to act as a cushion against adverse market conditions. The market risk capital requirements are obviously a function of the forecast VaR thresholds. The Basel Accord stipulates that the daily capital charge must be set at the higher of the previous day's VaR or the average VaR over the last 60 business days, multiplied by a factor *k* (see Table 3). The multiplicative factor *k* is set by the local regulators but must not be lower than 3. Thus the Basel Accord imposes penalties in the form of a higher multiplicative factor *k* on banks that use models that lead to a greater number of violations than would be expected given the specified confidence level of 1%. It is interesting to note that the Basel II penalty structure is concerned only with the frequency of violations and not the magnitude of any violation.

The empirical evidence presented by Berkowitz and O'Brien (2002) and Perignon et al. (2008) show that banks systematically overestimate their VaR which leads to excessive amount of regulatory capital which affects banks' profitability. Therefore, using models that deliver accurate estimates of this capital can lead to an increase in efficiency and accuracy of risk assessments made by investors and portfolio managers. McAleer et al. (2010) propose a decision rule for calculating daily capital charges in light of these competing forces [for further details see, for example, McAleer and da Veiga (2008a, b)].

We calculate the daily capital charges by using our VaR forecasts and the results are reported in Table 4. The table shows that the mean daily capital charge, which is a function of both the penalty and the forecast VaR, implied by GARCH-t is the largest for all metal cases, and also yields the lowest violations. This is consistent both with intuition and the empirical results reported in McAleer et al. (2010). A high capital charge is undesirable as it reduces profitability while large violations may lead to bank failures, as the capital requirements implied by the VaR threshold forecasts may be insufficient to cover the realized losses. This exercise shows that portfolio managers engaged in precious metals who want to follow a conservative strategy should calculate VaR using GARCH-t as this will yield fewer violations, though with lower profitability.

7. Conclusion

This paper examines the volatility dynamics in precious metals and explores the corresponding risk management implications. The conditional volatility and correlation dynamics in the price returns of gold, silver, platinum and palladium are modeled using daily data from January 1995 to November 2009. Value-at-Risk (VaR) is used to analyze the risk associated with precious metals, and to design optimal risk management strategies. We compute the VaR for all precious metals using the calibrated RiskMetrics, alternative empirical GARCH models, and the semi-parametric Filtered Historical Simulation approach.

Different risk management strategies are suggested based on conditional and unconditional statistical tests. The economic importance of our results is highlighted by calculating the daily capital charges from the estimated VaRs using different methods for

all precious metals. This exercise shows that portfolio managers engaged in precious metals who want to follow a conservative strategy should calculate VaR using GARCH-t as this will yield fewer violations, though with lower profitability. Our results are very timely and useful for financial market participants as the global financial markets continue to experience unprecedented volatility and the need for investment in precious metals remains high.[7]

[7] On May 6, 2010 the Dow Jones Industrial Average plunged by nearly 1,000 points (mostly due to Greek debt concerns) in twenty minutes making it the largest intra-day point decline in the market's history. Not surprisingly, gold prices among other precious metals increased dramatically as volatility in the market remained high. (See Economist article titled "America's stock market plunge: A few minutes of mayhem" on May 13, 2010). Such events remind us that financial markets remain unnerved.

References

Basel Committee on Banking Supervision, (1988), International Convergence of Capital Measurement and Capital Standards, BIS, Basel, Switzerland.

Basel Committee on Banking Supervision, (1995), An Internal Model-Based Approach to Market Risk Capital Requirements, BIS, Basel, Switzerland.

Basel Committee on Banking Supervision, (1996), Supervisory Framework for the Use of "Backtesting" in Conjunction with the Internal Model-Based Approach to Market Risk Capital Requirements, BIS, Basel, Switzerland.

Batten, J.M. and B.M. Lucey (2010). Volatility in the gold futures market. *Applied Economics Letters*, 17(2), 187-190.

Barone-Adesi, G., K. Giannopoulos and L. Vosper (1999). VaR without correlations for portfolios of derivative securities. *Journal of Futures Markets*, 19, 583-602.

Barone-Adesi, G., K. Giannopoulos and L. Vosper (2002). Backtesting derivative portfolios with filtered historical simulation. *European Financial Management*, 8, 31-58.

Baur, D.G. and B.M. Lucey (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45(2), 217-229.

Berkowitz, J. and J. O'Brien (2002). How accurate are value-at-risk models at commercial banks? *Journal of Finance*, 57(3), 1093-1111.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics,* 31: 307-327.

Brooks, C. and G. Persand (2003). Volatility forecasting for risk management. *Journal of Forecasting*, 22 (1), 1-22.

Cabedo, J.D. and I. Moya (2003). Estimating oil price 'value at risk' using the historical simulation approach, *Energy Economics*, 25(3), 239-253.

