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VOLATILITY TRANSMISSION ACROSS CURRENCY, COMMODITY AND EQUITY MARKETS UNDER MULTI-CHAIN REGIME SWITCHING: IMPLICATIONS FOR HEDGING AND PORTFOLIO ALLOCATION

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Volatility Transmission across Currency, Commodity and Equity Markets under Multi-Chain Regime Switching: Implications for Hedging and Portfolio Allocation

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Abstract

This paper uses the multi-chain Markov Switching model to examine the nature of the volatility transmission across currency, commodity and stock markets, and provide implications for hedging and asset allocation. Results generally indicate the dominant presence of interdependency, as opposed to spillover and comovement relationships, highlighting the mutual reciprocity of individual market shocks across assets. Furthermore, there is evidence that optimal hedge ratios and portfolio weights are regime dependent. For instance, we find that it is more expensive to hedge when the market is in turmoil than when it is tranquil, and portfolio weights are larger for assets that are in the low volatility state.

Keywords: volatility, interdependence, spillover, comovement, hedging, portfolio allocation.
JEL Classification: F37, G13, G15.

1 Introduction

Information flows are crucial to understanding return and volatility transmissions across markets. The importance of transmission mechanisms stems from the insights they provide for asset pricing, risk management and portfolio diversification, and for the theoretical implications they carry for information-based models and market efficiency. Ross (1976) demonstrates that under the condition of no arbitrage volatility is directly related to the rate of information flows. A logical extension to this argument is that interdependencies among markets may be viewed in the context of volatility linkages and information flows. Moreover, the mechanisms of volatility transmission are related to the possibility that abrupt changes in the volatility level of a certain market can lead to changes in the volatility level of related markets. This fact is consistent with the presence of regimes in the time series of volatility, corresponding to high and low levels of volatility.

The questions we ask in this study are as follows. Are the volatilities of currencies, commodities and equity markets linked? If so, what is the nature of the volatility transmissions across these various markets? Do tranquil and turmoil regimes in one market have a disproportionate influence on other markets? Answering these questions is a crucial component in helping us construct optimal hedge ratios and portfolio weights under different volatility regimes. Although, there have been several recent studies that deal with portfolio selection and hedging strategies (e.g., Hammoudeh and Yuan, 2008; Hammoudeh et.al., 2009; Choi and Hammoudeh 2010; Hammoudeh et al. 2010), to the best of our knowledge, there is a paucity in the literature pertaining to the examination of all three asset classes simultaneously in a regime changing environment that is able to ascertain the specific form of transmission mechanism.

The major contributions of the current study include:

(a) Examining volatility linkages across six major resource and non-resource (safe haven) currencies ($euro$, $Australian\ dollar$, $British\ pound$, $Swiss\ franc$, $Canadian\ dollar\ and\ Japanese\ yen$), four widely traded commodities (oil, $gold$, $silver\ and\ copper$) and the U.S. stock market (the $S\&P\ 500\ index$); (b) Distinguishing among the different types of volatility transmissions –spillover, interdependence and comovement- in the presence of changes in the volatility regimes; and (c) Providing implications for construction of optimal hedge ratios and portfolio weights under different regimes.

To achieve these objectives, we use a set of bivariate Multi-Chain Markov Switching (MCMS) models, introduced by Otranto (2005) and extended by Gallo and Otranto (2007, 2008), to analyze the volatility transmission mechanisms' forms. Different from the classical $Markov\ Switching$ (MS) models (Hamilton, 1990), the $MCMS$ model considers that the dynamics of each series of volatility is driven by an underlying state variable, that represents a particular volatility regime, and that each state variable can in turn influence the change in volatility regime in the other series. Notably, this framework provides a natural definition of spillover, interdependence, and comovement, a distinction not provided by classical MS models and other linear and nonlinear approaches (e.g., VAR, $logit$, etc.) that are commonly used to analyze volatility transmission in financial markets.

The results from our study suggest that, for the three asset classes considered, the most dominant and widespread pattern of volatility transmission is characterized as interdependence. Interdependence relationships are most evident for resource currencies, especially the Australian dollar (AUD), followed by the cyclical commodities: $silver$,

$copper$ and oil. The interdependence transmission also underscores the importance of mutual reciprocal shocks that originate in one asset market and affects another market. This is not surprising considering the heightened interplay between resource-driven and major currencies and commodity prices. Volatility spillover is the second most prevalent pattern of transmission. The most prominent spillovers originate from each of AUD and GBP to the three commodities oil, $copper$ and $gold$ and from CHF to both $copper$ and $gold$. Finally, the comovement or contemporaneous common dynamic relationships is found to be the weakest transmission pattern, supporting the relative importance of asset specific-shocks as opposed to common macroeconomic shocks and the business cycle. Comovement is rejected for all asset pairs, except between the $equity\ index$ and $gold$. The results also indicate that currencies have relatively larger impacts than commodities and equities within the transmission system. Extending these results, from an investment policy perspective, we find hedge ratios and portfolio weights to be regime-dependent and time-variant. For instance, hedging becomes more expensive if either one or both assets in the hedge are in the turmoil (or high volatility) state. Furthermore, when markets are tranquil, the optimal portfolio weights are more heavily tilted in favor of commodities and the equity market as opposed to currencies. The results also show that hedging a long position with a short position for most portfolios is much more effective under the $MCMS$ framework than traditional VAR.

The rest of the paper is organized as follows. Section 2 reviews the existing literature and section 3 provides the methodology. Section 4 describes the data and section 5 presents the empirical analysis of the results. Section 6 concludes the paper.

2 Literature Review

For the purpose of this study the relevant literature is classified into two broad strands. The first strand focuses on the relationships across the different metal markets. Employing daily data, Chan and Mountain (1988) find that the changes in silver prices exert a causal influence on the spot prices of gold. Escribano and Granger (1998) find clear and strong evidence of a simultaneous relationship between the returns of gold and silver (see also Honga et al., 2007 for more details). However, Ciner (2001) concludes that the stable relationship between gold and silver prices disappeared during the 1990s. Akgiray et al. (1991)find that the price series of precious metals exhibit time dependency and that $GARCH$ effects persist even after splitting the data into various sub-periods. Notably, the authors conclude that the constant variance pricing models are inappropriate for securities that are based on precious metal markets. Tully and Lucey (2005) and Batten and Lucey (2007) examine the conditional and unconditional daily mean-return variance estimated from spot prices for gold and silver contracts during the period 1982-2002. They note that when the mean and variance are analyzed simultaneously in a $GARCH$ framework, the leveraged $GARCH$ model provides the best fit for the data (Khalifa, 2009).

The second strand of the literature considers volatility comovements and dynamic characteristics across commodity and currency markets. Hammoudeh and Yuan (2008), Hamoudeh et al. (2009), Choi and Hammoudeh (2010) and Hammoudeh et al. (2010) use three “two factor” volatility models of the $GARCH$ family to examine the volatility behavior of $gold$, $silver$ and $copper$, in the presence of crude oil and interest rate shocks. Their results from the standard $GARCH$ models suggest that $gold$ and $silver$ have almost the same volatility persistence, which is relatively greater when compared to $copper$. They find that past oil shocks do not impact all three metals in the same manner. In addition, they explore the commodities' causal relationships with two macro financial variables including interest rates and exchange rates, and find that interest rates mediate the link between commodity prices and exchange rates. Sari et al. (2010) find evidence of a weak long-run equilibrium relationship but strong feedbacks in the short-run across the spot prices of four precious metals($gold$, $silver$, $platinum$, $and\ palladium$), the oil price and the $US\ dollar/euro$ exchange rate. The spot precious metal markets respond significantly (but temporarily) to a shock in any of the prices of the other metals and the exchange rates. More recently, Bubáket al. (2011) find evidence of statistically significant intra-regional volatility spillovers among the $central\ European$ currencies' foreign exchange markets. With the exception of the $Czech$ and $Polish$ currencies prior to the recent turbulent economic events, those authors find no significant spillovers running from the EUR/USD to the central European foreign exchange markets. Using the same family of MS models, Kritzman et al. (2012) show how to apply $Markov - switching$ models to forecast regimes in market turbulence, inflation, and economic growth. They find that the consideration of regime-switching in asset allocation significantly improves performance compared with an unconditional static alternative. Within the context of market interdependence, Aloui et al. (2011) show strong evidence of time-varying dependence between each of the $BRIC$ markets and the US market, but the dependency is stronger for commodity price -dependent markets than for finished-product export-oriented markets. They also observe high levels of dependency persistence for all market pairs during both bullish and bearish markets.

The current study attempts to fill the gap in the literature by distinguishing between the different types of volatility linkages of the volatility across different regimes, and constructing optimal hedge ratios and portfolio weights within a multi-chain regime-switching environment.

3 Research Methodology

As indicated earlier, this study uses the $bivariate\ MCMS\ regime - switching$ model proposed by Gallo and Otranto (2007; 2008) to examine identify and distinguish between the different mechanisms of volatility transmission dynamics. $Regime - switching$ models were originally introduced by Hamilton in 1989, and then applied to study market dependence and contagion in emerging equity markets by Edwards and Susmel (2001; 2003). Fratzscher (2003) applies this approach to currency crisis contagion where many variables undergo episodic shifts in prices.

