Time-varying betas in financial and commodity markets: a conditional regime-switching GARCH CAPM

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Abstract

This paper develops a methodology for estimating a conditional CAPM with time-varying betas and regime changes in conditional variance dynamics. Our research goal is related to documenting the strength of the market factor alone in the financial and commodity markets. Among stocks, there are significant time variations in betas across our models and regimes. This empirical feature is even more pronounced among prominent stocks such as the USA, the UK, Germany, France, China, and Malaysia. Among commodities, we find significant variations in betas, but the direction of the relation with market returns for crude oil, gold, copper, tin, rubber, aluminum and platinum is the same across two of our models. This result also holds for aggregate markets where most variations are found in the MS-GARCH model. Secondly, the mean filtered volatility results from the regime switching GARCH-CAPM shows that the most volatile stock (Turkey) is more than twice and thrice respectively, more volatile than the most volatile commodity (Rhodium) and aggregate market (World). Lastly, we demonstrate that the regime switching model delivers better estimates of one-day-ahead Value-at-Risk and that Expected Shortfall is highest for China but least for Latvia.

Keywords: Conditional CAPM; Regime-Switching; MS-GARCH; Risk Management

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1 Introduction

For over a half century, the Capital Asset Pricing Model (CAPM) first proposed by Sharpe (1964) and Lintner (1965) and extended by Mossin (1966), Fama (1968a; 1968b) and Long (1972) has offered a theoretical background for the estimation of asset prices with volatile returns. As early as the 1960s, from the work of Markowitz developed some years ago, Sharpe, Lintner, and Mossin proposed the equilibrium model of financial assets (CAPM) that have served as a foundation for modern financial theory. According to this model, the expected profitability of a security is explained by a factor (the market risk premium) with a sensitivity specific to each company (the beta). This model predicts that the relationship between expected returns across assets and their betas concerning the market portfolio is linear (Morana, 2009; Tsai, Chen and Yang 2014). The crucial second prediction of the CAPM is that all investors are the risk-averse utility of terminal wealth maximizers whose choice of stocks is mainly guided by mean-variance efficiency (Frazzini and Pedersen, 2013) and that investors' risk aversion are constant over time.

Early stream of studies offered significant empirical evidence in favor of CAPM especially regarding its crucial prediction that market portfolio be mean-variance efficient and this appeal laid a strong background for research in empirical finance for several years (see, e.g., Black, Jensen, and Scholes 1972; Blume and Friend 1973). However, Lettau and Ludvigson (2001) note that recent empirical implementations have revealed some downsides of the CAPM. However, despite the observed drawbacks, Jagannathan and Wang (1996) note that the CAPM is still the preferred model for MBA and other managerial finance courses. Even more, Vendrame, Guermat and Tucker (2018) note that the CAPM remains a simple, intuitive, and an economically sound theory and that the search for its replacement has led the researcher to either discard its central doctrines or adopt some statistical approaches that prove too complicated to be replicated by researchers and practitioners. Since then, the CAPM has had many applications, has been subjected to many empirical tests on all the financial markets but remains to this day an unavoidable model despite continual attacks, both theoretical and empirical.

Two key possibilities have been offered to explain the observed deficiencies of the CAPM. First, Lettau and Ludvigson (2001) argue that a significant explanation for the failure of CAPM is its assumption of the static specification which has failed in accounting for the effects of time-varying investment opportunities that may affect the calculation of an asset's risk. The static CAPM was derived from a hypothetical model in which investors are assumed to live for only one period. In the real world, investors live for many periods (Jagannathan and Wang, 1996), and their expectations as economic agents for future returns are conditioned on many factors (Klemkosky and Martin, 1975; Fabozzi and Francis 1978; Bos and Newbold, 1984, Collins and Ledolter, 1987; Bollerslev, Engel, Wooldrige, 1988; Bodurtha and Mark, 1991), implying that risk and risk premium are time-varying. The second is that systematic risk itself has more than one component and that beta is not the only measure of risk. Additional factors such as the ratio of earnings to price, level of market capitalization, leverage effects and the increasing synchronizations of global finance have been found to significantly influence systematic risk (Banz, 1981; Bhangari, 1988; Arouri et al. 2011).

Perhaps, the most obstructing of empirical applications of the static CAPM was its failure to capture cross-sectional variation average return on a portfolio containing assets with varying sizes and book-to-market equity ratios. In response to these anomalies, additional sensitivity components have been added to the CAPM such as in the famous three-factor model of Fama and French (1993), the consumption CAPM by Breeden (1979) and the four-factor model of Carhart (1997). Despite the success of these models especially the three-factor model, they have however not been enough to account for the central anomalies. For instance, the three-factor model has been criticized due to the controversies surrounding the interpretation of its proxies for unobserved common risk in portfolios. The consumption-based CAPM have failed in its formulation of the representative agent with time-separable power utility using U.S. data and has not done better in capturing cross-section of average returns on portfolios with assets of different sizes (Lettau and Ludvigson, 2001).

According to Vendrame et al. (2018), the most reoccurring explanation for the failure of CAPM has been that CAPM may hold conditionally rather than unconditionally. The conditional CAPM which offers a convenient approach to modelling the time-varying conditional variances and covariances in financial time series have been severally applied to study time variations in CAPM (see e.g. Campbell and Shiller, 1988; Bollerslev et al. 1988; Campbell 1991; Bodurtha and Nelson, 1991; Ferson and Harvey, 1991; Lamont 1998; Lettau and Ludvigson 2001; Cochrane 2001; Andersen et al. 2005; Ang and Chen, 2007; Morana 2009; Korkmaz et al. 2010; Cenesizoglu and Reevesm 2018; Tansuchat et al. 2018, Vendrame et al. 2018). For instance, Bodurtha and Nelson (1991) estimated a conditional CAPM with time-varying expected risk premium, variance and covariances using a GMM approach. They found sufficient evidence against the constant beta CAPM. Also, Ang and Chen (2007) examined a conditional CAPM with a conditional beta and time-varying risk premium using an autoregressive AR(1) latent process. They found that conditional betas were time-varying and positively correlated with the market risk premium.

In this paper, we propose a conditional CAPM with a time-varying beta that allows us to capture regime changes in the conditional variance dynamics. To do this, we follow a novel estimation approach proposed by Ardia et al. (2018) to implement the Markov switching GARCH specification of Haas et al. (2004a). A critical theoretical advantage of the Markov switching model is that it offers the opportunity to assess different GARCH behavior in each regime and reveals the difference in the conditional variance dynamics of low and high volatility regimes. In the empirical application of this model, the assumption that the model has a conditional mean zero usually require the model to be applied on a demeaned time series or when the series exhibits dynamics in the conditional mean, the demeaned time series becomes the residuals of the time series model (Ardia et al. 2018).

The first contribution of this paper is, therefore, to directly take into account the time variation of conditional betas, by estimating regime changes according to Markov-switching processes in the conditional variance dynamics. Our modeling strategy offers the advantage to compare the time-varying betas across three models, namely: the static CAPM, the regime-switching CAPM, and the conditional regime-switching GARCH-CAPM. The regime switching CAPM model permits us to estimate the variations in betas across regimes as well as the market regime probabilities. The regime switching GARCH-CAPM allows us to derive additionally, the conditional variance dynamics while using residuals from the static CAPM as demeaned time series. Secondly, the regime switching GARCH model permits us to derive the volatility forecasts which adapts to variations in the unconditional volatility levels for all our series using the mean fitted posterior volatility. Here, it is argued that if the evolution of volatility is heterogeneous across two regimes, it is possible that the regimes exhibit different unconditional volatility levels.

Further, Ardia et al. (2018) note that one of the critical empirical applications of the MS-GARCH model in quantitative finance is within the domain of wealth allocation among risky investment opportunities. Here, investors may wish to assess the quantile of their future distribution at given risk levels as well as the expected values below this level. Ardia et al. (2017a) argue that regime-switching models have proven to offer out-of-sample backtesting results than single-regime models. The third contribution of this paper is, therefore, to apply the MS-GARCH in the forecasting of important RiskMetrics such as the Value-at-Risk (VaR) and Expected Shortfall (ES). According to Engle and Manganelli (2004), VaR which offers a quantitative technique through which a single number that could quickly and easily convey significant information about the risk of a portfolio is estimated has recently become a necessary tool for risk managers, enabling them to appraise and allocate risk more efficiently. In simple terms, the VaR represents a quantile of the log-returns distribution at a prior determined horizon and confidence level whereas ES reflects the loss expected when the loss is above the VaR level.

Our results are as follows. First, among stocks, there are significant variations in size and the nature of relations between systematic risks and the markets from one model to another and across regimes and this is even more pronounced among prominent stocks such as the USA, the UK, Germany, France, China, and Malaysia. Secondly, we find variations mostly in the size of the beta parameters, but the direction of the relationship between prominent commodities such as crude oil, gold, copper, tin, rubber, aluminum and platinum, and the market is the same across two of our models. Variations in the relation between these commodities and the market are only witnessed in the MS-GARCH model. These results also hold for our aggregate markets where most variations are found in the MS-GARCH model. Thirdly, the mean filtered volatility from the MS-GARCH-CAPM shows that the most volatile stock (Turkey) is more than twice as volatile as the most volatile commodity (Rhodium) and about thrice as volatile as the most volatile aggregate market (World). Lastly, our risk management tests show that the regime switching model delivers better estimates of one-day-ahead VaR and that ES is highest for China but least for Latvia.

The rest of this paper proceeds as follows. Section 2 presents the methodology from where we show a detailed build-up to the nested model for this paper. Section 3 offers a description of the data. Section 4 compares results from the competing models, and contains returns volatility dynamics and risk management statistics from the regime switching models. We present the conclusions in section 5.

2 Methodology

The conditional regime-switching GARCH CAPM is a nested model that unfolds in three steps as follows.

2.1 CAPM

Our analysis begins with the Capital Asset Pricing Model whose basic output is the expected return of an asset i at time t with the assumption that investors are risk averse and that the market is complete (see e.g. Cortazar et al. 2013; Blitz et al. 2014). Return on asset i and the market portfolios with respect to indices may be expressed as follows:

$$R_{i,t} = ln\left\langle \frac{P_{i,t}}{P_{i,t-1}} \right\rangle$$

where $R_{i,t}$ is the log return on asset i in period t while $P_{i,t}$ is the price of asset i at time t. In its typical form, the CAPM is expressed as follows:

$$(R_{i,t} - R_{f,t}) = \alpha + \beta(R_{M,t} - R_{f,t}) + \epsilon_t \tag{1}$$

where $R_{i,t}$ denotes the log return on asset i at time t and $t = 1, 2, ..., T$ is the time horizon. Similarly, $R_{m,t}$ is the log return on the market portfolio at time t while $R_{f,t}$ is the risk free rate at time t. Therefore, excess return on asset i is denoted by $(R_{i,t} - R_{f,t})$ and the excess return on the market portfolio is represented by $(R_{M,t} - R_{f,t})$. Lastly, α is the intercept term, β is the beta which measures the systematic risk associated with asset i while ϵ_t is the error term at time t which is assumed to be an independently and identically distributed random variable that follows the normal distribution such that $\epsilon \sim N(0, \sigma^2)$.

One of the classical assumptions of the CAPM according to Sharpe (1964) and Lintner (1965) is that performing the expectations operator $E_t(\cdot)$ of equation (1) conditionally on information set up to time t, the condition below must hold:

$$E_t(r_i) = \beta E_t(r_m) \tag{2}$$

The above condition implies that if the CAPM holds, the intercept α must not be statistically different from zero (Cortazar et al. 2013).

2.2 MS-CAPM

Much like many economic times series, financial data also exhibits abrupt changes due to sudden changes in fundamentals which show up in asset prices (Ang and Bakaert 2003; Wei 2003; Hamilton 2005). In its classical form, the Markov-Switching models proposed in Hamilton (1989) for the non-stationary time series analysis of the business cycle, estimate regime switching endogenously.

In this paper, we use the Markov-switching model to test whether there are regime shifts in the Beta of different assets within the CAPM framework. Indeed, we seek to find out if two different states exist between returns on asset i and the returns on diversified equity portfolios. To do this, we follow He et al. (2018) to assume that there two different regimes and that s_t represents the state variable which reflects the current regime in the market. The Markov-switching CAPM equation may, therefore, be expressed as follows:

$$(R_{i,t} - R_{f,t}) = \alpha_{st} + \beta_{st}(R_{M,t} - R_{f,t}) + \epsilon_{st}, \tag{3}$$

where s_t denotes the two states of the model, ϵ_{s_t} is the error term which is assumed to be independently and identically distributed and follows the normal distribution such that $N(0, \sigma^2_{s_t})$. Therefore, s_1 reflects one regime with the following parameters $\propto_{s1}$, β_{s1}, σ^2_{s1} while s_2 denotes the second regime with the following corresponding parameters $\propto_{s2}$, β_{s2}, σ^2_{s2}. We allow for regime switching in the variances of the error term following Nelson et al. (2001) which notes that regime changes in economic and financial times series might be better modelled through a probabilistic process.