Chng, M.T. (2009). Economic linkages across commodity futures: Hedging and trading implications. *Journal of Banking and Finance*, 33(5), 958-970.

Christoffersen, P. (1998). Evaluating interval forecasts. *International Economic Review*, 39(4), 841-862.

Christoffersen, P. (2003). Elements of Financial Risk Management, San Diego: Academic Press.

Christoffersen, P. (2009). Value-at-risk models. In T. Andersen, R. Davis, J.-P. Kreiss, and T. Mikosch (Eds.), *Handbook of Financial Time Series*. Springer Verlag.

Conover, C.M., G.R Jensen, R.R Johnson and J.M Mercer (2009). Can Precious Metals Make your Portfolio Shine? *Journal of Investing*, 18(1), 75-86.

Draper, P., R.W. Faff and D. Hillier (2006). Do precious metals shine? An investment perspective. *Financial Analysts Journal*, 62(2), 98-106.

Giot, P. and S. Laurent (2004). Modelling daily value-at-risk using realized volatility and ARCH type models. *Journal of Empirical Finance*, 11(3), 379-398.

Hammoudeh, S. and Y. Yuan (2008). Metal volatility in presence of oil and interest rate shocks. *Energy Economics*, 30(2), 606-620.

Hammoudeh, S., Y. Yuan, M. McAleer and M. Thompson (2010). Precious metals-exchange rate volatility transmissions and hedging Strategies. *International Review of Economics and Finance* (forthcoming).

Jensen, G.R., R.R. Johnson and J.M. Mercer (2002). Tactical asset allocation and commodity futures. *Journal of Portfolio Management*, 28(4), 100-111.

JP Morgan (1996). *RiskMetrics*, Technical Document, 4th Edition, New York.

Khalifa, A.A., H. Miao and S. Ramchander (2010). Return distributions and volatility forecasting in metal futures markets: Evidence from gold, silver, and copper. *Journal of Futures Markets*, forthcoming.

Kuester, K., S. Mittnik, and M. Paolella (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics*, 4(1), 53-89.

Kupiec, P. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives* 3(2), 73-84.

McAleer, M. (2009). The ten commandments for optimizing value-at-risk and daily capital charges. *Journal of Economic Surveys*, 23(5), 831-848.

McAleer, M. and B. da Veiga (2008a). Forecasting value-at-risk with a parsimonious portfolio spillover GARCH (PS-GARCH) model. *Journal of Forecasting*, 27(1), 1-19.

McAleer, M. and B. da Veiga (2008b). Single index and portfolio models for forecasting value-at-risk thresholds. *Journal of Forecasting*, 27(3), 217-235.

McAleer, M., J.-A. Jimenez-Martin and T. Perez-Amaral (2009). The Ten Commandments for managing value-at-risk under the Basel II Accord. *Journal of Economic Surveys*, 23(5), 850-855.

McAleer, M., J.-A. Jimenez-Martin and T. Perez-Amaral (2010). A decision rule to minimize daily capital charges in forecasting value-at-risk. *Journal of Forecasting*, forthcoming.

Perignon, C., Z. Deng, and Z. Wang (2008). Do banks overstate their value-at-risk? *Journal of Banking and Finance*, 32(5), 783-794.

Perignon, C. and D. R. Smith. (2010). The level and quality of Value-at-Risk disclosure by commercial banks. *Journal of Banking and Finance*, 34(2) 2010, 362-377

Sari, R., S. Hammoudeh and U. Soytas (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, 32(2), 351-362.

Table 1: Descriptive Statistics on Precious Metal Returns

	Gold	Silver	Platinum	Palladium
Mean	0.000297	0.000359	0.000330	0.000221
Median	0.000158	0.000642	0.000388	0.000000
Maximum	0.070060	0.131632	0.100419	0.191608
Minimum	-0.079719	-0.203851	-0.096731	-0.169984
Std. Dev.	0.010512	0.018730	0.014770	0.023052
Skewness	0.069184	-1.017043	-0.306782	0.045495
Kurtosis	9.402129	14.89623	8.653893	9.679912
Jarque-Bera	6262.019	22243.17	4939.041	6815.296
Probability	0.000000	0.000000	0.000000	0.000000

Notes: All statistics are for daily returns from January 4, 1995 to November 12, 2009, yielding 3665 observations.