The $MCMS$ model considers different dynamics of each market within each state, where the market depends on its own previous value and the previous value of the state referred to the other market. In other words, mutual directional relationships between any two markets are allowed. Otranto and Gallo (2007, 2008) document that the $MCMS$ model has better forecasting performance than other existing models. Most notably, the

$MCMS$ model can distinguish between several types of inter-market linkages such as spillovers, interdependencies and comovements under different regimes as warranted in this study. Volatility spillover is defined as a situation in which a switch in the regime of a dominating asset market precedes or leads to a change in the regime of the dominated market. In contrast, in the case of interdependence it is not possible to distinguish between dominating and dominated markets: a switch in the regime of the first market leads to a change in the regime of the second market, but also a switch in the regime of the second market can cause a switch in the regime of the first market. The volatility comovement, on the other hand, is a contemporaneous change in regimes across markets due to common shocks. It is important to note that the spillover, interdependence and comovement relationships refer to the full time interval analyzed and not to single periods. For example, if at a certain date a variable seems to have a spillover effect on another variable, the first variable cannot be classified as a dominant asset if this behavior is not regularly repeated in the full data period analyzed.

Suppose we have the volatility series of n assets in a time interval $[0, T]$. Let $y_{j,t}$ be the variable representing the volatility of market j at time t. We define a two-dimension vector $y_t \equiv (y_{1,t}, y_{2,t})'$, where $y_{1,t}$ and $y_{2,t}$ are two of the n variables, which follows a $VAR(p)$ process as:

$$\begin{aligned} &y_t = \mu(s_t) + \textstyle\sum_{m=1}^{p} \Phi_m(s_t) y_{t-m} + \varepsilon_t \\ &\varepsilon_t \sim N\left(0, \textstyle\sum(s_t)\right) \end{aligned} \tag{3.1}$$

$$\sum(s_t) = \begin{bmatrix} \sigma_1^2(s_{1,t,\cdot}) & \rho(s_{1,t}, s_{2,t})\sigma_1(s_{1,t,\cdot})\sigma_2(\cdot, s_{2,t}) \\ \rho(s_{1,t}, s_{2,t})\sigma_1(s_{1,t,\cdot})\sigma_2(\cdot, s_{2,t}) & \sigma_2^2(\cdot, s_{2,t}) \end{bmatrix} \tag{3.2}$$

Here the parameters of the conditional mean, $\mu(s_t)$, and $\Phi_m(s_t), 1 \leq m \leq p$, as well as the variance-covariance matrix of the error terms ε_t all depend on the state vector $s_t = (s_{1,t}, s_{2,t})'$ with $s_{j,t}$ assuming values in $[0, 1]$, representing the state of time t, (where 0 indicates the quiet or low volatility state, while 1 denotes the turmoil or high volatility state. In practice, the state s_t is a combination of the two latent variables $s_{1,t}$ and $s_{2,t}$,for markets 1 and 2, respectively. In the variance-covariance matrix, the variances of each variable (related to the fourth moments of returns which we assume to exist) depend only on the variable's own state. The parameter $\rho(s_{1,t}, s_{2,t})$ refers to the correlation coefficient between the two markets at a certain state $s_t = (s_{1,t}, s_{2,t})'$. This specification implies that volatility is transmitted from one market to another, also causing some changes in the covariance structure, where as the changes or movements in the variance depend solely on its own state.

The state vector s_t can take at time t one of four possible values for the two variables: $(0, 0)'$, $(0, 1)'$, $(1, 0)'$, or $(1, 1)'$, at any time $0 \leq t \leq T$,, where in each cell the first number refers to the state of the first variable and the second number to the state of the second variable. Given the interpretation of the two states, for example,$s_t = (1, 0)'$ means that the first variable is at a high volatility state whereas the second variable is at the low volatility state.

The states are unobservable. We hypothesize that the dynamics of the bivariate variable s_t is driven by a Markov Chain, as in the classical MS model, in which the probability of a certain state at time t depends only on the value of the state at time $t-1$.The novelty of the MCMS model with respect to the MS model is that the variables are not necessarily in the same state and that the change in the state of one variable can affect the probabilities of the state of the other variable. The probabilities are collected in a transition probability matrix.

The transition probability matrix $P = \{Pr[s_t|s_{t-1}]\}$ is a $4x4$ matrix. We further suppose that conditional on $(s_{1,t-1}, s_{2,t-1})$, the two states $s_{1,t}$, and $s_{2,t}$ are independent. That is:

$$Pr[s_{1,t}, s_{2,t}|s_{1,t-1}, s_{2,t-1}] = Pr[s_{1,t}|s_{1,t-1}, s_{2,t-1}] \times Pr[s_{2,t}|s_{1,t-1}, s_{2,t-1}]$$

We can parameterize the right-hand side of equation (3) with logistic functions where each function explicitly depends on past states[21]:

$$\begin{aligned} Pr[s_{1,t} = h|s_{1,t-1} = h, s_{2,t-1}] &= \tfrac{exp\,[\alpha_1(h,\cdot)+\beta_1(h,1)s_{2,t-1}]}{1+exp\,[\alpha_1(h,\cdot)+\beta_1(h,1)s_{2,t-1}]} \\ Pr[s_{2,t} = h|s_{1,t-1}, s_{2,t-1} = h] &= \tfrac{exp\,[\alpha_2(\cdot,h)+\beta_2(1,h)s_{1,t-1}]}{1+exp\,[\alpha_2(\cdot,h)+\beta_2(1,h)s_{1,t-1}]} \end{aligned} \tag{3.3}$$

for $h = 0, 1$, (low and high volatility regimes). From the parameterization in (4), the parameters $\alpha_1(h,\cdot)$ and $\alpha_2(\cdot,h)$ are the constants of the logistic function. We can also note that $\beta_1(h,1)$ coefficient measures the influence of state of market 2 at time $t-1$ on the probability of market 1 to stay in state h. Similarly, $\beta_2(1,h)$ coefficient measures the influence of state of market 1 at time $t-1$ on the probability of variable 2 to stay in state h. In this way, the estimations of the probabilities in equation (4) show how the transition probabilities for market 1 change according to the regime of market 2, and vice versa.

Thus, the transition probability matrix makes the probability of staying at the same state for asset i conditional on the previous states of both assets. Since each asset has only two states, the probabilities of switching to another state can be estimated by the following equation:

$$Pr[s_{j,t} = k|s_{j,t-1} = h, s_{i,t-1}] = 1 - Pr[s_{j,t} = h|s_{j,t-1}, s_{i,t-1}] \tag{3.4}$$

for $h, k = 0, 1$ where $h \neq k$and $i, j = 1, 2, i \neq j$. Thus, the 4×4 transition probability matrix will be as follows:

[1]See Gallo and Otranto (2008) for additional details.

$$\begin{bmatrix} P(00|\,00) & P(01|\,00) & P(10|\,00) & P(11|\,00) \\ P(00|\,01) & P(01|\,01) & P(10|\,01) & P(11|\,01) \\ P(00|\,10) & P(01|\,10) & P(10|\,10) & P(11|\,10) \\ P(00|\,11) & P(01|\,11) & P(10|\,11) & P(11|\,11) \end{bmatrix}$$

where, for example, the transition probability $P(00|\,00)$ means $Pr(s_{1t} = 0, s_{2t} = 0|s_{1t-1} = 0, s_{2t-1} = 0)$.Now we have a system of equations (1) and (2), and also equations $(3, 4\ and\ 5)$ that can be estimated simultaneously in order to investigate the volatility dependence/independence structure, using a battery of tests.

The presence of statistical significance of all parameters in equations (4) would provide evidence in favor of interdependence. If the coefficient $\beta_1(h, 1) = 0$ but $\beta_2(1, h)$ is different from zero for each $h = 0, 1$, then the state of the market 2 at time $t - 1$ does not influence the probability of market 1 at time t to stay in the same regime, but the opposite is true. This is evidence in favor of the dominant status of market 1 or a spillover from market 1. Finally, the joint non-significance of all the coefficients $\beta_1(h, 1)$ and $\beta_2(h, 1)$ would provide evidence in favor of independence between markets. The statistical significance of $\alpha_1(h, \cdot), \alpha_2(\cdot, h), \beta_1(h, 1)$ and $\beta_2(1, h)$ are used jointly to test the comovements (responding to shocks other than the impacts of markets 1 and 2) between the two markets.

More precisely, after estimating the model, we follow the approach developed in Gallo and Otranto (2008) to evaluate the nature of the dependency between two markets. In particular, we test the following four null hypotheses, using the classical Wald statistics (see Gallo and Otranto, 2008, for details):

1. $H_0 : \beta_1(0, 1) = \beta_1(1, 1) = 0$. This hypothesis holds if there is no spillover effect from y_2 in period $t - 1$ to y_1 in period t.

2. $H_0 : \beta_2(1, 0) = \beta_2(1, 1) = 0$. This hypothesis holds if there is no spillover effect from y_1 in period $t - 1$ to y_2 in period t.

3. $H_0 : \beta_1(0, 1) = \beta_1(1, 1) = \beta_2(1, 0) = \beta_2(1, 1) = 0$. This hypothesis holds if there is no interdependence (i.e., no reciprocal spillover) between the two series between the periods $t - 1$ and t.