Following the 2-state regime-switching model of Hamilton (1989), the state variable s_t takes only binary values of 0 and 1. Therefore, the transition probabilities of the first order Markov chain may be modeled as follows:

$$Pr[S_t = 1/S_{t-1} = 1] = p$$
$$Pr[S_t = 2/S_{t-1} = 1] = 1 - p$$
$$Pr[S_t = 2/S_{t-1} = 2] = q$$
$$Pr[S_t = 1/S_{t-1} = 2] = 1 - q$$

0 < p < 1 0 <q < 1

where p and q are the fixed transition probabilities of being in low and high volatility regimes respectively. In equation (3), α_{st} is assumed to vary depending on the regimes.

The estimation of equation (3) following Maximum Likelihood approach is through the Expectation Maximization (EM) algorithm explained in Hamilton (1994), Krolzig (1997) and Korkmaz et al. (2010).

2.3 MS-GARCH-CAPM

2.3.1 Conditional variance dynamics

The build-up to the conditional variance model for this relies on the GARCH equation from Ardia et al. (2018) where given $t = 1, \ldots, T$ with T the sample size, ϵ_t is an MS-GARCH process if

$$y_t = \epsilon_t \tag{4}$$

with

$$\epsilon_t = \eta_t \sqrt{h_t(\Delta_t)}, \eta_t \sim IID(0, 1) \tag{5}$$

and there exists $\alpha_0(\Delta_t)$, $\alpha_i(\Delta_t)$, i = 1,..., q and $\gamma_l(\Delta_t), l = 1, ..., p$ such that

$$h_t(\Delta_t) = \alpha_0(\Delta_t) + \sum_{i=1}^{q} \alpha_i(\Delta_t)\epsilon^2_{t-1} + \sum_{l=1}^{p} \gamma_l(\Delta_t)h_{t-l}. \tag{6}$$

where η_t represents an identically and independently distributed (iid) random variable with zero mean and a unit variance while Δ_t is an information variable that specifies the condition of the world in time t following a Markov chain with fixed state space $S = 1, ..., k$, and a transition matrix P. Therefore, the probability to switch from one regime to another depends on the transition matrix P, expressed as follows:

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ldots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix}$$

where given the probability to be in state i at time $t-1$, $p_{ij} = p(\Delta_t = j|\Delta_{t-1} = i)$ is the probability to be in state j at time t. The following conditions apply: $0 < p_{i,j} < 1\forall_i, j\varepsilon\{1, ..., K\}$, and

$\sum_{j=1}^{K} p_{i,j} = 1, \forall_i \varepsilon \{1, ..., K\}$. Given the parameterization of $D(.)$ and the probability of transition from state j at time t ($s_t = j$) and to be in state i at time $t-1$ ($s_{t-1} = i$), we have $E[y_t^2 | s_t = k, \Delta_{t-1},] = h_{k,t},$. Therefore, $h_{k,t}$ is the variance of y_t conditional on the realization of $s_t = k$. However, given the difficulty in calculating the likelihood function for a sample of T observations as it requires the integration of k^T possible regime paths where k is the number of regimes, the MS-GARCH model was proposed by Gray (1996) under the assumption that the conditional variance at any state depends on the expectation of previous conditional variances. This implies that h_{t-1} is replaced by the conditional variance of the error term ϵ_{t-1} given the state of the world up to $t-2$ defined as follows:

$$h_t(\Delta_t) = \alpha_0(\Delta_t) + \alpha(\Delta_t)\epsilon_{t-1}^2 + \gamma(\Delta_t)\sum_{i=1}^{k} p(\Delta_{t-1} = i|\Omega_{t-2})h_{i,t-1} \tag{7}$$

where $h_{i,t}$ is the conditional variance in state i at time t, Ω_t is the information set up to time $t-1$ and $p = q = 1$. Recently, the MS-GARCH process has been modified severally. For instance, the information set up to $t-1$ has been extended such that the expectations of previous conditional variances is conditioned on all available observations as well as on the current state as shown below:

$$h_t(\Delta_t) = \alpha_0(\Delta_t) + \alpha(\Delta_t)\epsilon_{t-1}^2 + \gamma(\Delta_t)\sum_{i=1}^{k} p(\Delta_{t-1} = i|\Omega_{t-1}, \Delta_t = j)h_{i,t-1} \tag{8}$$

However, the modification by Haas et al. (2004) contrasts with the by conditioning each expectations of each specific conditional variance only on its own lag as follows:

$$h_t(\Delta_t) = \alpha_0(\Delta_t) + \alpha(\Delta_t)\epsilon_{t-1}^2 + \gamma(\Delta_t)h_{t-1}(\Delta_t). \tag{9}$$

This can be re-stated in matrix form as follows:

$$h_t = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \gamma h_{t-1},$$

where $\alpha_0 = [\alpha_{01}, \alpha_{02}, ..., \alpha_{0k}]'$, $\alpha_1 = [\alpha_{11}, \alpha_{12}, ..., \alpha_{1k}]'$, $\gamma = diag(\gamma_1, \gamma_2, ..., \gamma_k)$ while h_t is a vector of $k \times 1$ components.

2.3.2 Conditional distribution

The conditional distribution of the standardized innovations η_t, k for the above-specified models follows the Skewed Student-t distribution in each regime of the Markov Chain. As the most common distribution to model the process of financial log returns, each distribution is standardized to have a zero mean and unit variance. The student-t distribution is defined as follows:

$$f_S(\eta;\nu) \equiv \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{(\nu-2)\pi}\Gamma(\frac{\nu}{2})}\left\{1 + \frac{\eta^2}{(\nu-2)}\right\}^{-\frac{\nu+1}{2}}, \eta \in R \tag{10}$$

where $\Gamma(\cdot)$ is the Gamma function and $v > 2$ is imposed to ensure that the second order moment applies. The kurtosis of the skewed Student-t distribution increases as the value of v diminishes. The choice of the skewed Student-t distribution is further motivated by the predictive densities for each regime of the MS-GARCH-CAPM displayed in Figure 4 (see the Appendix) in the case of MSCI USA for illustrative purposes.

2.3.3 Model estimation

Given the difficulty in computing the likelihood function of the MSGARCH models specified earlier, it cannot be estimated by the Quasi-Maximum Likelihood (QML) approach but either through the Maximum Likelihood or the Markov Chain Monte Carlo (MCMC) / Bayesian techniques. In this study, we estimate our models by the MCMC/Bayesian techniques that require the evaluation of the likelihood function.

Given $\Psi \equiv (\theta_1, \xi_1, ..., \theta_k, \xi_K, P)$ is the vector of model parameters, the likelihood function may be stated as follows:

$$L(\Psi|\Delta_T) \equiv \prod_{t=1}^{T} f(y_t|\Psi, \Delta_{t-1}), \tag{11}$$

where $f(y_t|\Psi, \Delta_{t-1})$, represents the density of y_t conditioned by information set up to Δ_{t-1}), and the model parameters Ψ. The conditional density of y_t for the MS-GARCH process is stated as follows:

$$f(y_t|\Psi, \Delta_{t-1}) \equiv \sum_{i=1}^{K}\sum_{j=1}^{K} p_{i,j} z_{i,t-1} f_D(y_t|s_t = j, \Psi, \Delta_{t-1}), \tag{12}$$

where $z_{i,t-1} \equiv P[s_{t-1} = i|\Psi, \Delta_{t-1}]$ denotes the filtered probability of state i at time $t-1$ gotten through Hamilton's filter (see Hamilton (1989), and Hamilton (1994)).

The Maximum Likelihood estimator $\widehat{\Psi}$ is evaluated by maximizing the logarithm of the likelihood function in equation (11). However, for the MCMC / Bayesian estimation, the likelihood function is pooled with an erstwhile determined value for $f(\Psi)$ to form the kernel of the subsequent distribution $f(\Psi|\Delta_T)$. Following Ardia et al. (2018), we form the prior for this study using unrelated diffuse priors as shown below:

$$\begin{gathered} f(\Psi) = f(\theta_1, \xi_1) \cdots f(\theta_K, \xi_K) f(P) \\ f(\theta_k, \xi_k) \propto f(\theta_k) f(\xi_k) \Vert\{(\theta_k, \xi_k) \in CSC_k\}(k = 1, ..., K) \\ f(\theta_k) \propto f_N(\theta_k; \mu_{\theta k}, diag(\sigma^2_{\theta_k})) \Vert\{\theta_k \in PC_K\}(K = 1, ..., K) \\ f(\xi_k) \propto f_N(\xi_k; \mu_{\xi_k}, diag(\sigma^2_{\xi_k})) \Vert\{\xi_{k,1} > 0, \xi_{k,2} > 2\}(k = 1, ..., K) \\ f(P) \propto \prod_{i=1}^{K} \left\langle \prod_{j=1}^{K} p_{i,j} \right\rangle \Vert\{0 < p_{i,i} < 1\}, \end{gathered} \tag{13}$$

where PC_K denotes the positivity condition in state k, CSC_K represents the covariance-stationarity condition while $\xi_{k,1}$ and $\xi_{k,2}$ are the asymmetry and tail parameters of the skewed Student-t distribution in state k respectively. Also, μ and σ^2 represent vectors of predetermined means and variances while $f_N(\bullet; \mu, \sum)$ represents the multivariate normal density with mean vector μ and covariance matrix $\sum$.

3 Data

In this paper, we use an extensive dataset containing 81 monthly Stock Market Indices for 56 countries drawn from North/Latin America, Western Europe, Emerging Europe, the Middle East/Africa, Developed Asia, Emerging Asia, and Africa. The dataset also contains 22 commodity indices drawn from the main classes of commodities including Metals, Energy, and Agriculture. The data was collected over the period from August 1999 to January 2018. All the data are extracted from Thomson Datastream International. Moreover, we include three aggregated stock market indices for the World, Europe, and Emerging markets.

We employ the 30-day Treasury bills rate as the risk-free rate for each country while we use the 30-day Euro-Dollar interest rate for the selected commodities. Regarding the state of the economy in each country, we consider industrial production as an instrumental variable to reflect changes in the level of economic activity in each regime. For commodities and the World aggregate market, we use industrial production in the United States as a reflection of the level of global economic activity. Lastly, we use industrial production in China and Europe industrial production to measure the state of economic activities in emerging markets and Europe respectively.

Table 6 in the Appendix presents the descriptive statistics for all the 81 return series. It can be deduced that all the return series both for countries and commodities have positive mean except Italy, Latvia, and Portugal that have negative mean returns. Also, all the series are negatively skewed except Turkey, Columbia, United Arab Emirates, Chile, Malte, Gold, Ruthenium, Wool, Wheat, Cocoa, Coffee and Cotton which have positive values for the skewness while all the values for the kurtosis are above 3 as shown by positive excess kurtosis for all the series. Lastly, the $p - values$ for the Jarque Bera and the Lagrange Multiplier (LM) test for all the series are zero. These results imply asymmetric and fat tail characteristics and that all the return series do not follow the normal distribution under 5% significance level. Table 7 in the Appendix presents the exact names of the series and their designations as they appear in the three models.

4 Empirical results

We aim at comparing the βs estimated across the conditional regime-switching GARCH CAPM.

4.1 Results of the static CAPM estimation

To assess the behavior of beta and the asset pricing performance of different tests of CAPM, we estimated three models including the pure form of CAPM, the MS-CAPM and the MS-GARCH-CAPM for 81 markets. We first analyze the performance of the simple CAPM based on equation (1) by employing the linear regression technique with the assumption that the intercept in the CAPM is zero against the alternative that it is not equal to zero. To do this, we construct the excess return for each series by subtracting the risk-free rate from the index return. Similarly, we subtract the risk-free rate from the returns on the respective market portfolios to get the excess return for the portfolio index. We evaluate the validity of our model specifications using Dublin-Watson test for residual autocorrelation and the Q-statistics for residual normality and serial correlation. Lastly, the efficiency of the respective market portfolio index in the test of CAPM is assessed using the R-squared coefficients.

