

Risk Management of Precious Metals*

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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. Different risk management strategies are suggested, and 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. The risk-minimizing portfolio weights and dynamic hedge ratios between different metal groups are also analyzed.

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

JEL Classifications: 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, other than changes in supply and economic use, for volatility to occur in commodity markets. Introduction of new financial innovations, such as futures, options and ETFs (exchange-traded funds), 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. Surprisingly, despite the importance of precious metals and

their volatile nature, 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. This quantification is fundamental in designing sensible risk management strategies. 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. Finally, the economic significance of the estimates is underscored by estimating the risk-minimizing portfolio weights and dynamic hedge ratios between different metal groups, which may be used to formulate optimal risk management strategies for the four 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 recent most promising ETFs have been created for platinum and palladium. Although the

commodities literature is focusing more and more on important issues, the pace and coverage remains narrow, particularly in relation to precious metals, including platinum and palladium, and commodity risk management. 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 et 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, platinum, and silver. 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. They found in the standard univariate GARCH model 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 find that adding a 25% metals allocation to the equities of precious metals firms improves portfolio performance

substantially, and 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) examined 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.

Prices of precious metals have been highly volatile in the past, and even more so recently. The volatile precious metal price environment requires 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.

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)], stock markets [McAleer and da Veiga (2008a, b), McAleer (2009), McAleer et al. (2009, 2010)], oil 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 we use to estimate VaR for precious metals.

3.1. Defining Value-at-Risk

Let the asset return process be denoted by

$$R_t = \mu_t + \varepsilon_t \quad (1)$$

where $\varepsilon_t | I_{t-1} \sim (0, h_t)$, 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

$$Pr(R_t \leq VaR_{t|t-1}(p) | I_{t-1}) = p \quad (2)$$

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)].

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 estimates delivered by large US commercial banks. Brooks and Persaud (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. Based on this evidence, 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

3.2. RiskMetrics

The benchmark measure advocated in J.P. Morgan's (1996) RiskMetrics (RM) sets the conditional mean to be constant and specifies the variance as an exponential filter. Under the RiskMetrics approach, the variance is calibrated using an Exponentially Weighted Moving Average, which corresponds to the following Integrated GARCH model:

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.

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

where the contribution to the long-term persistence of unity, namely λ , is set to 0.94 for daily data, and hence is not estimated. RiskMetrics assumes that the standardized residuals are normally distributed, so that the VaR measure is given by

$$VaR_{t|t-1}^{RM}(p) = Z_p \sqrt{h_t} \quad (4)$$

where Z_p denotes the p -th percentile of a standard normal variable. For $p = 0.01$, it follows that $Z_p = -2.326$.

3.3. GARCH

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

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

where $\omega > 0$, $\alpha > 0$, $\beta > 0$, and $\alpha + \beta < 1$ are sufficient conditions to guarantee the positivity of the conditional variances and the stationarity of returns. The one-step ahead conditional quantile with coverage probability p is given as

$$VaR_{t|t-1}^{GARCH}(p) = Z_p \sqrt{h_t} \quad (6)$$

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

3.4. GARCH with t distribution

Most empirical applications of VaR assume that asset returns are normally distributed as this assumption considerably simplifies the computation of VaR. However, normality is inconsistent with the empirical evidence of asset returns which finds the

distribution to be skewed, fat-tailed, and peaked around the mean. This implies that extreme events are more likely to occur in practice than would be predicted by the symmetric and thinner-tailed normal distribution. This fact is painfully obvious in light of the recent financial crisis.

Thus normality assumption can produce VaR estimates that are inappropriate measures of the true risk faced by financial institutions or portfolio managers. Thus, in our paper we also estimate VaR thresholds assuming a t-distribution given as:

$$VaR^{GARCH-T}_{t|t-1}(p) = T_p(\hat{\nu}_t) \cdot \sqrt{\frac{\hat{\nu}_t - 2}{\hat{\nu}_t}} \cdot \sqrt{h_t} \quad (7)$$

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

3.5. GARCH - Filtered Historical Simulation

We know that the assumption of a normal distribution is not appropriate for most speculative assets at the daily frequency. Choosing an alternative distribution is difficult. Rather than imposing such a choice, we can also rely on a simple resampling scheme which in financial risk management is referred as Filtered Historical Simulation (FHS). The term “filtered” refers to the fact that we are not simulating from the set of raw returns but from a set of shocks, z_t , which are returns filtered by the GARCH model.

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:

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

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 Lagrange multiplier 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 the annual demand and production of gold are less than 10% of its above-ground supply, and its stock is a supply buffer against fundamental shocks. The low volatility of the gold price is also 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 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 Exchange-Traded Fund (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

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. Demand for gold in dollars Gold 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 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>

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.

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

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

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. This unconditional test counts violations over the entire period.

The results are presented in Table 4, 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:

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

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 4. 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 2). 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 which 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 3. 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. Estimating Portfolio Designs and Hedging Strategies

We now provide two examples using multivariate GARCH models for precious metals to analyze portfolio design and hedging strategies as part of our examination of risk management. Ewing and Malik (2005) undertake a similar exercise for small cap and large cap stock returns.