4. $H_0 : \begin{cases} \alpha_1(0, \cdot) = \alpha_2(\cdot, 0), \\ \alpha_1(0, \cdot) + \beta_1(0, 1) + \alpha_2(\cdot, 1), \\ \alpha_1(1, \cdot) + \beta_2(1, 0) + \alpha_2(\cdot, 0) = 0, \text{ and} \\ \alpha_1(1, \cdot) + \beta_1(1, 1) = \alpha_2(\cdot, 1) + \beta_2(1, 1) \end{cases}$

This fourth hypothesis verifies the presence of a comovement between y_1 and y_2 if valid. The form of this particular null hypothesis is not trivial, and the way to obtain it is explained in the final appendix in Gallo and Otranto (2008).

Finally, an important characteristic of the MS type models is the possibility to derive the smoothed probabilities of the states to make inference on the latent variable s_t.

Using the Hamilton filtering and smoothing (see Hamilton, 1994), we estimate for each time t the probability of a certain state conditional on the full data set. In general, if the model has a good fit, these probabilities are close to 0 or 1, so we can assign each observation to a certain regime or to another. In particular, for the MCMS model, we obtain the (smoothed) probabilities of each state, $P(s_{1t} = i, s_{2t} = j|I_T), (i, j = 0, 1)$, where I_T represents the full information available. To obtain the probabilities of the state of a single variable, it is sufficient to sum up over all the probabilities values of the other variable at the two states. For example, if we are interested in the smoothed probabilities of the first variable, it can be obtained as

$$P(s_{1t} = i|I_T) = P(s_{1t} = i, s_{2t} = 1|I_T) + P(s_{1t} = i, s_{2t} = 2|I_T) \text{ (where } i = 0, 1)$$

4 Data and Descriptive Statistics

We analyze the historical characteristics of the weekly currency (spot prices) series of the euro (EUR), the Australian dollar (AUD), the British pound (GBP), the Swiss franc (CHF), the Japanese yen (JPY) and the Canadian dollar (CAD). Three of the currencies, namely the AUD, GBP and CAD are resource-driven currencies because their economies are major producers of commodities, while JPY and CHF are commonly believed to be safe haven currencies. The selection of EUR reflects its relative importance in currency markets.

In addition, we select four widely traded commodity futures – $crude\ oil$, $gold$, $silver$ and $copper$ – and the $S\&P500$ equity index, as alternative asset classes related to the selected currencies under consideration. The sample period is from September 6, 1999 through February 3, 2012 (648 observations), and the data for all variables are obtained from Bloomberg. The start of the time period is dictated by the availability of data on the euro. With the exception of JPY, all bivariate exchange rates are expressed as the number of $U.S.\ dollars$ per one unit of the foreign currency. That is, an increase in any of the exchange rates, with the exception of JPY, implies an appreciation in the relevant non-dollar currency. The reliance on weekly data allows us to overcome the problem of different time zones and to better identify regime switches. Similar to Gallo and Otranto (2008), the proxy for the volatility of asset returns is computed weekly as follows: $(\ln(Max) - \ln(Min) * (1/4 * \ln(2)\hat{\ }0.5))^3$.
[2]

$Table$ 1 shows the main descriptive statistics for the volatility of the twelve markets for the time span selected. There is evidence of skewness in the volatility distributions

[2]The range-derived measures have been recognized as a good volatility indicator by many authors. For example, Parkinson (1980) and Alizadeh et al. (2002) have provided interesting discussions on their properties. Engle and Gallo (2006) also have shown that the range possesses good explanatory power in predicting future values of squared returns or realized variance. As a certain market becomes more volatile and its shocks are transmitted across other markets, the choice of the weekly frequency of analysis is always crucial in detecting the direction of the temporal relationship. With respect to the max, it is the maximum closing price of the week days. On the other hand, the min is the minimum closing price during the week days (Daily frequency prices)

as revealed by comparing the maximum values with the medians and minimum values. Furthermore, the table clearly shows the non-normality of the observations as displayed by the significance of the $Jarque - Bera$ statistic, compared with a critical value of a chi square distribution with 2 degrees of freedom. These data characteristics are consistent with the presence of switching regimes, as pointed out in many empirical applications (see Ang, and Timmermann, 2011; Candelon and Straetmans, 2006).

The characteristics can be better depicted by observing the volatility dynamics in the graphs of $Figure$ 1. They show several peaks characterizing the turmoil (or high volatility) periods with brief durations in contrast to longer periods of relative tranquility (or low volatility levels). In particular, all markets with the exception of silver show a high degree of volatility starting in 2008, and are markedly different from the pattern that prevailed during 1999- 2008.

$Table$ 2 displays the correlation matrix across the selected markets for the log of series of the eleven markets for the time span selected. We find that the resources currencies and the $euro$ share a high degree of correlation with the selected commodities. For example, the AUD correlations with oil, gold, silver and copper are 0.91, 0.9, 0.42 and 0.91, respectively. In contrast, the correlations of GBP with oil, $gold$, $silver$ and $copper$ are respectively 0.50, 0.21, 0.48 and 0.49. Finally, the correlations of JPY (yens per dollar) as a safe haven currency with oil, $gold$, $silver$ and $copper$ are 0.59, 0.80, 0.04 and 0.59, respectively.

5 Empirical Results

In this section, we discuss the various types of dynamic volatility relationships across the different asset classes, and provide inferences on regime shifts and optimal hedging and asset portfolio allocation strategies.

5.1 Forms of volatility transmission across currencies, commodities and equities

Results from the various bivariate volatility relationships are provided in the panels of $Table$ 3 for the pairs of the three asset classes. They distinguish between volatility spillover, interdependence and comovement effects for each pair of these assets[43]. For empirical tractability, we first present the influence of currencies on the equities ($the\ S\&P$ 500 $index$) and commodity markets in Panels A through F of $Table$ 3. In general, the application of $MCMS$ demonstrates the dominance of volatility interdependence over spillovers and comovements in the three asset classes. For instance, volatility spillover comes a close second to the volatility interdependence transmissions. On the other hand, comovement behavior is found to be the weakest among the different types of transmission mechanisms. It is also worth noting that, in general, volatility spillovers are more

[3]Intra-currency transmissions are delegated to future research to honor space limitation.

common than volatility interdependence when the source of the volatility shock is a currency, as opposed to commodities or the $S\&P$ 500 $index$, giving more differential weight to shocks specific to the currency markets than to the commodity markets.

The dominance of volatility interdependence underscores the relative importance of reciprocal market shocks pertinent to related individual asset markets, compared to common economy-wide shocks. AUD, GBP, oil and $copper$, followed by $gold$ and $silver$ stand out as the assets with the most interdependence relationships when each of them is the original source of the shock. The AUD for example is found to share volatility interdependencies with oil, $copper$ and the $S\&P$ 500 $index$ (see $Panel\ B$), while copper has interdependencies with AUD, GBP and $gold$ (see $Panel\ F$).

As indicated earlier, volatility spillovers are dominant particularly when the original volatility source is a currency rather than a commodity. It is strongly pronounced for shocks originating in the AUD, $copper$ and GBP followed by EUR, CHF and $gold$. A shock in the AUD market, for example, spills over to oil, $gold$, $silver$ and $copper$, while a shock in GBP spills over to oil, $gold$ and $copper$. Moreover, a shock that originates originated in copper is found to spills over toAUD, oil, $gold$ and $silver$. Among all the assets considered, only $gold$ has a spillover to the $S\&P$ 500 $index$ (see $Panel\ E$) which has the weakest linkages with the other assets.

Finally, the comovement is the weakest pattern of all types of transmission, corroborating the importance of asset specific-shocks. It is rejected for all the asset pairs except between the $S\&P$ 500 $index$ and $gold$.

The documented response behavior seems to have economic underpinnings. For instance, the role of Australia as a resource-dependent economy is clear, as seen by its currency's volatility interdependence and spillover relationship with commodities. Australia is a country with abundant natural resources endowment while British economy through the BP company is a major player in the oil and metals markets. GBP has both significant interdependence and spillovers to oil, $gold$ and $silver$ probably because London houses the second most oil and metals commodity exchange markets and its Brent oil is a global benchmark. Finally, CHF which is considered a safe haven currency has volatility spillovers to $gold$ and $silver$.

The volatility transmission results leave open the possibility that there may be some diversification gains across the three asset classes, and importantly the investment hedge ratios and portfolio weights are state contingent. This is examined in the next section.

5.2 Inference on regimes: the case of AUD and Copper

Given the multiplicity of variables, for the sake of expositional clarity we discuss the results only for the pair $(AUD,\ Copper)$[54]. We have chosen this pair because the two paired assets are found to be highly correlated (see $Table$ 2) and share a high degree of volatility interdependency with each other.

$Figure$ 2 displays the smoothed probabilities for the four combinations of the states of the two variables (AUD and $Copper$) in the pair which are$(00, 01, 10, 11)$ for the full

[4]The results on the remaining combinations are available on request.

sample period. The evidence shows that these probabilities are generally close to 0 or 1, which indicates a fairly precise inference on the regime. Interestingly, the particular state $(1, 0)$, which includes AUD in the high volatility state and *copper* in the low volatility state, has an expected duration of just 1 week, whereas the other states are found to have a relatively longer persistence. In comparison, the expected duration of the tranquility state $(0, 0)$ is equal to 10 weeks, and the two other cases $(0, 1)$ and $(1, 1)$ correspondingly have a duration of six weeks, respectively.