Table 1 reports the estimates of intercept and beta coefficients from the simple CAPM. First, it can be observed that the assumption of no intercept holds for all the markets as shown by the estimates which are statistically insignificantly different from zero. This implies that the simple CAPM correctly predicts the risk premium in our sampled stocks. Regarding beta estimates, the beta coefficient is statistically significant across all countries and portfolios but with positive and negative values except in Canada, Croatia, Hungary, Egypt, Switzerland, Bulgaria, Iceland, Russia, Mexico, Sweden, and Argentina. However, the beta coefficient is positive and statistically significant across all the commodities except in Gas, Platinum, and Rhodium and all aggregate markets and portfolios namely Europe, Emerging markets and World. Arshanapalli et al. (1998) note that positive beta coefficients imply that up-market movements drive a stock while negative beta coefficients suggest that stock appears to be less sensitive to market fluctuations.

Regarding the size of the beta coefficient across these markets and portfolio proxies, the beta estimate is about 0.2 for 23 countries, but this coefficient is negative for the UK, Italy, and China. It is around 0.3 for 14 countries but negative for only the UAE. It is around 0.4 for 4 countries and 0.5 for 2 countries while it is highest for Chile and Germany with about 0.6. However, the beta estimate is lowest with about 0.1 for Latvia and Qatar. Concerning the commodities indices, the beta estimate is around 0.1 for 11 commodities, around 0.2 for 2 commodities and highest with around 0.3 for 6 commodities. The beta coefficients for all the commodities indices have a positive sign. Also, the beta estimates for our aggregated markets are positive and around 0.2 except the emerging market index which is around 0.3. This model performed well based on the value of the Dublin-Watson test which falls within the acceptable range of 2 for all the stock markets. Similarly, the null hypothesis of serial correlation is rejected for all the markets. However, the R squared for all the markets are tiny ranging between 0.01 and 0.35.

Given that the beta coefficient for the world aggregated index is about 0.2, the following stylized facts emanate from the simple CAPM result. First, the systematic risk in 23 countries is about the same as the world average. Put differently, the systematic risks and expected excess returns in these markets are equivalent to the world average risk and return. Similarly, the beta coefficient for the markets which are higher than the world average implies that the systematic risk and expected excess returns are higher in these markets than in the world average. However, for the countries whose beta coefficients are higher than the world average, the implication is that investments in these stock markets have higher systematic risk and excess return than the world average (especially in Chile and Germany). In countries with lower beta coefficient than the world average such as Latvia and Qatar, systematic risks and return are lower than the world average.

Secondly, given that the beta coefficient for most commodities is less than the aggregate world average, this suggests that investment in most commodities carry lower systematic risks and returns. The implication is that most commodity stocks carry lower systematic risk and returns and serves as an alternative asset whose inclusion in an investment portfolio reduces risk especially during periods of turbulence in stock prices. However, the remaining commodities whose beta coefficient is either the same as the world aggregate stock or higher suggest that they carry similar risk and return as the world average stock or higher. This provides further empirical evidence in support of increasing financialization of commodities. Regarding the aggregate market indices, the higher beta coefficient in the emerging market than the coefficient for Europe and the world average suggests that investment in emerging stock markets carry higher expected returns but with higher systematic risks than investments in Europe and the mean world stock. This means that returns on investments in emerging market stocks appear to be more volatile than in European and the world average stocks.

Table 1: CAPM RESULTS

STOCKS	US S&P500	CAN TSX	GER DAX	AUS ASX	DEN OMX	FIN OMXHEX	SPNIBEX	SLOVSBITOP	UKFTSE100	ITAFTSEMIB
intercept	0.0077	0.0106	0.0116	0.0081	0.0111	0.0171	0.0064	0.0068	0.0162	0.0101
	[0.3482]	[0.2870]	[0.1162]	[0.3226]	[0.1828]	[0.1335]	[0.4697]	[0.4571]	[0.2496]	[0.4312]
Beta (β)	0.2471	0.0381	0.6123	0.232	0.2016	0.4876	0.1978	0.3627	-0.1797	-0.1745
	[0.0002]***	[0.5797]	[0.000]***	[0.0006]***	[0.0029]***	[0.000]***	[0.0029]***	[0.000]***	[0.0074]***	[0.0097]***
R-squared	0.0637	0.0014	0.3539	0.0533	0.0401	0.1613	0.0402	0.1015	0.0326	0.0304
Durbin-Watson	1.9727	2.0502	2.0201	1.9666	1.9064	1.7608	1.8499	1.9124	2.0654	2.0654
Q-stat	0.0282	0.1603	0.7928	0.0467	0.4311	0.2076	1.1872	0.3463	0.268	0.3132
	[0.867]	[0.689]	[0.373]	[0.829]	[0.511]	[0.647]	[0.276]	[0.556]	[0.605]	[0.576]

	THAI-SET50	MYL-FTSEKLCI	INDO-JCI	PHI-PSEI	SING-STI	CHIN-SSE	INDI-SENSEX	TAI-TWSE	KOR-KOSPI	HNGKNG-HIS
intercept	0.0086	0.0054	0.0101	0.009	0.0056	-0.0103	0.0086	0.0043	0.0101	0.0069
	[0.2182]	[0.2481]	[0.1947]	[0.3151]	[0.5111]	[0.7773]	[0.3896]	[0.4812]	[0.3213]	[0.4272]
Beta (β)	0.2017	0.1896	0.2436	0.2158	0.3095	-0.1663	0.3331	0.5155	0.2419	0.3572
	[0.0035]***	[0.0081]***	[0.0005]***	[0.0035]***	[0.000]***	[0.0160]**	[0.000]***	[0.000]***	[0.0017]**	[0.000]***
R-squared	0.0387	0.0319	0.0536	0.0387	0.096	0.0264	0.0967	0.2287	0.0445	0.1248
Durbin-Watson	2.1738	2.0695	2.1227	1.8994	2.0436	1.9824	2.0814	2.1367	1.8535	2.0097
Q-stat	1.7527	0.4358	0.8736	0.5167	0.1241	0.0023	0.3721	1.0419	1.0222	0.0144
	[0.186]	[0.509]	[0.350]	[0.472]	[0.725]	[0.962]	[0.542]	[0.307]	[0.312]	[0.905]

	LAT-OMXRIGA	EST-OMXTALLIN	TUR-XU100	CRO-CROBEX	LIT-OMXVILNIUS	HUN-BUX	EGY-EGX30	POR-PS-I20	CZECH-SEPX	BRA-BOVESPA
intercept	0.0062	0.0109	0.0155	0.0225	0.0063	0.0092	0.0093	0.0017	0.0094	0.0053
	[0.4210]	[0.2790]	[0.4079]	[0.2746]	[0.5563]	[0.7094]	[0.6995]	[0.7916]	[0.3302]	[0.5432]
Beta (β)	0.1296	0.2855	0.2242	-0.012	0.2874	0.0955	0.1056	0.2801	0.3359	0.3757
	[0.0446]**	[0.000]***	[0.0018]***	[0.8653]	[0.0003]***	[0.1950]	[0.1234]	[0.000]***	[0.000]***	[0.000]***
R-squared	0.0185	0.0655	0.044	0.0001	0.0598	0.0077	0.0109	0.0689	0.094	0.0965
Durbin-Watson	1.8544	1.8302	1.8115	2.0498	1.8138	2.0543	2.0378	2.1769	1.9824	2.1489
Q-stat	0.71	1.3428	1.4529	0.142	1.8428	0.1662	0.0814	1.7431	0.0093	1.267
	[0.399]	[0.247]	[0.228]	[0.706]	[0.175]	[0.684]	[0.775]	[0.187]	[0.923]	[0.260]

	SWTSMI	NZLNZX50	FRA-CAC	NOR-OSEAX	NETH-AEX	JAP-NIKKEI225	IRE-ISEQ	TUN-TUNINDEX	UKR-PFTS	BUL-SOFIX
intercept	0.03249	0.0023	0.0067	0.0078	0.0072	0.0064	0.0095	0.0025	-0.0058	0.0061
	[0.1512]	[0.5147]	[0.4315]	[0.3783]	[0.4005]	[0.4428]	[0.2810]	[0.5240]	[0.6126]	[0.8041]
Beta (β)	-0.086	0.3711	0.2072	0.1973	0.1738	0.1653	0.4367	0.1718	0.2589	0.0932
	[0.2416]	[0.000]***	[0.0013]***	[0.0045]***	[0.0108]**	[0.0121]**	[0.000]***	[0.0527]*	[0.0071]***	[0.1718]
R-squared	0.0077	0.1331	0.0463	0.0366	0.0296	0.0286	0.1614	0.0172	0.0328	0.0085
Durbin-Watson	2.0626	1.9617	1.9349	1.8167	1.8752	1.8354	1.8502	1.8821	1.9489	1.9616
Q-stat	0.1879	0.0377	0.195	1.6913	0.7412	1.4414	0.1905	0.7436	0.1316	0.0802
	[0.665]	[0.846]	[0.659]	[0.193]	[0.389]	[0.230]	[0.662]	[0.389]	[0.717]	[0.777]

	POL-WIG	ICE-SEICEX	RUS-MICEX	MALT-MALTEX	ISR-TA100	COL-COLCAP	BELG-BEL20	UAE-ADXGEN	CHIL-IGPA	MEX-S&PBMVIPC
intercept	0.0057	0.0096	0.0123	0.0081	0.0052	0.0128	0.0057	0.0085	0.0017	0.0127
	[0.5868]	[0.6729]	[0.5163]	[0.3786]	[0.5638]	[0.2163]	[0.5402]	[0.6687]	[0.8238]	[0.1266]
Beta (β)	0.2898	0.1019	-0.0746	0.3177	0.3196	0.2718	0.2566	-0.2922	0.5691	-0.1118
	[0.0002]***	[0.1346]	[0.3002]	[0.000]***	[0.000]***	[0.000]***	[0.0008]***	[0.000]***	[0.0000]***	[0.1544]
R-squared	0.0623	0.0103	0.0049	0.0776	0.0926	0.0534	0.0505	0.0827	0.2848	0.0093
Durbin-Watson	1.9547	1.9107	2.0189	1.9756	2.0066	1.7914	1.8557	2.0044	1.8974	1.8764
Q-stat	0.0797	0.4361	0.0244	0.0207	0.0144	2.3431	1.0553	0.002	0.4974	0.8276
	[0.778]	[0.509]	[0.876]	[0.886]	[0.905]	[0.126]	[0.304]	[0.964]	[0.481]	[0.363]

Note: Series names are given in Table 7.

	SWEOMX30	SERB-BELEX15	ARG-MERVAL25	ROM-BET	QAT-QE	LUX-LUXX
intercept	0.0233	0.0142	-0.0005	0.0031	0.01152	0.0099
	[0.3630]	[0.4688]	[0.9838]	[0.7515]	[0.2708]	[0.3264]
Beta (β)	0.0524	0.2704	-0.0805	0.2003	-0.1269	0.2432
	[0.4891]	[0.000]***	[0.2366]	[0.0067]***	0[0.063]*	[0.0020]***
R-squared	0.0026	0.0731	0.0064	0.0334	0.0158	0.043
Durbin-Watson	1.9897	1.9432	2.0194	1.8754	2.1518	1.9197
Q-stat	0.0048	0.1777	0.0249	0.7531	1.2897	0.321
	[0.945]	[0.673]	[0.875]	[0.386]	[0.256]	[0.571]

COMMODITIES	CRUDEOIL	GOLD	SILVER	GAS	COPPER	PLATINUM	PALLADIUM	NICKEL	TIN	ZINC
intercept	0.0053	0.0021	0.0089	0.0094	0.0077	0.011	0.0106	0.0083	0.0096	0.0061
	[0.6061]	[0.8374]	[0.7096]	[0.6820]	[0.3987]	[0.6390]	[0.2205]	[0.7157]	[0.2899]	[0.7949]
Beta (β)	0.1069	0.32011	0.1246	0.0922	0.3706	0.1077	0.2398	0.1257	0.3067	0.1282
	[0.0880]*	[0.000]***	[0.0660]*	[0.1342]	[0.000]***	[0.1092]	[0.000]***	[0.0509]*	[0.000]***	[0.0542]*
R-squared	0.0134	0.0732	0.0155	0.0103	0.1407	0.0118	0.0983	0.0172	0.1046	0.0169
Durbin-Watson	1.9056	2.1019	2.0125	1.9739	2.1943	1.999	1.8989	1.9564	2.1686	1.9902
Q-stat	0.4511	0.6095	0.0104	0.0328	2.2226	0	0.5387	0.0999	1.6321	0.0046
	[0.502]	[0.435]	[0.919]	[0.856]	[0.136]	[0.997]	[0.463]	[0.752]	[0.201]	[0.946]