7.1. Portfolio Weights

The first example follows Kroner and Ng (1998) by considering a portfolio that minimizes risk without lowering expected returns. If we assume the expected returns to be zero, the optimal portfolio weight of one commodity (or asset) relative to the other in a two commodity (asset) portfolio is given by:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \quad (11)$$

$$w_{12,t} = \begin{cases} 0, & \text{if } w_{12,t} < 0 \\ w_{12,t}, & \text{if } 0 \leq w_{12,t} \leq 1 \\ 1, & \text{if } w_{12,t} > 1 \end{cases} \quad (12)$$

where $w_{12,t}$ is the portfolio weight for asset 1 relative to asset 2 in a one-dollar portfolio of the two assets at time t , $h_{12,t}$ is the conditional covariance between asset returns, and $h_{22,t}$ is the conditional variance of the asset 2. The portfolio weight of the second asset in the one dollar portfolio is $1-w_{12,t}$.

The average values of $w_{12,t}$ based on our precious metals are reported in Table 5. For instance, the average value of $w_{12,t}$ of a portfolio comprising gold and silver is 0.80. This suggests that the optimal holding of gold in one dollar of gold/silver portfolio is 80 cents and 20 cents for silver. These optimal portfolio weights suggest that investors should own more gold than other commodities in their portfolios.

7.2. Hedge Ratios

As a second illustration, we follow Kroner and Sultan (1993) regarding risk-minimizing hedge ratios and apply it to our precious metals. Kroner and Sultan (1993) show that in order to minimize the risk of the portfolio that is \$1 long in asset 1, an investor should short β_t of the asset 2, where β_t is given as:

$$\beta_t = \frac{h_{12,t}}{h_{22,t}} \quad (13)$$

here β_t is the risk-minimizing hedge ratio for two assets, $h_{12,t}$ is the conditional covariance between asset 1 and 2, and $h_{22,t}$ is the conditional variance of the second asset. Table 5 reports the average values of β_t for the different commodity markets. For example, when holding a long position for \$100 in the silver portfolio, investors should short \$6.90 of gold.

8. 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. The risk-minimizing portfolio weights and dynamic hedge ratios between different metal groups are documented. The portfolio weights suggest that the precious metal portfolios should have more gold than any of silver, platinum and palladium in order to minimize risk without affecting expected returns. The hedging ratios indicate that using a short position to hedge a long position for precious metals is not expensive except for platinum/palladium. 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.⁶

⁶ 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.

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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 Kupiec (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 large.

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	0.071
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

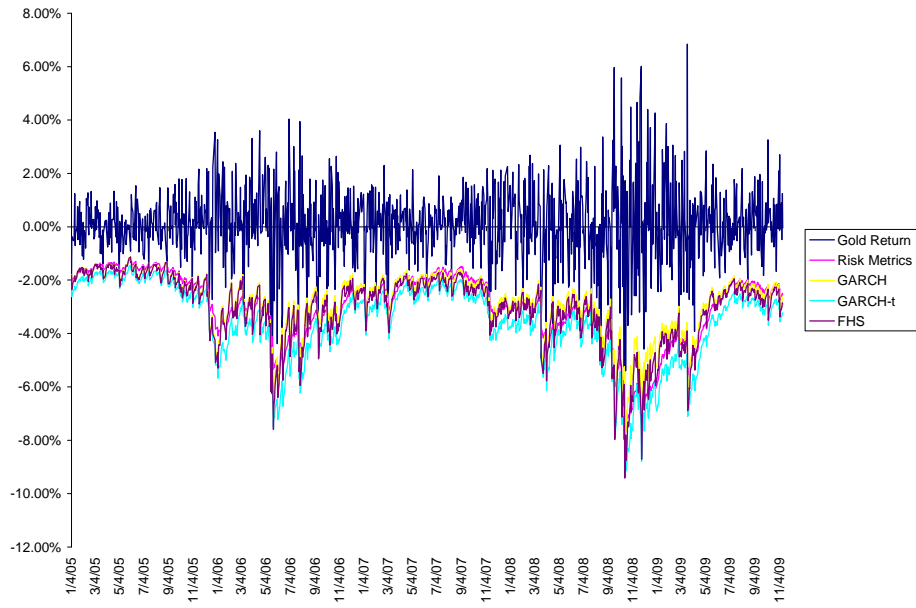
Notes: The daily capital charge is the higher of the negative of the previous day's VaR or the average VaR over the last 60 business days times $(3+k)$, where k is the penalty given in Table 3.