These results are derived from the estimated transition probability matrix[6]:
[5]

$$\begin{bmatrix} P(00|\,00) & P(01|\,00) & P(10|\,00) & P(11|\,00) \\ P(00|\,01) & P(01|\,01) & P(10|\,01) & P(11|\,01) \\ P(00|\,10) & P(01|\,10) & P(10|\,10) & P(11|\,10) \\ P(00|\,11) & P(01|\,11) & P(10|\,11) & P(11|\,11) \end{bmatrix} = \begin{bmatrix} 0.903 & 0.017 & 0.079 & 0.001 \\ 0.086 & 0.834 & 0.007 & 0.073 \\ 0.691 & 0.154 & 0.127 & 0.028 \\ 0.000 & 0.175 & 0.000 & 0.825 \end{bmatrix}$$

It seems that having the resource currency AUD in the high volatility state gives rise to a very short transitory period except i state $(1, 1)$. Generally, we must note that the states $(0, 0)$ and $(1, 1)$ when the same states persist from s_{t-1} to s_t have the highest expected durations.

A further review of $Figure$ 2 indicates that the first part of the series is characterized by a quiet period for both variables (in state$(0, 0)$), with some sporadic cases in which the AUD switches to the high volatility regime for one week (in state$(1, 0)$). This behavior characterizes the series until the third week of April 2004, and subsequently the two variables switch to the turmoil state in the first week of May 2004. From this date onwards, the regime-switching behavior is observed more frequently. A crucial interval is the 2006- 2007 period where during the first week of February 2006 *copper* switches to state 1 and stays in this regime until the fourth week of June 2007 corresponding to the onset of the global financial crises. After a month of tranquility following June 2007, both AUD and *copper* immediately switch to the turmoil period. For the balance of the period, the two series are characterized by frequent regime switches.

The results from the $Wald$ tests, shown in $Table$ 3 ($Panels\ B\ and\ F$), document the presence of interdependence between the two variables in the pair (AUD *and copper*), with some evidence of spillover from *copper to* AUD (the p-value of the statistic related to the null hypothesis of no spillover from *copper to* AUD is 0.013, whereas from AUD *to copper* is 0.046. This happens, in particular, when AUD is in regime 1and *copper* in regime 0 at $t-1$ (see the third row of the transition probability matrix above). in this case, there is a high probability ($i.e.$, $P(00|10) = 0.691$) that AUD will switch to regime 0 at the next time t. However, *copper* could also change state from $t-1$ *to* t with a probability $P(01|10)$ equal to 0.154. On contrast, other states show a certain persistence in the sense that variables will stay in the same states, as represented by the high probabilities on the diagonal of the transition probability matrix (except for the third position given by $P(10|10) = 0.127$).

The transition probability matrix shows that if *copper* is in state 0 at time $t - 1$ and AUD is in state 1, there is a strong probability that also AUD will switch to state 0 at

[5]The expected duration of the state (i, j) is obtained as $1/(1 - P(ij|ij)$.

time t. This probability is given by $P(00|10) + P(01|10) = 0.845$, but the opposite is not true as shown by $(P(00|01) + P(10|01) = 0.093)$. On the other side, AUD seems to have influence on $copper$ when AUD is in state 1 and $copper$ in state 0. In this case, the probability that, under this scenario at time $t-1$, $copper$ will switch to state 1 is given by $P(01|10) + P(11|10) = 0.182$. These results seem to suggest a particular kind of interdependence, where $copper$ is clearly dominant during the low volatility state, whereas AUD shows a small, but perceptible influence during the turmoil state.

5.3 State implications for hedge ratios and optimal portfolio weights

The study provides applications of the results by constructing optimal hedge ratios and portfolio weights, using estimates derived from the MCMS model for currencies, commodities and the equities.

5.3.1 Hedge ratios

The hedge ratios are obtained from the conditional volatility estimates (Kroner and Sultan, 1993). A long position in one market (say market i) can be hedged with a short position in a second market (say market j) at state s_t using four possible cases. The first case is the low state of market i and the low state of market j; the second is the low state of market i and the high state of market j; the third is the high state of market i and the low state of market j; and the fourth is the high state of market i and the high state of market j. A hedge ratio between market and market will be computed for each state and at time t as well using the following:

$$\beta_{ij,s,t} = \frac{h_{ij,s,t}}{h_{jj,s,t}} \tag{5.1}$$

where $\beta_{ij,s,t}$ is the risk-minimizing hedge ratio for each two markets at state s and time t, $h_{ij,s,t}$ is the conditional covariance between market i and $j$at a state s_t and time t and $h_{jj,s,t}$ is the conditional variance of market j at a state s_t and time t.

Table 4 shows the hedge ratios estimated by equation (6) using three approaches; the $state\ dependent - MCMS$, $time - variant\ MCMS$[76] and VAR models. For the time variant hedge ratio, estimated by $MCMS$ for each pair, we show the mean of the time-varying hedge ratios for the full sample period. Generally speaking, in the case of the state dependent $MCMS$ model, the results demonstrate that the hedging cost becomes more expensive if one or both the hedged and hedging assets are in the turmoil state or if the hedged asset in the long position is more volatile. For example, example examining the $GBP - silver$ pair, a $\$1$ long position in the GBP can be hedged for 4 cents with a short position in the silver market if both of the two markets are at the dual tranquility regime State $(0, 0)$. On the other hand, in the dual turmoil State $(1, 1)$, the corresponding cost of hedging the same $\$1$ long position in the GBP is 10 times higher, about 40 cents. Moreover, a $\$1$ long position in GBP can be hedged for 62 cents with a short position

[6] $The\ time\ variant - MCMS$ is the weighted average value (with weights equal to the smoothed probabilities of each state at time t) of the time variant hedging ratios. The value in the table is the mean of $the\ time - variant\ MCMS$

in the silver market if GBP is at a turmoil regime and $silver$ market is at a tranquility regime (State$(1,0)$). It is clearly evident that the hedge ratios are regime dependent. A similar type of analysis is applicable to the other pairs. It is interesting to note that oil is the most expensive commodity to hedge when either one or both states are in turmoil probably because of its high volatility. For example, it takes 76 cents to hedge oil with $gold$ in the state $(1,0)$, while it takes $\$1.31$ to do the same hedging in state $(1,1)$.

$Table$ 4 also provides the constant hedging costs that are obtained using the VAR model. For example, a $\$1$ long position in GBP can be hedged for about 5 cents with a short position in the silver market. In addition to not being able to control for varying regimes, , the VAR estimated cost may mask the true underlying cost estimated using the $MCMS$ model which ranges from 62 to 40 cents for turmoil States $(1,0)$ and $(1,1)$, respectively.

One can apply a similar analysis for the remaining pairs of assets. In general, the hedge ratios estimated using the $time - variant$ $MCMS$ are on average substantially lower than those estimated using the VAR model. Examples include: EUR and $silver$; EUR and the $S\&P$ 500 $index$; GBP and oil; GBP and $gold$; and GBP and $copper$. In the case of the $MCMS - time\ variant$ model, the $time - varying$ hedging costs for these pairs are 2.7 cents, 1.9 cents, 1.8 cents, 0.8 cents and 2.9 cents, respectively. In contrast, the VAR model indicates that the hedge costs are 5.7 cents, 9.9 cents, 4.9 cents, 3.6 cents and 8.3 cents, respectively. Overall, the results indicate that it is cheaper to hedge currencies with commodities than the other way around.

Hedging effectiveness for currencies, commodities and equities also differs when the short position is in equities as opposed to commodities. Using $MCMS$, it seems that hedging GBP with silver is more expensive than hedging it with oil, $copper$ and the $S\&P$ 500 $index$. The most expensive hedges are between the following pairs: $(EUR/copper)$, $(GBP/silver)$, $(CHF/copper)$, $(oil/silver)$, $(oil/copper)$ at the state $(1,0)$. As indicated above, hedging becomes more expensive if only the hedged market (that is in the long position) is in turmoil. Interestingly, it appears that hedging is less expensive when both markets are in turmoil as opposed to a situation where only the hedged market is in turmoil.

$Figure$ 3 displays the dynamic trajectory of hedging ratios for bivariate portfolios for selected pairs calculated from the results of the $state - variant$ $MCMS$ model, the $time - variant$ $MCMS$ model and the VAR model. $Table$ 4 indicates that in the portfolio comprising AUD and $S\&P$ 500, hedging a long position in the AUD with a short position in the $S\&P$ 500 $index$ is much more effective under the $time - variant$ $MCMS$ model than the VAR. The same holds for the portfolio that holds the AUD and $copper$. For the third portfolio that holds the AUD and $gold$, there is no clear pattern on hedging effectiveness. However, there are some time periods in 2008 and 2009 when the VAR model provides hedging cost estimates that are lower than the $MCMS$.

5.3.2 Regime Change and Asset Allocations

The conditional volatilities from the $MCMS$ model is used to construct optimal portfolio weights (Kroner and Ng, 1998). By considering a portfolio that minimizes risk without lowering expected returns, the portfolio weight of two market holdings is given by:

$$\omega_{ij,s} = \frac{h_{jj,s,t} - h_{ij,s,t}}{h_{ii,s,t} - 2h_{ij,s,t} + h_{jj,s,t}}$$

$$\omega_{ij,s,t} = \begin{cases} 0 & \text{if} \omega_{ij,s,t} < 0 \\ \omega_{ij,s,t} & \text{if} 0 \leq \omega_{ij,s,t} \leq 1 \\ 0 & \text{if} \omega_{ij,s,t} \geq 1 \end{cases} \tag{5.2}$$

In constructing portfolio weights between two markets, $\omega_{ij,s,t}$ is the weight of the first market in a one dollar portfolio comprised of two markets (market i , market j) at state s_t at time t, $h_{ij,s,t}$ is the conditional covariance between market i and j at state s_t and time t and $h_{jj,s,t}$ is the conditional variance of market j at state s_t and time t. The weight of the second market is $1 - \omega_{ij,s}$.