	COCOA	COFFEE	COTTON	RHODIUM	RUTHENIUM	CORN	RUBBER	SOYABEAN	WOOL	ALUMINIUM
intercept	0.0059	-0.0037	0.0008	0.01165	0.0105	-0.0016	0.0045	0.0032	0.0026	0.0057
	[0.7981]	[0.8760]	[0.9809]	[0.6261]	[0.6568]	[0.9432]	[0.6329]	[0.7332]	[0.7740]	[0.8042]
Beta (β)	0.1372	0.1636	0.1191	0.05642	0.1367	0.1581	0.1728	0.3539	0.3223	0.1121
	[0.0377]**	[0.0157]**	[0.0727]*	[0.3968]	[0.0392]**	[0.0195]**	[0.0050]***	[0.000]***	[0.000]***	[0.0998]*
R-squared	0.0197	0.0266	0.0147	0.0033	0.0194	0.0245	0.0358	0.1163	0.0819	0.0124
Durbin-Watson	1.9897	2.0091	1.9569	1.8697	1.9815	2.0378	1.8445	2.2123	2.0051	1.9352
Q-stat	0.0046	0.0051	0.1027	0.9213	0.0153	0.082	1.2238	2.6107	0.0054	0.2305
	[0.946]	[0.943]	[0.749]	[0.337]	[0.902]	[0.775]	[0.269]	[0.106]	[0.941]	[0.631]

	LEAD	WHEAT
intercept	0.0114	-0.0052
	[0.6214]	[0.6056]
Beta (β)	0.1266	0.3417
	[0.0584]*	[0.000]***
R-squared	0.0164	0.114
Durbin-Watson	1.9342	2.1575
Q-stat	0.234	1.5416
	[0.629]	[0.214]

AGGREGATES	WORLD	EUROPE	EMERGING MARKETS
intercept	0.0056	0.0053	0.0039
	[0.5141]	[0.5607]	[0.6561]
Beta (β)	0.2352	0.2347	0.3008
	[0.0006]***	[0.0006]***	[0.000]***
R-squared	0.0531	0.0523	0.0915
Durbin-Watson	1.9604	1.9584	1.9702
Q-stat	0.0554	0.0616	0.0314
	[0.814]	[0.804]	[0.859]

4.2 Results of Markov-switching model

We now proceed to estimate our next model for the MS-CAPM as stated in equation (3). Here, the intuition is to employ the Markov Switching regression technique in the estimation of intercepts and CAPM beta under a regime switching framework. Huang (2003) argues that whereas the underlining theory of CAPM maintains that a stable and linear relationship exists between asset returns and risk, evidence abounds suggesting significant variations in market beta. For instance, Jagannathan and Wang (1996) note that relative risks associated with variations in a firm's cash flow over the business cycle may induce some switching behavior in market risk. Given this, our MS-CAPM follows Huang (2000) by allowing the systematic risk of β to come from two different regimes to show whether it is unstable over the regimes. Put differently; this model would enable us to determine if the estimates of alpha and beta coefficients are significantly different between low and high volatility regimes and if they are consistent with the static CAPM. Finally, the transition probabilities matrix is constructed with values that indicate how difficult it is to switch from one volatility regime to the other.

From Table 2 and Figure 1, some interesting results stand out. First, following Korkmaz et al. (2010), the low and high volatility regimes are distinguished based on the size of the estimated standard errors of the regression. In the low volatility regime, the estimates of the beta coefficient of the securities of Slovenia, France, the UK, Sweden, Switzerland, Norway, Japan, Ireland, China, Singapore, and Bulgaria are statistically significant and less than one showing that the securities in these countries are less risky than the respective markets. However, estimates of the beta coefficients in this same period for Finland, Malaysia, Philippines, Taiwan, Hong Kong, Serbia, New Zealand, Portugal, and Chile are less than zero and statistically significant indicating that returns in these countries move in an opposite direction with movements in market returns. The returns on securities in Sweden is the riskiest as indicated by the highest beta coefficient of 0.59 while that of that of France is the least risky as shown by a beta parameter of approximately 0.003. Lastly, the beta coefficients of the remaining markets are not statistically significant indicating that they do not have relation with the market during the low volatile regime.

Concerning the high volatility regime, estimates of the beta parameter for securities in Germany, Finland, France, UK, New Zealand, Ireland, Malaysia, Philippines, and Taiwan are less than 1 and statistically significant indicating that returns on these securities are less risky than the respective market returns in this regime. Whereas estimates of the beta parameter for securities from Norway and Thailand are less than zero and statistically significant indicating that they move in the opposite direction with movements in the market returns during this period. Also in this period, returns on securities in Finland is the riskiest with a beta coefficient of 0.84 while that of France is the least risky with a beta coefficient of 0.02. The beta parameters of the remaining countries are found to be statistically insignificant suggesting that they do not have relation with the market return or an inefficient market.

Regarding the commodity indices, in the low volatility regime, the estimates of beta coefficient for Silver, Platinum, Rhodium, Ruthenium, Corn, Rubber, Aluminum and Cocoa are less than one and statistically significant. This suggests that returns on these commodity securities are less risky than the market return. In the same period, only the beta coefficients for Copper is less than zero but statistically insignificant indicating that its return moves in the opposite direction with the market return. More so, Rubber is the most dangerous commodity in this regime with a beta coefficient of about 0.43 while Silver is the least risky with about 0.17 beta coefficient. The estimates of beta coefficients for the remaining commodity indices are statistically insignificant showing that they are not related to the market return in the low volatility regime.

In the high volatility regime, among the commodity indices, only the estimates of beta coefficients of Wheat and Cotton are less than one and statistically significant. This shows that in this period, only these two securities are less risky than the market returns. Similarly, only the beta coefficients for Palladium and Tin are less than zero and statistically significant indicating that they move in the opposite direction to the movement of market returns. Whereas, the remaining commodity indices have no relation with the market return as suggested by their statistically insignificant beta coefficients. In the high volatility regime, Wheat is the riskiest commodity but with a beta coefficient of only 0.28 while Cotton is the least risky with a beta coefficient of about

0.17. The implication is that commodity indices are less risky in both low and high volatility regimes compared to country securities. This is as suggested by the estimates of beta coefficients for the least as well as the riskiest securities in both regimes.

Regarding the aggregate markets, only the World aggregate security is statistically significant and less than one with a beta coefficient of about 0.30 while the remaining aggregate securities including Europe and Emerging market are statistically insignificant suggesting that they do not have relation with the market in the low volatility regime. More so, in the high volatility regime, all the estimates of beta coefficients for all the aggregate markets are statistically insignificant. This implies that they do not have relation with the market during the high volatility period. Concerning the probabilities of transition from one volatility regime to the other, the probability of switching from the low volatility regime to the high volatility regime is higher than the probability of switching from the high volatility to low volatility regime for the World market security. The transition probability for the low volatility regime is 0.26 whereas it is 0.21 for the high volatility regime.

Concerning the probabilities of transition from one regime to the other for the countries, it is generally less likely to switch from low volatility regime to high volatility regime as indicated by low values of P_{12}. The highest value of P_{12} is 0.61 for Bulgaria. However, the probability of transition from high to low volatility regime is relatively higher as shown by higher P_{21} values. For instance, the P_{21} value for Germany is 0.99. Similarly, among commodity indices, it is also less likely to switch from low to high volatility regime as suggested by P_{12} values. The P_{12} value is highest for Copper with about 0.21 whereas it is relatively more likely to switch from high to low volatility regime. The P_{21} value is highest for Tin with 0.24. This result generally suggests that the probability of transition from any regime to the other is relatively higher in conventional financial assets class than in the commodity market.

In Figure 1 we present the filtered and smoothed probabilities from the MS-CAPM regimes for 12 selected markets including Argentina, Bulgaria, China, Denmark, Gasoline, Italy, Platinum, Rhodium, Silver, Turkey, the USA, and Zinc. The pattern displayed by the filtered and smoothed probabilities in regime 1 suggest that in the earlier part of the sample, high volatility level dominate in Argentina, Bulgaria, Platinum, Silver, Turkey, and the USA but decreases substantially towards the middle of the sample. Towards the middle of the sample, high volatility levels are incidental and transitory, whereas, towards the end of the sample, high volatility levels seem to gather more again. However, in the same regime, periods of low volatility level predominate especially among commodities such as Gasoline, Rhodium, Zinc before periods of high volatility levels clustered towards the middle and the end of the sample. Lastly, the entire sample period was dominated by a constellation of high volatility levels throughout regime 1 for Denmark whereas the converse held for Italy where the entire sample period was dominated by low volatility levels except at the beginning of the second half of the sample but decreased substantially till the end of the sample.

The pattern of filtered probabilities for regime 2 suggests that high volatility levels dominated the entire sample period in China, Italy, Turkey, and the USA but were incidental and transitory after the middle but clustered towards the end of the sample in Gas, Rhodium, and Zinc. In Bulgaria, Platinum, and Silver, the pattern shows that low volatility levels dominated but was mixed with periods of high volatility levels in the USA until the middle of the sample. The second half of the sample is characterized by periods of high volatility levels with persistence of low volatility levels before high volatility levels clustered towards the end of the sample. However, low volatility levels evolved throughout the first half of the sample before the appearance of high volatility levels in the second half in Bulgaria. On the contrary, in Argentina, the pattern shows that low volatility levels persisted in most of the sample but with high volatility levels present in the earlier part of the sample and towards the middle and at the end of the sample. In Denmark, the pattern shows that volatility rose slowly throughout the entire regime except around the middle of the sample during when it appears to have gone up.

Generally, the filtered probabilities for both regimes show significant consistency with the empirical pattern displayed by the results of MS-CAPM. Towards the middle of our sample coincides with the period of the past financial crisis. The implication is that the years of financial crisis, U.S quantitative easing and the European sovereign debt crisis which influenced financial market investors' risk appetite and therefore, asset prices and returns may have increased volatility levels especially among commodities such as Gasoline, Rhodium, and Zinc in regime 1.

Table 2: MS-CAPM Results

STOCKS	MSCI USA	SD	MSCI CAN		MSCI GER		MSCI AUS		MSCI DEN		MSCI FIN		MSCI SPN	
Regime 1														
intercept	-0.0228	[0.0080]***	0.0078	[0.0332]	-1.0609	[0.0001]***	0.0132	[0.0137]	0.0212	[0.0182]	0.1719	[0.000]***	0.0105	[0.0136]
Beta (β)	-0.1606	[0.1518]	-0.1739	[0.1285]	0.3705	[0.0303]***	0.0097	[0.0972]	0.0442	[0.1123]	0.8412	[0.000]***	0.0537	[0.0853]
Regime 2														
intercept	0.0258	[0.0185]	-0.0055	[0.0050]	-0.0517	[0.0001]***	-0.0165	[0.0065]**	-0.0158	[0.0074]***	-0.1719	[0.000]***	-0.0194	[0.0069]***
Beta (β)	0.0225	[0.1139]	0.1101	[0.0845]	-0.0047	[0.0058]	-0.1148	[0.1792]	0.0494	[0.1077]	-0.0391	[0.000]***	0.1398	[0.1220]
p12	0.1629		0.0249		0.01		0.1034		0.1667		0.08		0.0723	
p21	0.1582		0.0871		0.99		0.0753		0.1884		0.91		0.038	

	MSCI SLOV		MSCI FRA		MSCI UK		MSCI ITA		MSCI SWE		MSCI SWT		MSCI NZL	
Regime 1														
intercept	-0.0079	[0.0078]	-0.9592	[0.4355]**	0.6456	[0.5236]	0.0511	[0.0820]	0.0088	[0.0068]	0.1278	[0.1004]	0.0038	[0.0097]
Beta (β)	0.3082	[0.0017]***	0.0027	[0.0010]***	0.0031	[0.0004]***	-0.1316	[0.2033]	0.5927	[0.0598]***	-0.1604	[0.1721]	0.5578	[0.2270]**
Regime 2														
intercept	0.0076	[0.0165]	0.0326	[0.0002]***	-0.0043	[0.1137]	-0.0133	[0.0050]**	0.0775	[0.1269]	-0.022	[0.0056]	-0.0013	[0.0048]
Beta (β)	-0.0291	[0.0976]	0.0229	[0.0034]***	0.1667	[0.0349]***	0.0099	[0.0494]	-0.0096	[0.1771]	0.2605	0.084]***	-0.3166	[0.1008]***
p12	0.1171		0.06		0.12		0.0656		0.0869		0.0805		0.3592	
p21	0.1606		0.94		0.88		0.3598		0.0171		0.3224		0.6839	