Table 2: Backtesting VaR for Precious Metals

Gold	RiskMetrics	GARCH	GARCH-t	GARCH-FHS
LR_{uc}	11.881*	22.408*	0.050	10.365*
LR_{ind}	1.131	1.722	0.279	1.044
LR_{cc}	13.013*	24.131*	0.330	11.409*

Silver	RiskMetrics	GARCH	GARCH-t	GARCH-FHS
LR_{uc}	11.881*	11.881*	1.082	0.600
LR_{ind}	1.131	1.131	1.624	1.843
LR_{cc}	13.013*	13.013*	2.707	2.443

Platinum	RiskMetrics	GARCH	GARCH-t	GARCH-FHS
LR_{uc}	24.400*	15.104*	0.050	1.082
LR_{ind}	10.136*	13.293*	0.279	0.424
LR_{cc}	34.536*	28.397*	0.330	1.507

Palladium	RiskMetrics	GARCH	GARCH-t	GARCH-FHS
LR_{uc}	4.209*	1.082	2.653	0.003
LR_{ind}	0.666	0.424	0.080	0.238
LR_{cc}	4.875*	1.507	2.734	0.241

Notes: * denotes that we reject the null hypothesis at the 10% level implying that the model is inadequate. LR_{uc} is the unconditional coverage test given by Kuipic (1995) while LR_{ind} and LR_{cc} are conditional coverage tests given in Christoffersen (1998, 2003). Critical values for rejecting the null hypothesis for LR_{uc}, LR_{ind} and LR_{cc} at the 10% level are 2.70, 2.70, and 4.60, respectively. The degree(s) of freedom are 1 for the first two tests and 2 for the third test. If the calculated test statistic is greater than the critical value, we reject the VaR model. A 10% level is typically used as the consequences of accepting a poor VaR model are very severe.

Table 3: Basel Accord Penalty Zones

Zone	Number of Violations	k
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Note: The number of violations is given for 250 business days.

Table 4: Daily Capital Charges for Precious Metals

Panel A: Gold

Model	Number of Violations	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	21	0.1167	0.2410	0.0522
GARCH	28	0.1145	0.2208	0.0654
GARCH-t	12	0.1272	0.2621	0.0677
GARCH-FHS	20	0.1157	0.2357	0.0599

Panel B: Silver

Model	Number Of Violations	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	21	0.1985	0.4340	0.0974
GARCH	22	0.2008	0.4277	0.0861
GARCH-t	15	0.2221	0.4778	0.0998
GARCH-FHS	15	0.2205	0.5010	0.1008

Panel C: Platinum

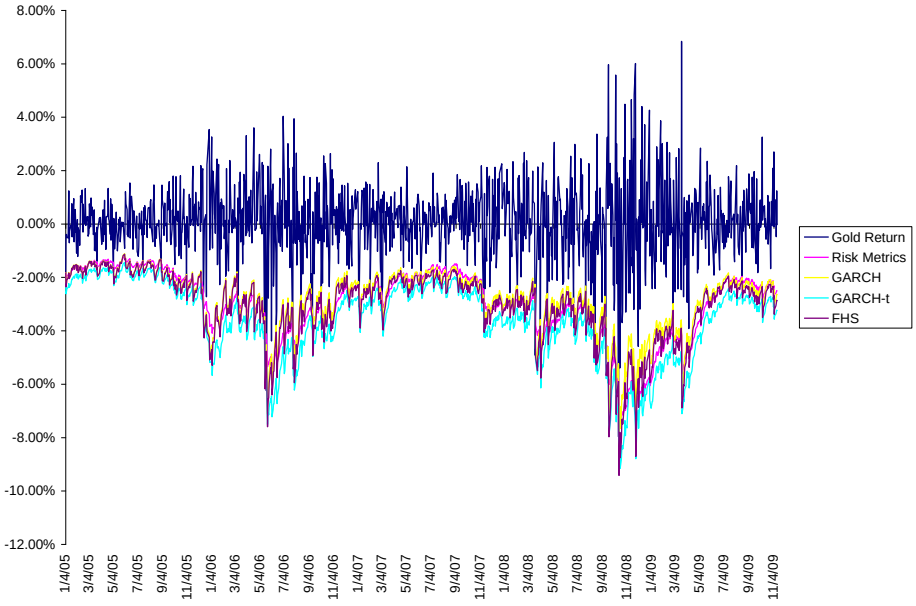
Model	Number Of Violations	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	26	0.1437	0.3534	0.0640
GARCH	23	0.1394	0.3317	0.0716
GARCH-t	13	0.1451	0.3588	0.0709
GARCH-FHS	14	0.1425	0.3755	0.0669