$Table$ 5 shows the optimal weights for different pairs of currencies, commodities and equities obtained using the different models. It demonstrates the importance of regime changes on asset allocation by providing the sensitivity of each pair to the prevailing state of the market for each asset in that pair. For example, in the state $(0, 1)$, when a currency is at the tranquil state and the $S\&P$ 500 $index$ or a commodity is in turmoil, results suggest that investors should hold the majority of their portfolios in currencies. This is evident from examining the pairs (AUD/oil), $(AUD/gold)$, $(AUD/silver)$, $(AUD/copper)$ and $(AUD/S\&P$ 500), where the relative weight for the currency is more than 98, 77, 92, 97 and 88 cents for AUD vis-à-vis the commodity in the state $(0, 1)$. A qualitatively similar pattern holds for the rest of the currencies.

Similarly, one can explain the results for the state $(1, 0)$ when only the currencies are in turmoil. In this case, results suggest that investors should tilt their portfolios towards commodities and equities. For example, in the pairs (AUD/oil), $(AUD/gold)$, $(AUD/silver)$, $(AUD/copper)$ and $(AUD/S\&P$ 500 $index)$, the relative weight for the currency (AUD) is close to 56, 13, 6, 20 and 14 cents. These weights capture the high degree of substitutability between AUD and oil in the $(1, 0)$ state, suggesting that investors can be indifferent about allocating them in their portfolios. However, AUD is more risky than the commodity that may be protected by futures contracts. A similar pattern holds for other currencies in the sample.

In the interesting dual turmoil state $(1, 1)$, results indicate that investors are generally better off overweighting currencies in the portfolio, with the exception of AUD. In the turmoil state, portfolio pairs that contain AUD should more weight allocated to gold and the $S\&P$ 500 $index$ than AUD, possibly because gold is recognized as a safe haven asset and the $S\&P$ 500 $index$ is more highly diversified than the heavy resource currency, AUD. For example, in the pairs $(AUD/gold)$ and $(AUD/S\&P$ 500 $index)$, the weight for the currency (AUD) is 4.9 and 11.1 cents, respectively. This result indicates that at times of turmoil, AUD, the $S\&P$ 500 $index$ and commodities are more risky than the currencies EUR, CAD, CHF, GBP and JPY. The evidence corresponding to other states are provided in $Table$ 5 $(Panels$ A and $B)$.

With respect to the $S\&P$ 500 $index$- commodities portfolio, the optimal weight for the low state $(0, 0)$ is 0.50 on average. This indicates that for a \$1 portfolio, 50 cents should be invested in the $S\&P$ 500 $index$, while the other 50 cents should go to $gold$, $silver$ or oil. However, when the $S\&P$ 500 $index$ and a commodity market are at different regimes, for example, when the first market (the $S\&P$ 500 $index$) is in the tranquil state and the commodity is in the turmoil regime (that is, state $(0, 1)$), then the optimal weights change significantly in favor of the $S\&P$ 500 $index$.

In contrast, under State $(1, 0)$ the optimal weights are mixed among the three asset classes. In the interesting dual turmoil state $(1, 1)$, the results suggest that investors should be holding more of the commodity futures within ($S\&P$ 500 $index/oil$) and (the $S\&P$ 500 $index/copper$) pairs, probably because the commodity prices are based on futures contracts which are used as a hedge during tumultuous times.

Finally, within the commodities, $Table$ 5 also demonstrates the state dependent nature of optimal portfolio weights. In general, we find that more weight is given to an individual commodity that is in the tranquil state. For example, at the tranquil state $(0, 0)$ for the two commodities in the $oil/gold$ portfolio, the optimal weight is 0.5, which indicates that for a \$1 portfolio 50 cents should be invested in the oil, while 50 cents should be invested in $gold$. This result is similar to pairs that include the $S\&P$ 500 and a commodity. However, when the oil and other individual commodities are at different regimes, for example, when the first market (oil) is in the tranquility regime and the other market is in the turmoil regime (state $(0, 1)$), then the optimal weight changes significantly in favor of oil, which is also similar to the case with the $S\&P$ 500 $index$.

In the dual turmoil state $(1, 1)$ of the $oil/gold$ pair, results indicate that it would be optimal for investors to invest 100% of the portfolio in $gold$. A similar analysis is undertaken for the $oil/silver$ pair where we find that it is optimal for investors to invest 92% of the portfolio in $silver$, affirming the safety status of this metal. With respect to the oil/copper at the tranquility state $(0, 0)$ for the assets in the $oil/copper$ portfolio, the optimal weight is 0.22 which indicates that for a \$1 portfolio 22 cents should be invested in oil, while 78 cents should be invested in $copper$.

6 Conclusions

This paper uses the $multic\ hain\ Markov - switching$ ($MCMS$) model to investigate the type of volatility transmission: spillover, interdependence and co movements across seven currencies, the $U.S.$ $S\&P$ 500 $index$ and four commodities in a regime-changing environment. Furthermore, the paper provides important asset allocation implications by comparing time-varying portfolio weight obtained from $MCMS$ model with constant weights estimated from VAR. The advantage of the $MCMS$ model is that it enables us to distinguish between different volatility transmission mechanisms, a feature that structural VAR models cannot accommodate. Specifically, the $MCMS$ model is able to discern the form of transmission to the source of volatility shock which may be attributed to reciprocity between specific markets, specificity to a common source such as the overall economy and the business cycle, or to shocks in one specific market that spills over to another market but with a lag.

Results establish the relative importance of volatility interdependence behavior between the three asset classes, particularly when the source of the shock comes from a commodity or commodity backed currency. This finding highlights the sensitivity of each individual market to shocks that are specific to its own prices as well as to shocks from related markets. Interdependent relationships are most clearly evident for asset pairs that include $Australian\ dollar$, $British\ pound$, oil and $copper$.

The spillover pattern while not as dominant as interdependence is also found to be important in characterizing volatility transmission behavior. The spillover shock signifies that volatility in one market in a given period is transmitted to another market in the next period. Spillover is pronounced for shocks that originate from the $Australian\ dollar$, $British\ pound$ and $copper$, with weaker effects originating from the $euro$, $Swiss\ franc$ and $gold$. The practical guidance offered to investors is that since the spillover transmission effects come with a lag, it may offer investors an opportunity to react before the asset prices are impacted.

The weakest pattern among all transmission types is comovement, which points us away from the importance of common shocks in the system. This form of transmission is rejected for almost all asset pairs. A notable exception is the documented comovement between $gold$ and the $S\&P500\ index$.

An analysis of hedge ratios and optimal portfolio weight indicates that both set of variable are contingent on the volatility regime and the type of volatility transmission. In general, the hedge ratios obtained from employing $MCMS$ are found to be lower than the associated ratios estimated from the VAR model. We find that it is more expensive to hedge an asset when it is in a high volatility state than when it is in tranquil. Interestingly, hedging between a currency and a commodity is more expensive than hedging between two non-currency assets like the $S\&P$ 500 $index$ and commodity futures. Notably, the most expensive hedge involves oil which may perhaps be explained by its heightened sensitivity to economic, political, weather and idiosyncratic shocks.

Consistent with expectations we find that the optimal portfolio weights are relatively larger for the asset that is the tranquil state compared to the turmoil state. Precious metals, owing to their safe haven status, comprise a larger weight in portfolios that contain either one of these two commodities.

On a broader front, our findings on the nature of the transmission mechanism and its implications for constructing portfolios provide important insights for traders and investors. An understanding of the volatility transmission characteristics that are contingent on the state of the volatility regime would be crucial in managing an active asset allocation program where the hedge ratios and optimal portfolio weights are $time-and\ state-variant$.

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Table 1: Descriptive Statistics of the volatility indices of the selected markets

	EUR	GBP	CAD	JPY	CHF	AUD	SP500	OIL	GOLD	SILVER	COPPER
Mean	0.61	0.53	0.51	0.64	0.58	0.73	1.05	2.06	0.93	0.41	1.44
Median	0.55	0.47	0.43	0.58	0.5	0.61	0.85	1.72	0.74	0.29	1.17
Max	2.31	3.16	3.17	4.82	3.21	5.26	6.73	11.37	6.16	6.78	9.36
Min	0.07	0.04	0.06	0.06	0.09	0.12	0	0.06	0.03	0	0.01
Std. Dev.	0.32	0.31	0.34	0.38	0.35	0.52	0.77	1.34	0.68	0.5	1.04
Skewness	1.29	2.46	2.72	3.53	1.85	3.58	2.46	2.37	2.51	6.05	2.31
Kurtosis	5.98	14.92	16.69	31.72	9.9	26.17	12.99	12.07	13.71	62.93	11.82
J-B	417.51	4491.68	5860.98	23616.26	1652.9	15885.79	3350.41	2826.09	3778.55	100925.1	2676.45