Table 5: Optimal Portfolio Weights and Hedge Ratios for Precious Metals

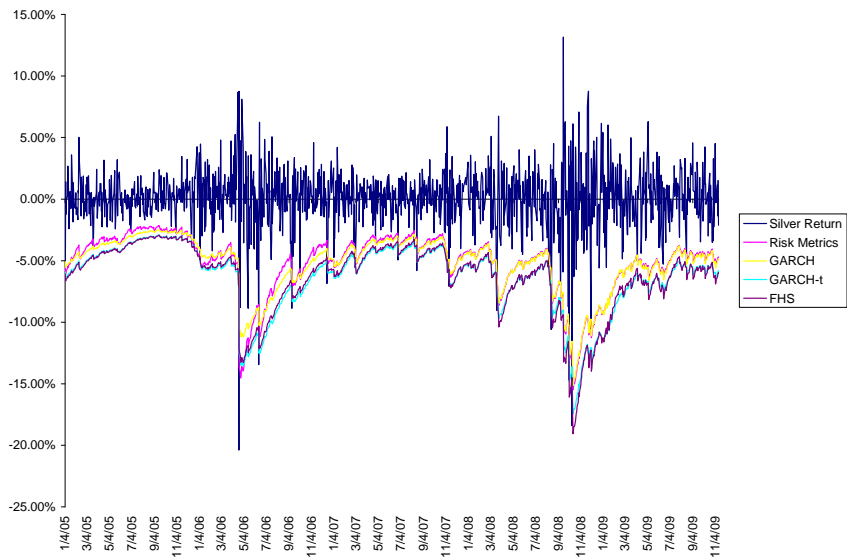
Portfolio	Average $w_{12,t}$	Average β_t
Gold/Silver	0.8075	0.0690
Gold/Platinum	0.8273	0.1980
Gold/Palladium	0.9659	0.0617
Silver/Platinum	0.4427	0.1592
Silver/Palladium	0.7886	0.0918
Platinum/Palladium	0.4209	0.7381

Notes: $w_{12,t}$ is the portfolio weight of two assets holdings at time t and average β_t is the risk-minimizing hedge ratio for two precious metals. We used the BEKK parameterization for the multivariate GARCH model for computations.

Figure 1: VaR estimates

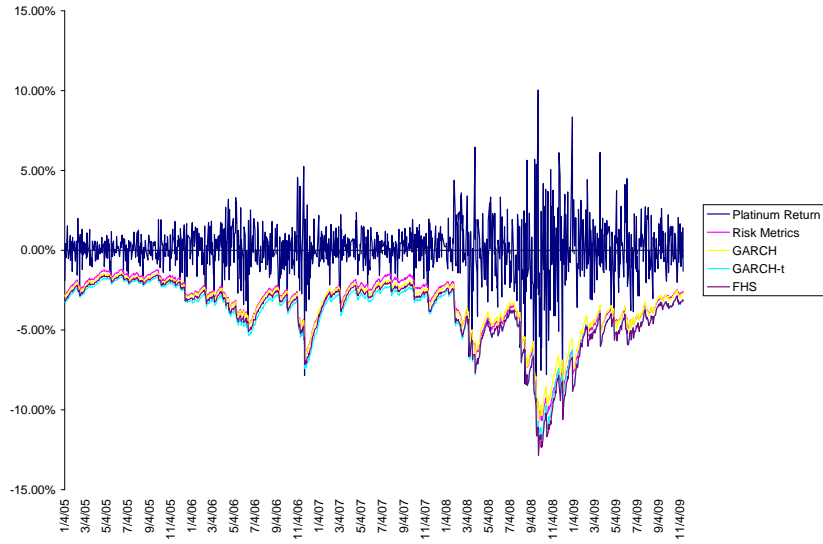


Panel A: Gold

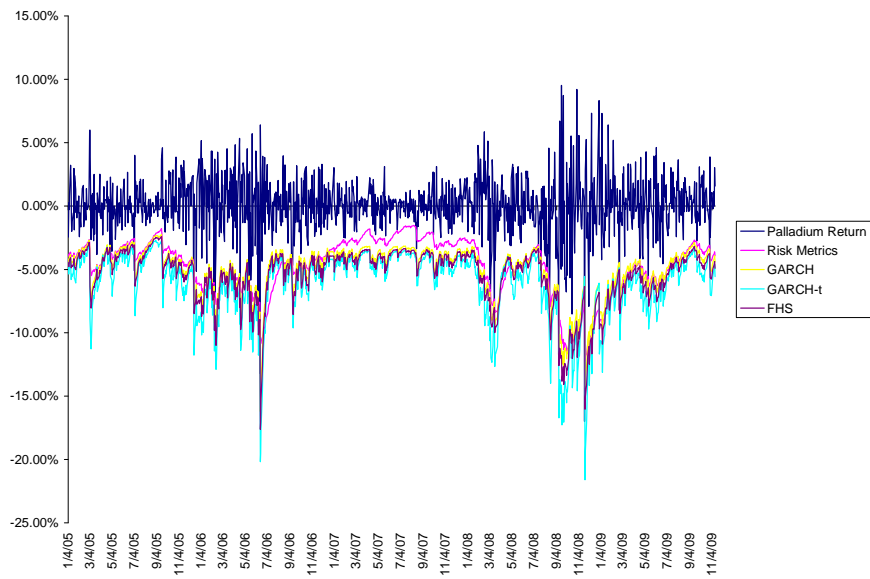


Panel B: Silver

Figure 1: VaR estimates (continued)



Panel C: Platinum



Panel D: Palladium