Panel D: Palladium

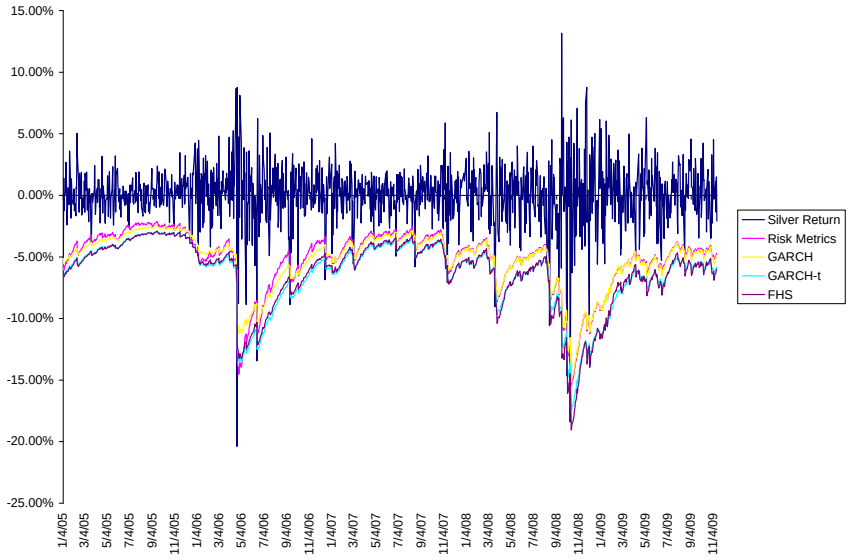
Model	Number Of Violations	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	17	0.1688	0.3877	0.0599
GARCH	13	0.1706	0.3546	0.1031
GARCH-t	5	0.1959	0.3810	0.1182
GARCH-FHS	9	0.1768	0.3374	0.1106

Notes: The daily capital charge is the higher of the negative of the previous day's VaR or the average VaR over the last 60 business days times (3+k), where k is the penalty given in Table 3.

Figure 1: VaR estimates

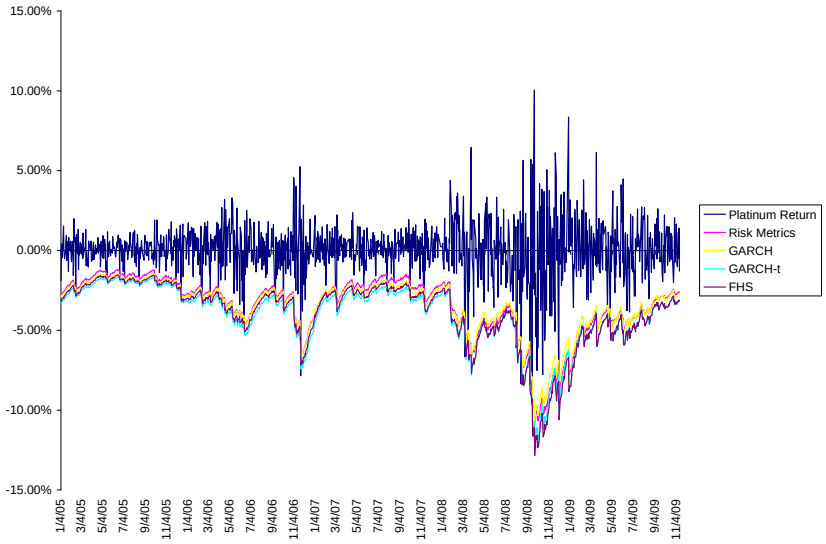


Panel A: Gold

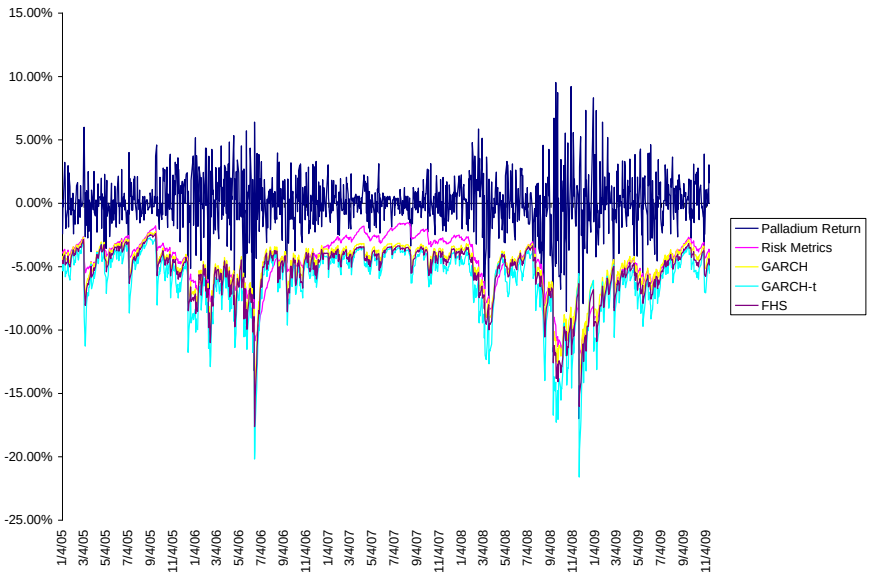


Panel B: Silver

Figure 1: VaR estimates (continued)



Panel C: Platinum



Panel D: Palladium