Table 2: Correlation Coefficients of the log of the selected markets

	AUD	EUR	CAD	CHF	GBP	JPY	SP500	OIL	GOLD	SILVER	COPPER
AUD	1	0.91	0.96	0.94	0.5	-0.72	0.26	0.91	0.9	0.42	0.91
EUR	0.91	1	0.91	0.92	0.64	-0.55	0.07	0.88	0.83	0.6	0.86
CAD	0.96	0.91	1	0.91	0.5	-0.64	0.28	0.96	0.92	0.52	0.97
CHF	0.94	0.92	0.91	1	0.38	-0.77	-0.02	0.87	0.94	0.46	0.86
GBP	0.5	0.64	0.5	0.38	1	0.13	0.41	0.5	0.21	0.48	0.49
JPY	-0.72	-0.55	-0.64	-0.77	0.13	1	0.02	-0.59	-0.8	-0.04	-0.59
SP500	0.26	0.07	0.28	-0.02	0.41	0.02	1	0.28	0.04	-0.07	0.33
Oil	0.91	0.88	0.96	0.87	0.5	-0.59	0.28	1	0.88	0.55	0.95
GOLD	0.9	0.83	0.92	0.94	0.21	-0.8	0.04	0.88	1	0.45	0.91
SILVER	0.42	0.6	0.52	0.46	0.48	-0.04	-0.07	0.55	0.45	1	0.5
COPPER	0.91	0.86	0.97	0.86	0.49	-0.59	0.33	0.95	0.91	0.5	1

Table 3: Hypothesis testing of the null (no spillover, no interdependence and co-movement)

Panel A: EUR or CAD as the x variable							
Market	EURO(x)			Market	CAD (x)		
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
S&P 500	0.15* (0.69)	0.144 (0.7)	7564 (0.000)	S&P 500	0.99 (0.6)	0.014 (0.9)	59 (0.00)
OIL	0.70* (0.39)	0.014 (0.905)	65.5 (0.000)	OIL	0.28* (0.591)	0.288 (0.591)	262.5 (0.000)
GOLD	5.05 (0.08)	0.004 (0.951)	34.7 (0.000)	GOLD	0.21 (0.643)	0.214 (0.643)	134.4 (0.000)
SILVER	4.74 (0.029)	4.748 (0.029)	77.45 (0.000)	SILVER	6.75 (0.03)	5.59 (0.018)	54.8 (0.000)
COPPER	1.61 (0.44)	1.5 (0.220)	193.8 (0.000)	COPPER	0.68 (0.71)	0.068 (0.794)	61.3 (0.000)

Panel B: CHF or AUD as the x variable							
Market	CHF (x)			Market	AUD (x)		
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
S&P 500	1.32 (0.51)	0.7 (0.4)	44854 (0.00)	S&P 500	1.43 (0.488)	2.87 (0.08)	29.0 (0.00)
OIL	3.38 (0.18)	4.78 (0.029)	65.4 (0.000)	OIL	16.17 (0.00)	14.28 (0.00)	28.10 (0.00)
GOLD	6.36 (0.01)	0.29 (0.589)	23.8 (0.000)	GOLD	4.766 (0.09)	0.0104 (0.91)	23.8 (0.00)
SILVER	9.26 (0.009)	0.092 (0.761)	1953 (0.000)	SILVER	16.99 (0.000)	0.0107 (0.917)	242.96 (0.00)
COPPER	0.00* (1)	0.355 (0.551)	1323.6 (0.000)	COPPER	3.97 (0.046)	16.68 (0.00)	192.7 (0.00)

Panel C , GBP or JPY as the x variable							
Market	GBP(x)			Market	JPY(x)		
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
S&P 500	3.32 (0.189)	1.29 (0.26)	27 (0.00)	S&P 500	0.00 (1)	0.032 (0.86)	68 (0.00)
OIL	14.78 (0.000)	12.125 (0.000)	67.1 (0.000)	OIL	0.945 (0.623)	1.06 (0.303)	43.2 (0.000)
GOLD	7.25 (0.026)	3.35 (0.067)	97.5 (0.000)	GOLD	2.80 (0.245)	0.592 (0.442)	10.7 (0.030)
SILVER	0.000 (1)	0.000 (1)	78.2 (0.000)	SILVER	7.041 (0.029)	0.015 (0.904)	13.1 (0.011)
COPPER	7.75 (0.02)	10.44 (0.001)	91.6 (0.000)	COPPER	0.134 (0.934)	0.033 (0.855)	10.9 (0.028)

Panel D: S&P 500 as the x variable							
Market	S&P 500 (x)						
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
OIL	1.065 (0.587)	0.26 (0.61)	61 (0.00)	AUD	4.321 (0.11)	2.87 (0.089)	29 (0.00)
GOLD	0.774 (0.678	0.0075 (0.93)	6.167 (0.18)	EUR	0.0394 (0.84)	0.14 (0.701)	7564 (0.000)
SILVER	0.183 (0.91)	1.07 (0.29)	41 (0.00)	CAD	0.0227 (0.98)	0.015 (0.9)	59 (0.00)
COPPER	0.34 (0.55)	0.35 (0.55)	182 (0.00)	CHF	*	0.7 (0.4)	444854 (0.00)
GBP	0.268 (0.874)	1.29 (0.26)	27 (0.000)	JPY	0.077 (0.96)	0.032 (0.85)	68 (0.00)

Panel E: OIL or GOLD as the x variable							
Market	OIL (x)			Market	GOLD (x)		
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
EUR	2.9 (0.22)	0.014 (0.905)	65.5 (0.000)	EUR	0.082 (0.95)	0.004 (0.951)	34.7 (0.000)
CAD	0.000* (1)	0.288 (0.591)	262.5 (0.000)	CAD	*	0.214 (0.643)	134.4 (0.000)
CHF	3.28 (0.19)	4.7 (0.029)	65.4 (0.000)	CHF	0.287 (0.59)	0.292 (0.589)	23.8 (0.000)
AUD	0.00* (1)	14.3 (0.000)	28.1 (0.000)	AUD	1.75 (0.51)	0.01 (0.918)	23.84 (0.000)
GBP	*	12.125 (0.000)	67.178 (0.000)	GBP	2.727 (0,25)	3.347 (0.067)	97.481 (0.000)
JPY	1.07 (0.58)	1.06 (0.303)	43.3 (0.000)	JPY	0.00 (1)	0.59 (0.442)	10.75 (0.030)
S&P 500	0.242 (0.88)	0.26 (0.61)	61 (0.00)	S&P 500	4.64 (0.098)	0.0075 (0.93)	6.17 (0.18)
GOLD	0.841 0.656)	1.01 (0.316)	115 (0.000)	OIL	0.83 (0.659)	1.01 (0.316)	115 (0.000)
SILVER	0.15 (0.69)	0.15 (0.700)	62.56 (0.000)	SILVER	1.05 (0.592)	0.05 (0.816)	30.03 (0.000)
COPPER	0.025 (0.87)	0.010 (0.922)	46.5 (0.000)	COPPER	3.54 (0.059)	10.6 (0.001)	98.7 (0.000)

Panel F: SILVER or COPPER as the x variable							
Market	Silver (x)			Market	Copper (x)		
	No spillover	No interdependence	Co movement		No spillover	No interdependence	Co movement
EUR	*	4.75 (0.029)	77.45 (0.000)	EUR	0.00 (1)	1.5 (0.220)	193 0.000)
CAD	*	5.59 (0.018)	54.86 (0.000)	CAD	0.176 (0.92)	0.068 (0.794)	61.3 (0.000)
AUD	0.18 (0.91)	0.011 (0.917)	242.9 (0.000)	AUD	8.58 (0.013)	16.7 (0.000)	192.7 (0.000)
CHF	0.12 (0.94)	0.092 (0.761)	1953 (0.000)	CHF	0.356 (0.55)	0.35 (0.551)	1323 (0.000)
GBP	0.000 (1)	0.000 (1)	78.2 (0.000)	GBP	2.6 (0.27)	10.4 (0.001)	91.64 (0.000)
JPY	1.48 (0.475)	0.015 (0.904)	13.1 (0.011)	JPY	*	0.033 (0.855)	10.9 (0.028)
S&P 500	1.28 (0.25)	1.07 (0.29)	41 (0.00)	S&P 500	0.00 (1)	0.35 (0.55)	182 (0.00)
OIL	*	0.15 (0.700)	62.56 (0.000)	OIL	0.0094 (0.92)	0.010 (0.922)	46.5 (0.000)
GOLD	0.000 (1)	0.054 (0.816)	30.04 (0.000)	GOLD	4.31 (0.037)	10.6 0.001)	98.7 (0.000)
COPPER	0.34 (0.84)	0.95 (0.329)	137.68 (0.000)	SILVER	4.98 (0.082)	0.95 (0.329)	137.68 (0.000)

* The coefficient is significant because it is deterministic. The numbers in the parentheses are the p-values (joint hypothesis test).

** If the null hypothesis is no spillover. and the number in the parenthesis (the p-value) is less than 0.01, then we reject the null at 1% size. This means that there is a spillover from x to y in the pairs (y, x).

If the null hypothesis is no interdependence and the number in the parenthesis (the p-value) is less than 0.01, we reject the null at 1% size, which means that there is interdependence between x to y.

If the H0 is co-movement and the number in the parenthesis (p-value) is less than 0.01, we reject the null hypothesis at 1% size, which means that there is no co-movement between x to y.