	MSCI NOR		MSCI NLD		MSCI JAP		MSCI IRE		MSCI THAI		MSCI MYL		MSCI INDO	
Regime 1														
intercept	0.0095	[0.0187]	-0.0185	[0.0075]**	0.0039	[0.0077]	0.0037	[0.999]	-0.0017	[0.0181]	0.0083	[0.0043]	0.0088	[0.0072]
Beta (β)	0.459	[0.1039]***	-0.0757	[0.1393]	0.2311	[0.0886]***	0.4096	[0.0017]***	-0.6918	[0.2172]***	-0.177	[0.0554]***	-0.1044	[0.0789]
Regime 2														
intercept	-0.012	[0.0097]	0.011	[0.0133]	-0.0062	[0.0186]	-0.0037	[0.0976]	0.0063	[0.0072]	-0.0268	[0.0155]	-0.0443	[0.0332]
Beta (β)	-0.2939	[0.1131]**	0.0553	[0.0868]	-0.0471	[0.1106]	0.0808	[0.0137]***	0.1103	[0.0589]	0.7869	[0.2831]***	-0.0397	[0.1739]
p12	0.4391		0.0955		0.06411		0.61		0.4545		0		0.0721	
p21	0.5341		0.1552		0.0407		0.39		0.9203		0.4119		0.1402	

	MSCI PHI		MSCI SING		MSCI CHIN		MSCI INDI		MSCI TAI		MSCI KOR		MSCI HNGKNG	
Regime 1	-0.0213	[0.0158]	0.0284	[0.0272]***	0.0263	[0.0149]	-0.0109	[0.0100]	0.0504	[0.0875]	-0.0163	[0.0082]**	0.0298	[0.0190]
intercept	-0.3613	[0.1123]***	0.0338	[0.1375]	0.2119	[0.0710]***	-0.2112	[0.1090]	0.3817	[0.1792]**	-0.1195	[0.0981]	0.0673	[0.1197]
Beta (β)														
Regime 2	0.0251	[0.0216]	-0.0128	[0.0063]**	-0.059	[0.0897]	0.0153	[0.0254]	-0.0095	[0.0057]	0.0202	[0.0223]	-0.03	[0.0077]***
intercept	0.5312	[0.1663]***	-0.1747	[0.0816]**	-0.0491	[0.1208]	0.0321	[0.1288]	-0.2688	[0.0638]***	0.1625	[0.1172]	-0.2955	[0.0926]***
Beta (β)														
	0.6646		0.0866		0.2534		0.2816		0.0469		0.2981		0.2877	
p12	0.6579		0.2053		0.1634		0.1741		0.808		0.2661		0.3107	
p21														

	MSCI SERB		MSCI UKR		MSCI BUL		MSCI ROM		MSCI POL		MSCI ICE		MSCI RUS	
Regime 1														
intercept	0.0087	[0.049]	-0.0239	[0.0308]	0.0255	[0.0680]	-0.0081	[0.0056]	-0.0056	[0.0296]	-0.0054	[0.0095]	-0.0187	[0.0744]
Beta (β)	0.3258	[0.2477]	0.0329	[0.1205]	-0.0468	[0.1242]	0.1244	[0.0821]	0.1316	[0.1296]	0.2566	[0.0525]	-0.0732	[0.1534]
Regime 2														
intercept	-0.0094	[0.0057]	0.0138	[0.0081]	-0.0008	[0.0092]	0.0437	[0.0552]	0.0038	[0.0097]	0.0139	[0.0745]	0.0036	[0.0123]
Beta (β)	-0.2633	[0.0226]***	-0.0234	[0.0992]	0.269	[0.0495]***	-0.0062	[0.1618]	-0.1151	[0.0909]	-0.0034	[0.1808]	0.1015	[0.0892]
p12	0.1237		0.0211		0.0401		0.3481		0.0211		0.0606		0.0355	
p21	0.2019		0.0456		0.076		0.0617		0.054		0.0333		0.1178	

Note: Series names are given in Table 7. p12 and p21 are the transition probabilities of moving from one regime to the other.

	MSCI MALT		MSCI ISR		MSCI LAT		MSCI EST		MSCI TUR		MSCI CRO		MSCI LIT	
Regime 1														
intercept	-0.0143	[0.0071]	-0.0192	[0.0093]**	0.0029	[0.0436]	0.0374	[0.0365]	0.1821	[0.1072]	0.0059	[0.0093]	0.0097	[0.0418]
Beta (β)	-0.092	[0.0997]	0.0914	[0.1181]	0.0734	[0.1628]	0.1196	[0.1463]	0.0252	[0.1866]	0.1112	[0.0680]	0.2079	[0.1321]
Regime 2														
intercept	0.0114	[0.0165]	0.0285	[0.0191]	0.0013	[0.0043]	-0.0172	[0.0093]	-0.035	[0.011]***	-0.009	[0.0536]	-0.0084	[0.0075]
Beta (β)	0.0226	[0.0960]	-0.0687	[0.1123]	-0.0286	[0.0803]	-0.0111	[0.0875]	-0.0754	[0.0733]	-0.0472	[0.1186]	0.0081	[0.0531]
p12	0.1095		0.2678		0.0169		0.068		0.0467		0.1267		0.1107	
p21	0.1284		0.2533		0.0553		0.1719		0.21		0.0819		0.3952	

	MSCI HUN		MSCI EGY		MSCI POR		MSCI CZECH		MSCI BRA		MSCI ARG		MSCI COL	
Regime 1														
intercept	0.0025	[0.0819]	0.0064	[0.0094]	0.0075	[0.0114]	-0.0036	[0.0091]	-0.0082	[0.0160]	-0.0225	[0.0939]	0.0136	[0.0267]
Beta (β)	-0.0352	[0.1219]	0.2024	[0.0508]	-0.3737	[0.0544]***	-0.0371	[0.0877]	0.042	[0.1578]	0.024	[0.1489]	0.1584	[0.1425]
Regime 2														
intercept	-0.0001	[0.0105]	-0.0081	[0.0624]	-0.0096	[0.0128]	0.0087	[0.0289]	0.0039	[0.0126]	0.005	[0.0117]	-0.0079	[0.0123]
Beta (β)	0.0211	[0.1075]	-0.0659	[0.1223]	0.3844	[0.2819]	0.033	[0.1342]	-0.1621	[0.1006]	0.0102	[0.0931]	0.0269	[0.0965]
p12	0.0258		0.07652		0.719		0.2346		0.2609		0.0284		0.2583	
p21	0.0529		0.0454		0.4484		0.1125		0.5859		0.1062		0.4076	

	MSCI BEL		MSCI UAE		MSCI CHIL		MSCI MEX		MSCI QAT		MSCI TUN		MSCI LUX	
Regime 1														
intercept	-0.0057	[0.0078]	0.0387	[0.0483]	0.0036	[0.0056]	0.0072	[0.0218]	-0.0115	[0.0499]	-0.001	[0.0085]	-0.0125	[0.007]
Beta (β)	0.0678	[0.0944]	0.0535	[0.1145]	-0.162	[0.0686]**	0.0734	[0.1207]	-0.4087	[0.2358]	0.0732	[0.1819]	-0.0429	[0.0930]
Regime 2														
intercept	0.0277	[0.0447]	-0.0193	[0.0149]	0.0049	[0.0848]	-0.0049	[0.0064]	0.0036	[0.0073]	0.001	[0.0049]	0.0147	[0.0161]
Beta (β)	0.0637	[0.1728]	0.1173	[0.0931]	0.4321	[0.4117]	0.0073	[0.0809]	0.1029	[0.0615]	0.0513	[0.1237]	0.0613	[0.0891]
p12	0.2068		0.0479		0.3024		0.0245		0.0549		0.4656		0.1061	
p21	0.0506		0.0757		0.0276		0.9754		0.2131		0.5198		0.1705	

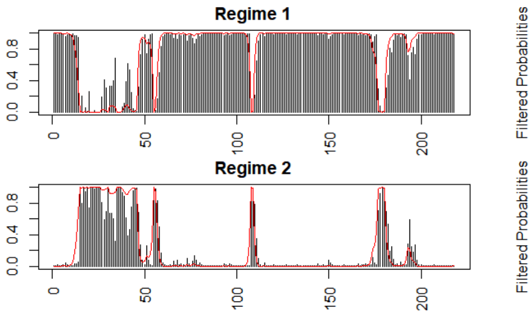
AGGREGATES	MSCI WORLD		MSCI Europe		MSCI EM	
Regime 1						
intercept						
Beta (β)	0.0255	[0.0151]	0.0128	[0.0149]	-0.0142	[0.0074]
	-0.1677	[0.1131]	0.001	[0.3035]	0.0426	[0.1204]
Regime 2						
intercept						
Beta (β)	-0.0246	[0.0071]***	-0.018	[0.0068]**	0.0123	[0.0149]
	0.307	[0.0938]***	-0.0319	[0.0409]	-0.0055	[0.1001]
p12	0.2689		0.0698		0.0311	
p21	0.2142		0.0538		0.0429	

COMMODITIES	MSCI OIL		MSCI GOLD		MSCI SILVER		MSCI GAS		MSCI Copper		MSCI Platinum	
Regime 1												
intercept	0.0206	[0.0159]	0.014	[0.0126]	0.0029	[0.0640]	0.0053	[0.0639]	0.0312	[0.0204]	0.0016	[0.0097]
Beta (β)	0.1201	[0.0970]	-0.1263	[0.0907]	-0.041	[0.1247]	0.016	[0.1181]	-0.0467	[0.1336]	0.2433	[0.0530]***
Regime 2												
intercept	-0.0347	[0.0214]	-0.0397	[0.0628]	0.0058	[0.0102]	0.001	[0.0121]	-0.0235	[0.0144]	0.0121	[0.0610]
Beta (β)	-0.1318	[0.1022]	-0.0286	[0.1711]	0.1795	[0.0594]***	0.0122	[0.0931]	-0.2927	[0.0984]***	-0.036	[0.1204]
p12	0.1966		0.08143		0.06012		0.0267		0.2128		0.0516	
p21	0.8033		0.02208		0.1093		0.0529		0.2951		0.0305	

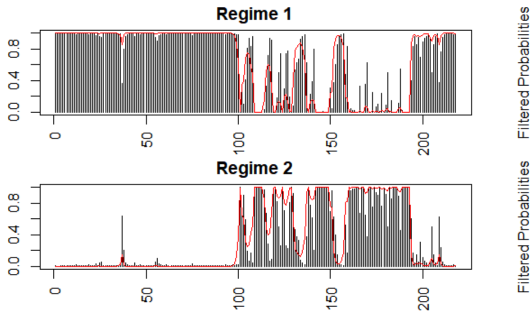
	MSCI Palladium		MSCI Nickel		MSCI Tin		MSCI Zinc		MSCI Rhodium		MSCI Ruthernium	
Regime 1												
intercept	-0.0267	[0.0092]***	0.008	[0.0123]	-0.0425	[0.0143]***	-0.0006	[0.0089]	0.0199	[0.0643]	-0.0037	[0.0094]
Beta (β)	-0.2215	[0.1085]**	0.0189	[0.0822]	-0.2589	[0.1035]**	0.0301	[0.0806]	0.026	[0.1236]	0.209	[0.0485]
Regime 2												
intercept	0.0134	[0.0145]	0.0003	[0.0263]	0.0348	[0.017]**	0.0117	[0.0674]	-0.0014	[0.0092]	0.0229	[0.0635]
Beta (β)	0.0761	[0.1024]	0.031	[0.1208]	-0.089	[0.1074]	0.0094	[0.1184]	0.2742	[0.0472]***	-0.0303	[0.1227]
p12	0.0814		0.0557		0.2145		0.0628		0.0383		0.0587	
p21	0.1217		0.0268		0.2427		0.0313		0.0683		0.0331	

	MSCI Corn		MSCI Rubber		MSCI Soyabean		MSCI Wool		MSCI Aluminium		MSCI Lead	
Regime 1												
intercept	0.0216	[0.0562]	0.0044	[0.0201]	0.0027	[0.0070]	0.0038	[0.0191]	-0.0004	[0.0080]	0.0092	[0.0096]
Beta (β)	-0.0561	[0.1157]	-0.0076	[0.1040]	-0.0091	[0.1002]	-0.0648	[0.1043]	0.218	[0.0481]***	0.2115	[0.0530]
Regime 2												
intercept	-0.0028	[0.0091]	-0.0012	[0.0062]	-0.0007	[0.0255]	-0.0014	[0.0067]	0.0151	[0.0565]	-0.0028	[0.0655]
Beta (β)	0.2342	[0.0485]***	0.4376	[0.0895]***	-0.1324	[0.1019]	0.261	[0.1363]	0.0103	[0.1154]	-0.0037	[0.1086]
p12	0.038		0.0359		0.0705		0.0349		0.0449		0.0903	
p21	0.0561		0.0539		0.0563		0.0502		0.0295		0.0477	