Table 4: Hedge Ratios using MCMS and VAR

State	Hedge Ratios-ij-MCMS and time Var.					VAR
	00	01	10	11	Time Var.*	
eur-oil	0.039	0.000	0.347	0.053	0.047	0.043
eur-gold	0.051	0.106	0.000	0.179	0.045	0.022
eur-silver	0.025	0.099	0.000	0.208	0.027	0.057
eur-copper	0.004	0.047	0.635	0.054	0.067	0.050
eur-S&P	0.014	0.045	0	0.197	0.019	0.099
gbp-oil	0.000	0.007	0.180	0.018	0.018	0.049
gbp-gold	0.005	0.096	0.000	0.000	0.008	0.036
gbp-silver	0.041	0.000	0.624	0.400	0.113	0.047
gbp-copper	0.000	0.036	0.129	0.114	0.029	0.083
gbp-S&P	0.027	0.1234	0.394	0.35	0.054	0.077
cad-oil	0.035	0.000	0.788	0.047	0.035	0.046
cad-gold	0.078	0.000	0.100	0.080	0.080	0.071
cad-silver	0.005	0.025	0.097	0.000	0.021	0.045
cad-copper	0.042	0.006	0.087	0.124	0.044	0.111
cad-S&P	0.084	0.044	0.026	0.304	0.091	0.195
jpy-oil	0.000	0.019	0.000	0.018	0.003	0.036
jpy-gold	0.013	0.000	0.000	0.184	0.019	0.061
jpy-silver	0.000	0.062	0.000	0.067	0.003	0.018
jpy-copper	0.040	0.020	0.000	0.134	0.034	0.059
jpy-S&P	0.022	0.000	0.059	0.044	0.026	0.124

* The time variant MCMS is the weighted average value (with weights equal to the smoothed probabilities of each state at time t) of the time variant hedging ratios.

Table (4-continued): Hedge Ratios using MCMS and VAR

State	Hedge Ratios-ij-MCMS and time Var.					VAR
	00	01	10	11	Time Var.*	
chf-oil	0.0167	0.00	0.364	0.14	0.024	0.044
chf-gold	0.000	0.000	0.000	0.000	0.000	0.026
chf-silver	0.000	0.005	0.084	0.131	0.016	0.042
chf-copper	0.000	0.040	1.124	0.000	0.053	0.041
chf-S&P	0.223	0.0158	0	0	0.173	0.196
aud-oil	0.030	0.000	0.102	0.000	0.040	0.075
aud-gold	0.000	0.035	0.000	0.651	0.011	0.116
aud-silver	0.003	0.000	0.000	0.000	0.002	0.040
aud-copper	0.086	0.029	0.000	0.355	0.095	0.195
aud- S&P	0.031	0.055	0.000	0.561	0.037	0.338
S&P- oil	0.046	0.0005	0.28	0	0.104	0.15
S&P- gold	0	0	0	0.23	0.0029	0.153
S&P- silver	0	0.018	0	0	0.0022	0
S&P-copper	0.184	0.057	0.148	0.258	0.157	0.182
oil-gold	0.000	0.375	0.759	1.312	0.132	0.247
oil-silver	0.000	0.250	1.322	0.000	0.196	0.000
oil-copper	0.251	0.158	0.511	0.251	0.238	0.343
gold-silver	0.040	0.042	0.000	0.000	0.029	0.064
gold-copper	0.000	0.000	0.000	0.093	0.017	0.099
silver-copper	0.000	0.008	0.120	0.616	0.037	0.019

* The time variant MCMS is the weighted average value (with weights equal to the smoothed probabilities of each state at time t) of the time variant hedging ratios.

Table 5: Portfolio Weights using MCMS and VAR

State	Wij-MCMS-State and Time Variant					Wij-VAR
	00	01	10	11	Time Var.*	
eur-oil	0.510	0.985	1	1	0.083	0.020
eur-gold	0.513	1	0.555	1	0.52	0.80
eur-silver	0.506	1	0.223	1	0.308	0.703
eur-copper	0.501	0.964	0.315	0.794	0.79	0.93
eur-S&P	0.504	0.989	0.402	1	0.59	0.88
gbp-oil	0.500	0.997	0.753	0.954	0.078	0.007
gbp-gold	0.501	1	0.431	0.817	0.350	0.175
gbp-silver	0.511	0.969	0.076	1	0.55	0.72
gbp-copper	0.500	1	0.421	0.925	0.87	0.98
gbp-S&P	0.506	0.97	0.344	0.514	0.798	0.878
cad-oil	0.509	0.987	1	0.947	0.059	0.011
cad-gold	0.520	0.971	0.649	0.967	0.85	0.84
cad-silver	0.501	0.990	0.253	0.954	0.37	0.72
cad-copper	0.511	0.983	0.507	1	0.83	1
cad-S&P	0.522	0.997	0.278	1	0.75	0.989
jpy-oil	0.500	1	0.780	0.981	0.086	0.037
jpy-gold	0.503	0.955	0.352	0.938	0.279	0.216
jpy-silver	0.500	1	0.183	0.990	0.28	0.66
jpy-copper	0.510	0.979	0.546	1	0.74	0.92
jpy-S&P	0.506	0.959	0.437	0.865	0.77	0.87

*The time variant MCMS is the weighted average value (with weights equal to the smoothed probabilities of each state at time t) of the time variant weights.

Table (5- continued): Portfolio Weights using MCMS and VAR

State	Wij-MCMS-State and Time Variant					Wij-VAR
	00	01	10	11	Time Var.*	
chf-oil	0.504	0.97	0.27	0.77	0.12	0.04
chf-gold	0.500	0.917	0.239	0.714	0.64	0.74
chf-silver	0.500	0.957	0.238	1	0.28	0.62
chf-copper	0.500	0.989	0	0.761	0.80	0.88
chf-S&P	0.563	0.95	0.203	0.85	0.41	0.65
aud-oil	0.507	0.989	0.561	0.906	0.129	0.068
aud-gold	0.500	0.778	0.133	0.049	0.74	0.635
aud-silver	0.501	0.925	0.060	0.700	0.256	0.50
aud-copper	0.523	0.970	0.201	0.899	0.732	0.93
aud- S&P	0.508	0.88	0.145	0.118	0.76	0.796
S&P- oil	0.512	0.973	0.445	0.854	0.757	0.866
S&P- gold	0.50	0.567	0.108	0.0962	0.505	0.546
S&P- silver	0.50	0.70	0.032	0.24	0.235	0.333
S&P-copper	0.55	0.983	0.196	0.746	0.663	0.713
oil-gold	0.500	1	0.015	0	0.29	0.16
oil-silver	0.500	0.383	0	0.084	0.1005	0.12
oil-copper	0.215	0.749	0.026	0.230	0.356	0.299
gold-silver	0.510	0.971	0.065	0.622	0.339	0.352
gold-copper	0.500	0.945	0.209	0.695	0.695	0.73
silver-copper	0.500	0.973	0.121	0.620	0.817	0.81

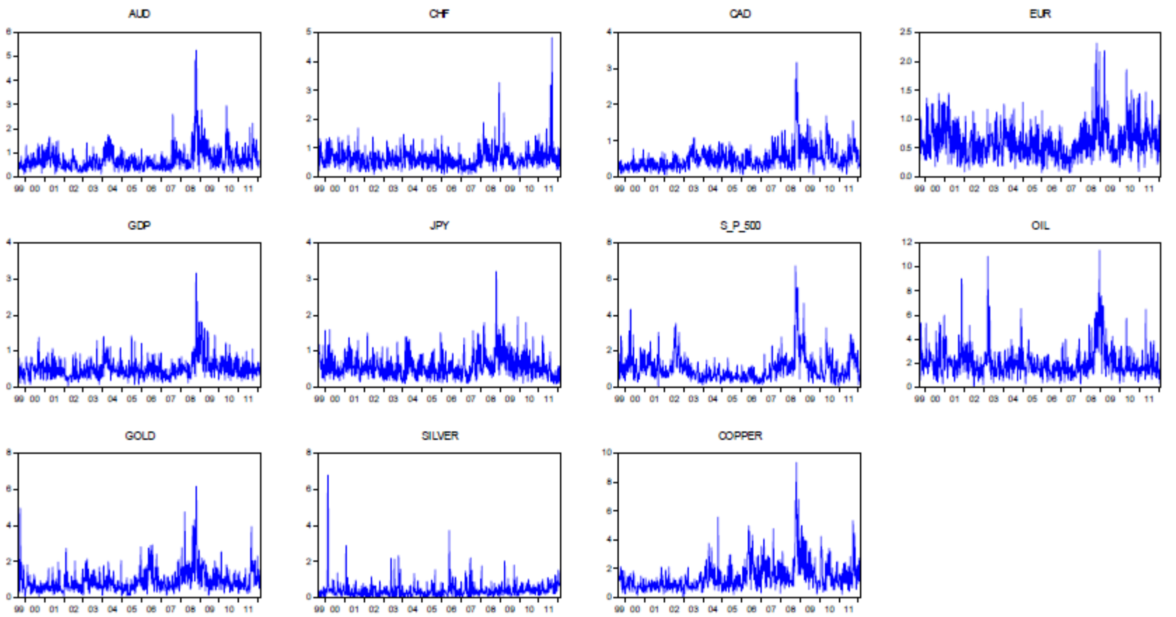
*The time variant MCMS is the weighted average value (with weights equal to the smoothed probabilities of each state at time t) of the time variant weights.