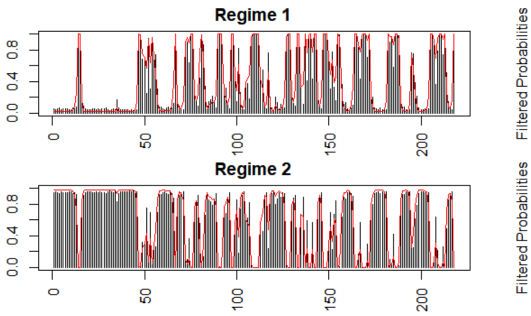
	MSCI Wheat		MSCI Cocoa		MSCI Coffee		MSCICotton	
Regime 1								
intercept	0.0086	[0.0227]	-0.0077	[0.0108]	0.0216	[0.0658]	0.0293	[0.0565]
Beta (β)	-0.2631	[0.1124]	0.1882	[0.0578]***	0.015	[0.1168]	-0.0003	[0.0322]
Regime 2								
intercept	-0.0032	[0.0081]	0.0303	[0.0623]	-0.0094	[0.0100]	-0.0105	[0.0099]
Beta (β)	0.2886	[0.1156]**	-0.0284	[0.1213]	-0.077	[0.0819]	0.1726	[0.0566]***
p12	0.0462		0.0431		0.0285		0.0206	
p21	0.0828		0.0244		0.0536		0.0321	



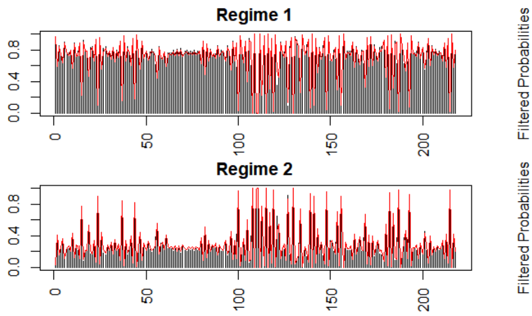
(a) Argentina



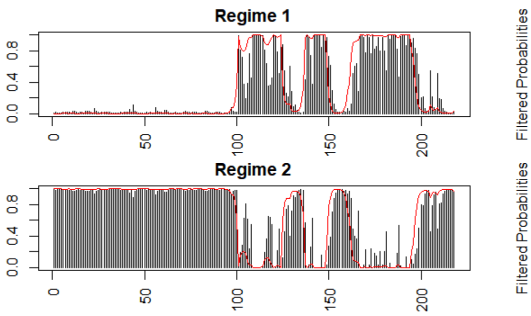
(b) Bulgaria



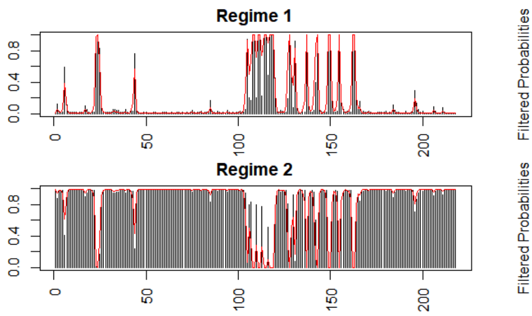
(c) China



(d) Denmark

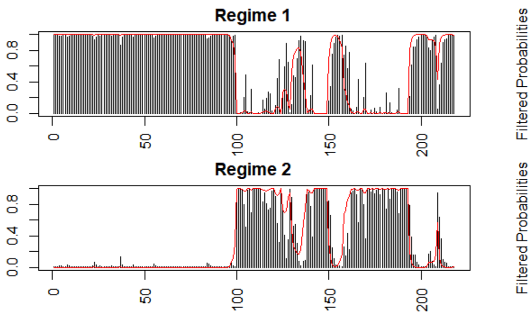


(e) Gasoline

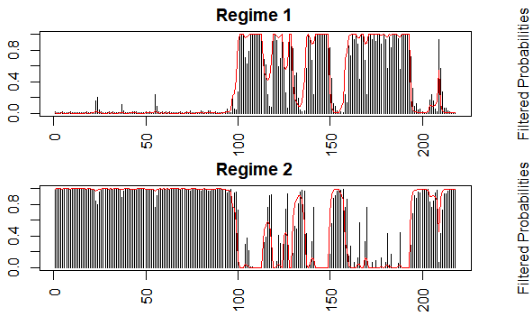


(f) Italy

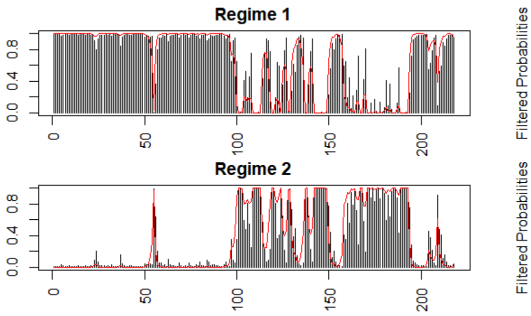
Figure 1: MS-CAPM Regimes for 12 selected high-volatility markets



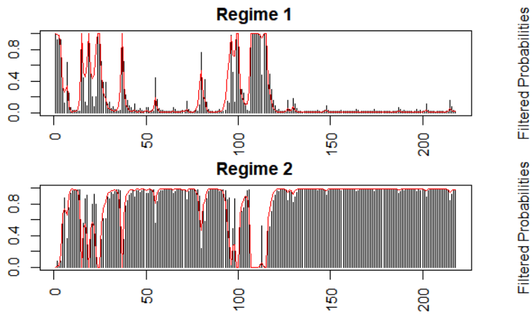
(g) Platinum



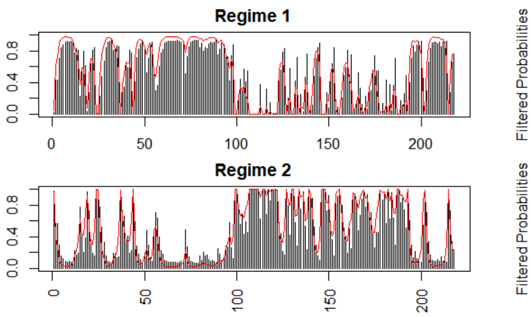
(h) Rhodium



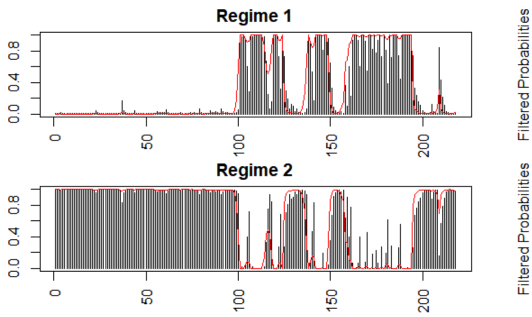
(i) Silver



(j) Turkey



(k) USA



(l) Zinc

Figure 1: MS-CAPM Regimes for 12 selected high-volatility markets (continued)

4.3 MS-GARCH-CAPM

Given the observed advantage of the MS-CAPM over the unconditional CAPM in accounting for instability of systematic risk especially by allowing beta coefficients to evolve through two volatility regimes, we proceed to estimate the MS-GARCH-CAPM as stated in equation (9) expecting that more realistic results could be acquired. The Markov Switching GARCH model is reputed in the analysis of systematic risks for several reasons. For instance, in addition to allowing the measure of systematic risks to be estimated from two regimes and the respective periods of duration in both volatility regimes to varying over time, under the Haas et al. (2004a) specification, the conditional variance is set to vary depending on the past data as well as the current regime. Also, it returns estimates of the posterior mean stable probabilities and the Bayesian predictive conditional volatility forecasts which have significant implications for risk management.

An acceptable way of comparing the two regimes from a regime switching GARCH model is through the means of the regimes variables which are obtained by averaging of the regimes which are the posterior mean stable probabilities of the states. Bauwens et al. (2010) note that a mean state close to 1 corresponds to a high probability to be in the second regime. To see this, we present in Table 3 and Figure 2 results of parameter estimates and the mean filtered volatility from the MS-GARCH-CAPM. It is evident that this model performed better than the previous two models in providing a wider range of insights into most of the stock markets in our sample as shown by the higher number of statistically significant estimates of beta in both the low and high volatility regimes.

Specifically, in the low volatility period, all the country stocks have estimates of beta coefficients that are statistically significant, positive and less than 1 except in Finland, the United Kingdom, and Italy. This suggests that in all these markets, the stocks are less risky than the respective markets. The beta coefficients for Finland, United Kingdom, and Italy are not found to be statistically significant implying that do not have relations with the market whereas the beta coefficient for Ireland is statistically significant but negative, implying that the securities move in the opposite direction with the market. Generally, in this period, the values of beta coefficients varied widely across these markets with Taiwan, Mexico having the least beta of about 0.002 and 0.004 respectively while it is highest in Belgium and the United Arab Emirate with 0.97 and 0.93 respectively.

Regarding the high volatility regime, the model also offers broad insight into most of the markets in our sample as the estimates of beta coefficients are statistically significant, positive and less than 1 in all the country stocks except in Finland, United Kingdom and Ireland suggesting that the stocks of these countries are less risky than the respective markets. The beta coefficients for Finland, United Kingdom, and Ireland are statistically insignificant suggesting that they do not follow movements in the market whereas the beta coefficients for Germany and France are statistically significant, but less than 0 suggests that the securities move in opposite direction to movements in the market. Similarly, the beta coefficients vary widely throughout the markets with Tunisia and Hong-Kong having the least beta of about 0.08 each while Poland has the highest beta coefficient of about 0.94. The estimates of the predictive conditional volatility forecasts for both volatility periods reveal that regime 2 is generally more volatile than the first regime. The conditional volatility forecast for regime 2 is highest in Russia with about 187.1 whereas, in regime 1, it is highest in Turkey with about 11.8.

Concerning the low volatility regime in the commodity market, the estimates of beta coefficients are statistically significant, positive and less than 1 in all the markets indicating that they are less risky than the respective markets. However, the beta coefficient for Ruthenium is about 1, suggesting that its securities risk is equivalent to that of the market. Similarly, Results from the high volatility regime in the commodity market corroborates that of the low volatility period as all estimates of beta coefficients are all statistically coefficient, positive and less than 1. However, the beta coefficients for Lead and Coffee are about 1 implying that there are as risky as the market in this period. In both volatility regimes, the conditional volatility forecasts remained predominantly higher in regime 2 with the highest being about 163.8 for Rhodium whereas it is 0.5 for Zinc.

Lastly, the beta coefficients in both the low and high volatility periods for the aggregate markets are statistically significant, positive and less than 1. The world aggregate securities have the least beta coefficients of about 0.12 and 0.32 in low and high volatility period respectively whereas Emerging-market stocks have the highest beta of 0.42 in the low volatility period. Securities for the European market has the highest beta coefficient of 0.77 in the high volatility period. Similarly, regime 1 is characterized by low conditional volatility forecast levels with the World aggregate stocks being the highest with about 4.43 whereas regime 2 is characterized by high conditional volatility forecasts with securities in Europe being the most volatile with about 131.

Concerning the probabilities of transition from one beta regime to the other as represented by P_{12} and P_{12}, among the countries in our sample, it is generally more likely to move from high volatility regime to low volatility regime in most of the markets. It is only more likely to move from low volatility regime to high volatility regime in Finland, Slovenia, France, the UK, Sweden, Ireland, Thailand, Malaysia, Philippines, Hong-Kong, Bulgaria, Poland, Latvia, Turkey, Croatia, Czech, Argentina, Qatar, and Tunisia. It may be observed that Belgium that exhibited the highest distribution of systematic risks in both beta regimes, the transition probabilities of both regimes are large. This result suggests that the beta process has a little chance of staying for an extended period in any of the beta regimes. In converse, Taiwan which exhibits the least beta across both regimes, the transition probabilities suggest that there is a very high chance of moving to the low beta regime and a relatively low chance of moving to the high beta regime. This result implies that there is a very high chance of staying relatively longer in the low beta regime.

Further, among the commodity stocks, the transition probabilities suggest that it is also more likely to switch from high volatility regime to low volatility regime in all the markets except in Platinum, Palladium, Ruthenium, Rubber, and Wool. These results imply that most commodity stocks have a higher chance of staying longer in the low beta regime than in the high beta better regime. For instance, in both Lead and Coffee that demonstrate unusually high beta regimes almost 1, the transition probabilities suggest that there is relatively a very high chance of moving to the low beta regime while it may take a longer time in the low beta regime before switching to a high beta regime. Similarly, for the aggregate stocks representing the World and Europe, the transition probabilities suggest that both markets demonstrate very high chances of switching to the low beta regime whereas the likelihood of moving to the high beta regime is relatively low. This implies that these markets have higher chances of being longer in the low beta regime process than the high beta regime. In contrast, the transition probabilities for emerging market suggest that the chance of switching to the high beta regime is higher than that of moving to the low beta regime.

By way of comparison, it is evident that the CAPM beta is unstable over the three models namely unconditional CAPM, MS-CAPM, and MS-GARCH-CAPM. Even more, the instability of beta can also be seen across different regimes in the regime-switching models. This violates the prediction of the traditional model of CAPM that the beta of risky assets is constant over time. For instance, notable structural changes may be found in frontline markets such as the USA, the UK, Germany, France, Finland, Ireland, China, Malaysia, Philippines, Taiwan, Oil, Copper, Palladium, and Tin. In the USA and Oil markets, results from the unconditional CAPM and MS-GARCH-CAPM suggest that stock returns are risky and move in the same direction with the market whereas the MS-GARCH model suggests that these stocks do not have relation with the market.

Further, in the UK and China, results from the CAPM suggest that these stocks move in an opposite relation with the market whereas both the MS-GARCH and the MS-GARCH-CAPM models suggest these securities move in the same direction with the markets. Also, in Germany, France, and Ireland, the CAPM and MS-CAPM imply that these securities move in the same direction with the markets whereas the MS-GARCH-CAPM suggest that these stocks move in an opposite relation with the market. In the rest of the markets, the CAPM and MS-GARCH-CAPM results show that these securities move in the same direction with the market whereas the MS-CAPM suggest that these stocks move in the opposite direction with the market.

The instability of beta can also be noticed across regimes in the regime-switching models. For instance, the MS-CAPM reports that stocks in Germany and China move in the direction with the market in regime 1 but do not have relation with the market in regime 2 whereas Palladium and Tin securities move in the opposite direction with the market in regime 1 but also have no relation with the market in regime 2. Also in this model, stocks in Finland and Taiwan move in the same direction with the market in regime 1 but move in the opposite direction in regime 2. Stocks in Malaysia and Philippines move in the opposite direction with the market in regime 1 while they move in the same direction with the market in regime 2 whereas Copper securities do not have relations with the market but move in opposite direction in regime 2. Results from the MS-GARCH-CAPM suggest in most of the markets, the size of the beta coefficient changes but the relationship between the stocks and the market remains stable across both regimes. However, this is not the case for Germany where the stocks move in the opposite direction with the market in regime 1 but in the regime have no relation with the market whereas the contrast holds in France and Ireland.

Table 3: MS-GARCH-CAPM results

MSCI USA_MS_GARCH			**MSCI CAN_MS_GARCH**			**MSCI GER_MS_GARCH**		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0005	[0.000]***	**intercept**	0.0065	[0.0007]***	**intercept**	-0.0272	[0.0024]***
Beta (β)	0.4361	[0.0141]***	**Beta (β)**	0.4845	[0.0543]***	**Beta (β)**	-1.6969	[0.1697]***
nu_1	82.39	[3.2578]***	nu_1	24.47	[7.6849]***	nu_1	0.324	[0.0985]***
xi_1	8.3793	[0.5317]***	xi_1	1.1288	[0.0639]***	xi_1	0.6759	[0.0919]***
posterior mean stable probability_1	0.4735		posterior mean stable probability_1	0.7163		posterior mean stable probability_1	0.6851	
Volatility	0.5158		Volatility	0.7335		Volatility	0.02	
Regime 2			**Regime 2**			**Regime 2**		
intercept	0.0108	[0.0016]***	**intercept**	0.0085	[0.0011]***	**intercept**	6.6109	[0.2252]***
Beta (β)	0.4269	[0.0538]***	**Beta (β)**	0.766	[0.0364]***	**Beta (β)**	0.0588	[0.1113]
nu_2	24.32	[2.4409]***	nu_2	45.12	[3.1213]***	nu_2	1.267	[5.8906]
xi_2	0.9363	[0.0101]***	xi_2	11.48	[1.2579]***	xi_2	0.7516	[0.2795]***
p12	0.3707		p12	0.9365		p12	0.0708	
p21	0.566		p21	0.1603		p21	0.0298	
posterior mean stable probability_2	0.5265		posterior mean stable probability_2	0.2837		posterior mean stable probability_2	0.3104	
Volatility	6.4406		Volatility	3.1636		Volatility	0.19	
cc.p-value	0.5987		cc.p-value	0.0152		cc.p-value	0.5987	
dq.p-value	0.9998		dq.p-value	0.0074		dq.p-value	0.9998	

MSCI AUS_MS_GARCH			**MSCI DEN_MS_GARCH**			**MSCI FIN_MS_GARCH**		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0009	[0.0001]***	**intercept**	0.0095	[0.0014]***	**intercept**	0.0034	[0.0000]***
Beta (β)	0.7568	[0.0257]***	**Beta (β)**	0.4464	[0.0371]***	**Beta (β)**	0.003	[0.1750]
nu_1	11.42	[2.9584]***	nu_1	9.6682	[1.1795]***	nu_1	0.2505	[0.0646]***
xi_1	1.76	[0.0486]***	xi_1	1.6655	[0.0940]***	xi_1	0.7494	[0.0683]***
posterior mean stable probability_1	0.6917		posterior mean stable probability_1	0.8746		posterior mean stable probability_1	0.6344	
Volatility	1.2957		Volatility	2.4321		Volatility	0.2102	
Regime 2			**Regime 2**			**Regime 2**		
intercept	0.0205	[0.0056]***	**intercept**	0.3331	[0.0622]***	**intercept**	-0.3186	[0.0130]***
Beta (β)	0.3188	[0.0494]***	**Beta (β)**	0.3581	[0.0198]***	**Beta (β)**	-0.0028	[0.0034]
nu_2	55.65	[3.2174]***	nu_2	6.4586	[1.6323]***	nu_2	0.6257	[0.4084]
xi_2	1.152	[0.1219]***	xi_2	9.7138	[1.5358]***	xi_2	0.7701	[0.0543]***
p12	0.9137		p12	0.9724		p12	0.0173	
p21	0.1937		p21	0.1929		p21	0.0282	
posterior mean stable probability_2	0.3083		posterior mean stable probability_2	0.1254		posterior mean stable probability_2	0.3611	
Volatility	3.6197		Volatility	10.111		Volatility	0.7953	
cc.p-value	0.5987		cc.p-value	0.5987		cc.p-value	0.5987	
dq.p-value	0.9998		dq.p-value	0.9998		dq.p-value	0.9998	

MSCI HUN_MS_GARCH			**MSCI EGY_MS_GARCH**			**MSCI POR_MS_GARCH**		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0071	[0.0001]***	intercept	0.0099	[0.0001]***	intercept	0.0037	[0.0001]***
Beta (β)	0.5664	[0.0028]***	Beta (β)	0.0258	[0.0001]***	Beta (β)	0.2729	[0.0027]***
nu_1	5.4554	[0.0746]***	nu_1	99.24	[0.0180]***	nu_1	73.57	[0.4166]***
xi_1	1.0787	[0.0020]***	xi_1	1.5153	[0.0057]***	xi_1	4.1175	[0.1044]***
posterior mean stable probability_1	0.8469		posterior mean stable probability_1	0.6753		posterior mean stable probability_1	0.508	
Volatility	3.2939		Volatility	1.7575		Volatility	1.4935	
Regime 2			Regime 2			Regime 2		
intercept	0.5485	[0.0051]***	intercept	0.0982	[0.0007]***	intercept	0.0068	[0.0001]***
Beta (β)	0.1815	[0.0039]***	Beta (β)	0.2196	[0.0022]***	Beta (β)	0.2837	[0.0032]***
nu_2	45.74	[0.6060]***	nu_2	99.36	[0.0273]***	nu_2	67.76	[0.4824]***
xi_2	9.1403	[0.1606]***	xi_2	0.9369	[0.0027]***	xi_2	2.8034	[0.0801]***
p12	0.9659		p12	0.9628		p12	0.7679	
p21	0.1889		p21	0.0773		p21	0.2397	
posterior mean stable probability_2	0.1531		posterior mean stable probability_2	0.3247		posterior mean stable probability_2	0.492	
Volatility	147.4		Volatility	11.61		Volatility	2.2976	
cc.p-value	0.5987		cc.p-value	0.5987		cc.p-value	0.7175	
dq.p-value	0.9998		dq.p-value	0.9998		dq.p-value	0.4824	

Note: Series names are given in Table 7. nu_1, nu_2, xi_1, xi_2 are volatility parameters from the MS-GARCH model. p12 and p21 are the transition probabilities of moving from one regime to the other. cc and dq are, respectively, conditional coverage and dynamic quantile test parameters.

MSCI SPN_MS_GARCH		
Regime 1		SE
intercept	0.1253	[0.05077]***
Beta (β)	0.8696	[0.0083]***
nu_1	7.8557	[0.4288]***
xi_1	1.0939	[0.0144]***
posterior mean stable probability_1	0.7853	
Volatility	0.6135	
Regime 2		
intercept	0.1965	[0.0062]***
Beta (β)	0.7134	[0.0051]***
nu_2	99.339	[0.0601]***
xi_2	10.197	[1.3141]***
p12	0.9342	
p21	0.2406	
posterior mean stable probability_2	0.2147	
Volatility	3.5814	
cc.p-value	0.7175	
dq.p-value	0.0074	

MSCI SLOV_MS_GARCH		
Regime 1		SE
intercept	0.041	[0.0024]***
Beta (β)	0.5578	[0.0191]***
nu_1	99.983	[0.0016]***
xi_1	10.449	[0.5087]***
posterior mean stable probability_1	0.3247	
Volatility	0.6797	
Regime 2		
intercept	0.0055	[0.0012]***
Beta (β)	0.693	[0.0299]***
nu_2	65.638	[2.5985]***
xi_2	1.0604	[0.0064]***
p12	0.5165	
p21	0.2324	
posterior mean stable probability_2	0.6753	
Volatility	3.655	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI FRA_MS_GARCH		
Regime 1		SE
intercept	0.061	[0.0000]***
Beta (β)	-0.7325	[0.9516]
nu_1	0.1273	[0.0397]***
xi_1	0.8508	[0.0419]***
posterior mean stable probability_1	0.3801	
Volatility	0.032	
Regime 2		
intercept	-0.8216	[0.4016]**
Beta (β)	-0.6169	[0.1181]***
nu_2	0.1678	[0.0673]**
xi_2	0.8431	[0.0492]***
p12	0.6178	
p21	0.3822	
posterior mean stable probability_2	0.6155	
Volatility	0.075	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI UK_MS_GARCH		
Regime 1		SE
intercept	0.1208	[0.0000]***
Beta (β)	0.0531	[0.2670]
nu_1	0.3818	[0.0770]***
xi_1	0.6181	[0.0988]***
posterior mean stable probability_1	0.897	
Volatility	0.3743	
Regime 2		
intercept	-0.6208	[0.0488]***
Beta (β)	-0.1585	[0.1085]
nu_2	1.2173	[0.7969]
xi_2	0.3587	[0.1553]**
p12	0.0345	
p21	0.4133	
posterior mean stable probability_2	0.0982	
Volatility	1.0832	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI ITA_MS_GARCH		
Regime 1		SE
intercept	0.0773	[0.0008]***
Beta (β)	0.1786	[0.0034]***
nu_1	7.6729	[0.4463]***
xi_1	1.9299	[0.0671]***
posterior mean stable probability_1	0.6538	
Volatility	3.7448	
Regime 2		
intercept	0.0435	[0.0005]***
Beta (β)	0.0491	[0.0016]***
nu_2	83.905	[0.5037]***
xi_2	12.508	[0.1440]***
p12	0.5163	
p21	0.9134	
posterior mean stable probability_2	0.3462	
Volatility	9.5149	
cc.p-value	0.0034	
dq.p-value	0.000003	

MSCI SWE_MS_GARCH		
Regime 1		SE
intercept	0.0112	[0.0002]***
Beta (β)	0.1807	[0.0037]***
nu_1	10.142	[0.3218]***
xi_1	0.5606	[0.0107]***
posterior mean stable probability_1	0.4475	
Volatility	2.4272	
Regime 2		
intercept	0.0257	[0.0005]***
Beta (β)	0.2213	[0.0041]***
nu_2	3.2532	[0.0210]***
xi_2	0.7026	[0.0108]***
p12	0.9876	
p21	0.0101	
posterior mean stable probability_2	0.5525	
Volatility	3.6173	
cc.p-value	0.1384	
dq.p-value	0.0074	