Table 6: Estimating Parameters of the MCMS model for AUD and Copper

Panel A-Switching Coefficients-Constants Term								
Market	AUD Equation				Copper Equation			
	$\mu_{1(0,0)}$	$\mu_{1(0,1)}$	$\mu_{1(1,0)}$	$\mu_{1(1,1)}$	$\mu_{2(0,0)}$	$\mu_{2(0,1)}$	$\mu_{2(1,0)}$	$\mu_{2(1,1)}$
Coeff.	0.430	0.430	0.737	1.159	0.569	1.400	1.614	1.819
S. Error	0.045	***	0.115	1.159	0.0723	0.153	0.123	0.312
Panel B-Autoregressive Terms								
Market	AUD Equation				Copper Equation			
	ϕ^1_{11}	ϕ^1_{12}	ϕ^2_{11}	ϕ^2_{12}	ϕ^1_{21}	ϕ^1_{22}	ϕ^2_{21}	ϕ^2_{22}
Coeff.	0.013	0.154	0.086	0.134	0.1480	0.000	0.422	1.046
S. Error	0.063	0.046	0.069	0.038	0.040	0.000	0.144	0.080
Panel C- Switching Coefficients and Correlation Terms								
	Switching Coefficients-Standard Deviation				Switching Coefficients-Correlation Terms			
Market	AUD		Copper					
	$\sigma_{1(0,.)}$	$\sigma_{1(1,.)}$	$\sigma_{2(.,0)}$	$\sigma_{2(.,1)}$	$\rho(0,0)$	$\rho(0,1)$	$\rho(1,0)$	$\rho(1,1)$
Coeff.	0.287	0.767	0.385	1.173	0.116	0.1197	0.543	2.44
S. Error	0.012	0.108	0.0421	0.098	0.047	0.1114	0.078	0.396
Panel D-Probability Parameters								
Market	AUD Equation				Copper Equation			
	$\alpha_{1(0,.)}$	$\beta_{1(0,1)}$	$\alpha_{1(1,.)}$		$\beta_{1(1,1)}$		$\alpha_{2(.,0)}$	$\alpha_{2(.,1)}$
Coeff.	0.00	3.98	3.24		2.27		-2.47	0.138
S. Error	0.23	0.419	1.14		0.309		1.24	0.045
Pane E- (Transition Probability Matrix (P4 $\times$ 4))								
$s_t \mid s_{t-1}$	(0,0)		(0,1)		(1,0)		(1,1)	
(0,0)	0.903		0.0169		0.078		0.0015	
(0,1)	0.085		0.834		0.0075		0.073	
(1,0)	0.691		0.154		0.127		0.028	
(1,1)	0		0.175		0		0.825	

Notes: Robust standard errors are in parenthesis. $*$ represents significance at 1% significance level and ** It is significant a 5% significance level

Figure 1: Range Volatility proxy of Oil, FX and Metals.



Notes: the exchange rates are dollars per foreign currency, except for JPY. AUD is the Australian dollar, CAD is the Canadian dollar, CHF is the Swiss franc, EUR is the euro, GBP is the British pound and JPY is the Japanese yen.

Figure 2: Smoothed Probabilities under Regime Switching for Pair (AUD, Copper).

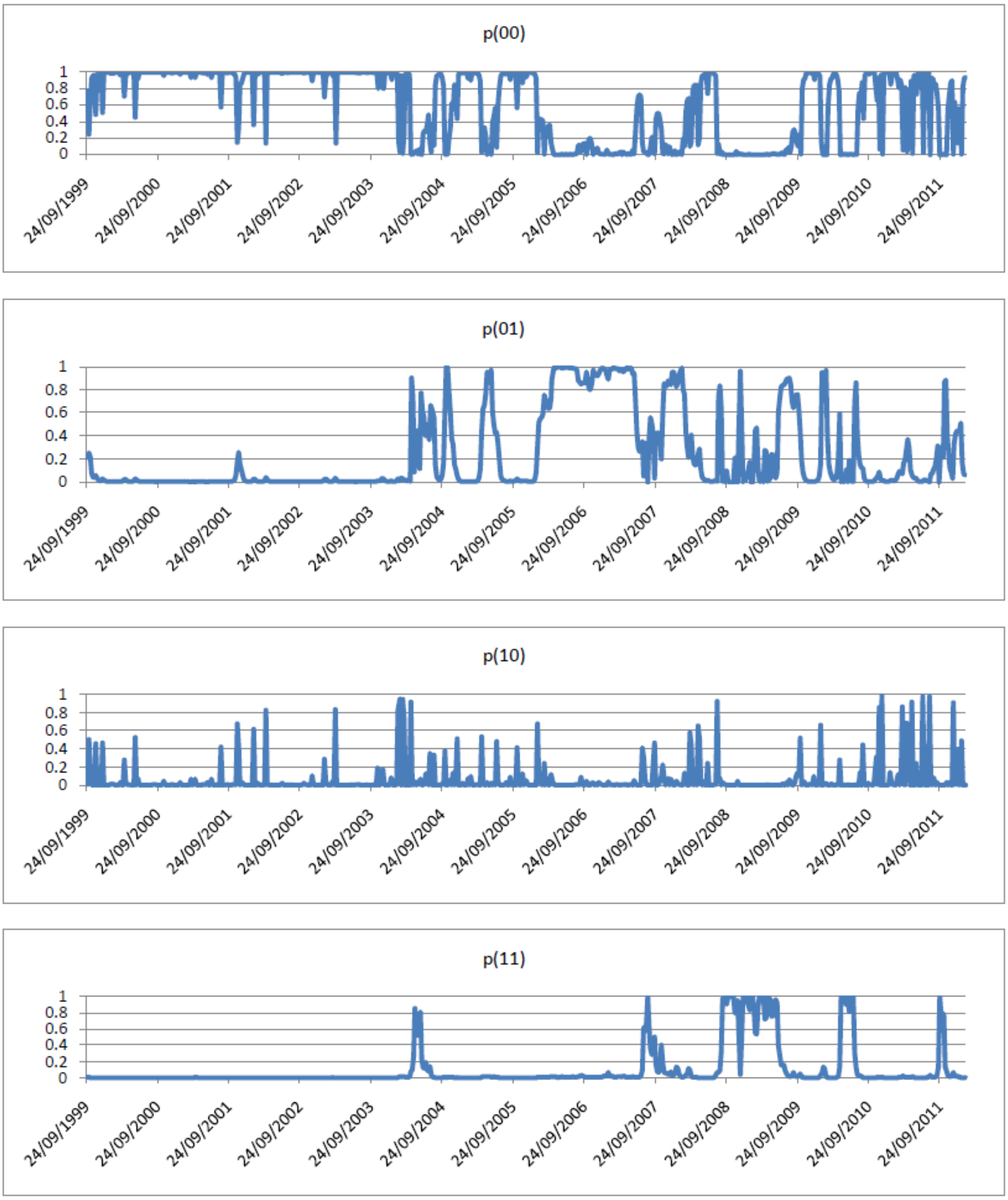
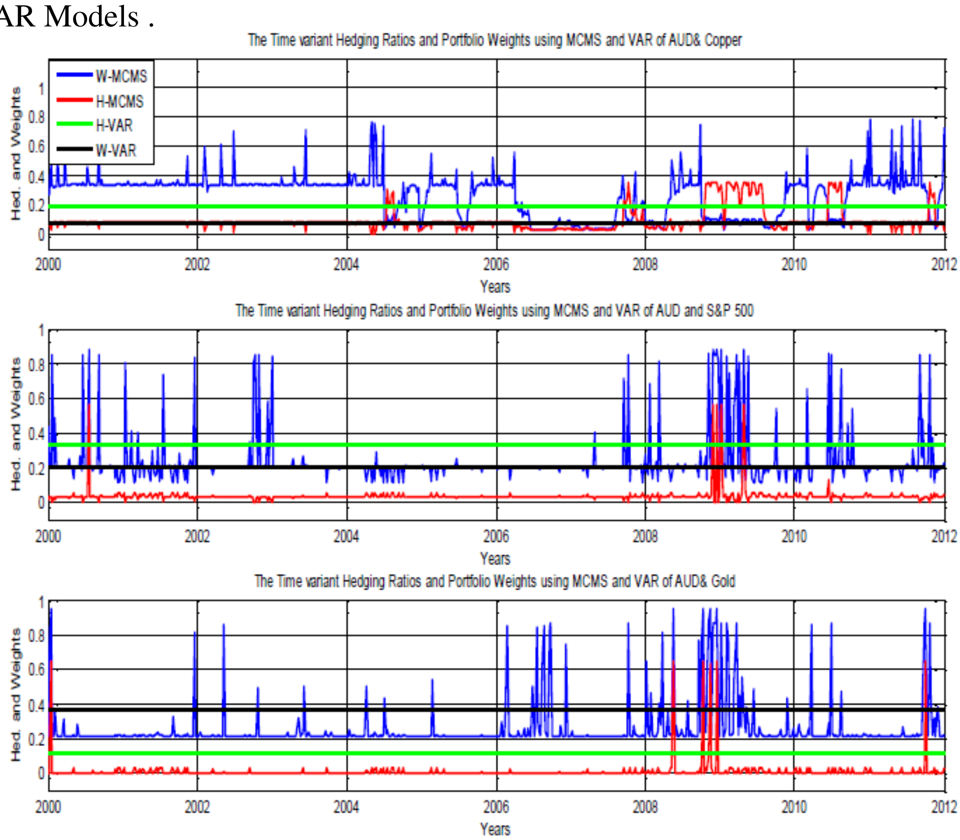


Figure 3: Time-Variant Hedging Ratios and Portfolio Weights Estimated from MCMS and VAR Models .



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