MSCI TUR_MS_GARCH		
Regime 1		SE
intercept	0.1571	[0.0023]***
Beta (β)	0.2977	[0.0040]***
nu_1	2.1208	[0.0012]***
xi_1	6.0725	[0.1400]***
posterior mean stable probability_1	0.5304	
Volatility	11.87	
Regime 2		
intercept	0.2666	[0.0041]***
Beta (β)	0.2638	[0.0040]***
nu_2	2.1073	[0.0004]***
xi_2	5.4584	[0.1117]***
p12	0.3222	
p21	0.7656	
posterior mean stable probability_2	0.4696	
Volatility	16.89	
cc.p-value	0.1889	
dq.p-value	0.3074	

MSCI CRO_MS_GARCH		
Regime 1		SE
intercept	0.1004	[0.0029]***
Beta (β)	0.653	[0.0051]***
nu_1	41.87	[0.6060]***
xi_1	0.8551	[0.0164]***
posterior mean stable probability_1	0.1388	
Volatility	7.9041	
Regime 2		
intercept	0.0231	[0.0015]***
Beta (β)	0.8981	[0.0033]***
nu_2	12.15	[0.4227]***
xi_2	1.0856	[0.0066]***
p12	0.8667	
p21	0.0215	
posterior mean stable probability_2	0.8612	
Volatility	5.6969	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI LIT_MS_GARCH		
Regime 1		height SE
intercept	0.0043	[0.0002]***
Beta (β)	0.0178	[0.0014]***
nu_1	95.87	[0.1613]***
xi_1	3.3727	[0.0827]***
posterior mean stable probability_1	0.4216	
Volatility	1.3141	
Regime 2		
intercept	0.0045	[0.0001]***
Beta (β)	0.7461	[0.0024]***
nu_2	66.19	[0.4270]***
xi_2	0.8918	[0.0072]***
p12	0.3428	
p21	0.4791	
posterior mean stable probability_2	0.5784	
Volatility	4.3352	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI SWT_MS_GARCH		
Regime 1		SE
intercept	0.0493	[0.0019]***
Beta (β)	0.8407	[0.0060]***
nu_1	2.1959	[0.0042]***
xi_1	12.949	[0.1437]***
posterior mean stable probability_1	0.5643	
Volatility	6.0847	
Regime 2		
intercept	0.1898	[0.0022]***
Beta (β)	0.492	[0.0054]***
nu_2	2.3414	[0.0033]***
xi_2	3.9149	[0.0925]***
p12	0.8579	
p21	0.184	
posterior mean stable probability_2	0.4357	
Volatility	11.721	
cc.p-value	0.7176	
dq.p-value	0.9998	

MSCI NZL_MS_GARCH		
Regime 1		SE
intercept	0.1475	[0.0016]***
Beta (β)	0.3673	[0.0034]***
nu_1	80.942	[0.3445]***
xi_1	0.9679	[0.0246]***
posterior mean stable probability_1	0.9902	
Volatility	0.9873	
Regime 2		
intercept	0.2244	[0.0031]***
Beta (β)	0.118	[0.0024]***
nu_2	93.863	[0.2165]***
xi_2	6.1689	[0.0465]***
p12	0.9923	
p21	0.7844	
posterior mean stable probability_2	0.0098	
Volatility	22.098	
cc.p-value	0.7176	
dq.p-value	0.3673	

MSCI NOR_MS_GARCH		
Regime 1		SE
intercept	0.0194	[0.0005]***
Beta (β)	0.4044	[0.0042]***
nu_1	50.995	[0.3874]***
xi_1	0.9544	[0.0023]***
posterior mean stable probability_1	0.6509	
Volatility	1.3817	
Regime 2		
intercept	0.0381	[0.0002]***
Beta (β)	0.0875	[0.0015]***
nu_2	64.548	[0.2122]***
xi_2	0.957	[0.0035]***
p12	0.9755	
p21	0.0457	
posterior mean stable probability_2	0.3491	
Volatility	3.2359	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI NLD_MS_GARCH		
Regime 1		SE
intercept	0.13	[0.0014]***
Beta (β)	0.8022	[0.0018]***
nu_1	11.851	[0.1752]***
xi_1	1.1142	[0.0025]***
posterior mean stable probability_1	0.8235	
Volatility	1.0917	
Regime 2		
intercept	0.0353	[0.0010]***
Beta (β)	0.2286	[0.0032]***
nu_2	57.257	[0.4198]***
xi_2	1.1571	[0.0157]***
p12	0.8705	
p21	0.6043	
posterior mean stable probability_2	0.1765	
Volatility	5.4342	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI JAP_MS_GARCH		
Regime 1		SE
intercept	0.0056	[0.00001]***
Beta (β)	0.2042	[0.0026]***
nu_1	7.5191	[0.0564]***
xi_1	1.1636	[0.0031]***
posterior mean stable probability_1	0.6556	
Volatility	1.3148	
Regime 2		
intercept	0.0088	[0.0002]***
Beta (β)	0.626	[0.0033]***
nu_2	4.8333	[0.0256]***
xi_2	1.0234	[0.0026]***
p12	0.9822	
p21	0.0338	
posterior mean stable probability_2	0.3444	
Volatility	4.9535	
cc.p-value	0.7175	
dq.p-value	0.7074	

MSCI IRE_MS_GARCH		
Regime 1		SE
intercept	-0.0113	[0.0064]***
Beta (β)	0.0778	[0.4686]
nu_1	0.2163	[0.0559]***
xi_1	0.7836	[0.0563]***
posterior mean stable probability_1	0.8561	
Volatility	0.046	
Regime 2		
intercept	-0.0319	[0.0079]***
Beta (β)	-0.5687	[0.0462]***
nu_2	34.847	[10.14]***
xi_2	0.7878	[0.0679]***
p12	0.1625	
p21	0.8374	
posterior mean stable probability_2	0.1393	
Volatility	0.146	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI ISR_MS_GARCH		
Regime 1		SE
intercept	0.0026	[0.0001]***
Beta (β)	0.2327	[0.0032]***
nu_1	21.63	[0.4126]***
xi_1	2.6745	[0.0721]***
posterior mean stable probability_1	0.3523	
Volatility	1.0664	
Regime 2		
intercept	0.0166	[0.0003]***
Beta (β)	0.1169	[0.0029]***
nu_2	34.18	[0.5750]***
xi_2	1.8378	[0.0564]***
p12	0.0847	
p21	0.4979	
posterior mean stable probability_2	0.6477	
Volatility	2.9427	
cc.p-value	0.7175	
dq.p-value	0.9998	

MSCI LAT_MS_GARCH		
Regime 1		SE
intercept	0.0023	[0.0002]***
Beta (β)	0.3932	[0.0050]***
nu_1	80.3	[0.4103]***
xi_1	0.9093	[0.0042]***
posterior mean stable probability_1	0.4185	
Volatility	0.99	
Regime 2		
intercept	0.2287	[0.0051]***
Beta (β)	0.0052	[0.0005]***
nu_2	2.2538	[0.0047]***
xi_2	1.1137	[0.0038]***
p12	0.9246	
p21	0.0543	
posterior mean stable probability_2	0.5815	
Volatility	7.314	
cc.p-value	0.7175	
dq.p-value	0.9998	

MSCI EST_MS_GARCH		
Regime 1		SE
intercept	0.1429	[0.0081]***
Beta (β)	0.3643	[0.0047]***
nu_1	8.9251	[0.4945]***
xi_1	1.4412	[0.0220]***
posterior mean stable probability_1	0.85	
Volatility	5.6219	
Regime 2		
intercept	0.2679	[0.0046]***
Beta (β)	0.1038	[0.0031]***
nu_2	90.43	[0.5035]***
xi_2	9.3742	[0.1311]***
p12	0.9807	
p21	0.1092	
posterior mean stable probability_2	0.15	
Volatility	153.4	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI THAI_MS_GARCH		
Regime 1		SE
intercept	0.0027	[0.0001]***
Beta (β)	0.4302	[0.0054]***
nu_1	89.162	[0.3384]***
xi_1	0.6854	[0.0144]***
posterior mean stable probability_1	0.3723	
Volatility	1.4547	
Regime 2		
intercept	0.0112	[0.0005]***
Beta (β)	0.5316	[0.0064]***
nu_2	79.331	[0.4330]***
xi_2	0.9716	[0.0129]***
p12	0.6097	
p21	0.2315	
posterior mean stable probability_2	0.6277	
Volatility	2.9873	
cc.p-value	0.1483	
dq.p-value	0.9998	

MSCI MYL_MS_GARCH		
Regime 1		SE
intercept	0.001	[0.0001]***
Beta (β)	0.3374	[0.0037]***
nu_1	53.687	[0.6078]***
xi_1	0.4453	[0.0262]***
posterior mean stable probability_1	0.2839	
Volatility	0.6575	
Regime 2		
intercept	0.0058	[0.0001]***
Beta (β)	0.1756	[0.0035]***
nu_2	12.598	[0.4456]***
xi_2	0.8671	[0.0064]***
p12	0.6701	
p21	0.1308	
posterior mean stable probability_2	0.7161	
Volatility	1.4281	
cc.p-value	0.7176	
dq.p-value	0.9998	

MSCI INDO_MS_GARCH		
Regime 1		SE
intercept	0.2714	[0.0020]***
Beta (β)	0.5257	[0.0025]***
nu_1	55.835	[0.5014]***
xi_1	0.6199	[0.0019]***
posterior mean stable probability_1	0.9859	
Volatility	2.0485	
Regime 2		
intercept	0.0524	[0.0024]***
Beta (β)	0.5780	[0.0055]***
nu_2	33.957	[0.5144]***
xi_2	1.6748	[0.0610]***
p12	0.9958	
p21	0.2905	
posterior mean stable probability_2	0.0141	
Volatility	0.1426	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI PHI_MS_GARCH		
Regime 1		SE
intercept	0.017	[0.0003]***
Beta (β)	0.2117	[0.0039]***
nu_1	60.109	[0.6903]***
xi_1	1.042	[0.0149]***
posterior mean stable probability_1	0.4273	
Volatility	3.4551	
Regime 2		
intercept	0.0547	[0.0008]***
Beta (β)	0.4349	[0.0041]***
nu_2	12.006	[0.5131]***
xi_2	1.0945	[0.0052]***
p12	0.6849	
p21	0.2351	
posterior mean stable probability_2	0.5727	
Volatility	4.2098	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI SING_MS_GARCH		
Regime 1		SE
intercept	0.0029	[0.0002]***
Beta (β)	0.7178	[0.0022]***
nu_1	30.188	[0.5131]***
xi_1	0.8138	[0.0048]***
posterior mean stable probability_1	0.54	
Volatility	2.0606	
Regime 2		
intercept	0.1437	[0.0012]***
Beta (β)	0.2333	[0.0034]***
nu_2	2.919	[0.1394]***
xi_2	5.0358	[0.0956]***
p12	0.6418	
p21	0.4204	
posterior mean stable probability_2	0.46	
Volatility	4.3937	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI CHIN_MS_GARCH		
Regime 1		SE
intercept	0.4134	[0.0031]***
Beta (β)	0.4442	[0.0023]***
nu_1	99.816	[0.0121]***
xi_1	0.7488	[0.0026]***
posterior mean stable probability_1	0.8014	
Volatility	1.612	
Regime 2		
intercept	0.5769	[0.0052]***
Beta (β)	0.0972	[0.0021]***
nu_2	81.29	[0.4540]***
xi_2	0.1915	[0.0084]***
p12	0.8188	
p21	0.7312	
posterior mean stable probability_2	0.1986	
Volatility	48.5137	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI ICE_MS_GARCH		
Regime 1		SE
intercept	0.0038	[0.0001]***
Beta (β)	0.7108	[0.0031]***
nu_1	3.7096	[0.0326]***
xi_1	1.0941	[0.0025]***
posterior mean stable probability_1	0.7629	
Volatility	2.1245	
Regime 2		
intercept	0.1428	[0.0034]***
Beta (β)	0.2537	[0.0026]***
nu_2	7.6092	[0.0450]***
xi_2	1.0697	[0.0087]***
p12	0.9772	
p21	0.0733	
posterior mean stable probability_2	0.2371	
Volatility	19.02	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI RUS_MS_GARCH		
Regime 1		SE
intercept	0.0118	[0.0007]***
Beta (β)	0.5834	[0.0026]***
nu_1	4.9777	[0.1661]***
xi_1	0.979	[0.0258]***
posterior mean stable probability_1	0.9532	
Volatility	5.706	
Regime 2		
intercept	0.3273	[0.0036]***
Beta (β)	0.2683	[0.0031]***
nu_2	45.82	[0.4945]***
xi_2	10.53	[0.1230]***
p12	0.9768	
p21	0.473	
posterior mean stable probability_2	0.0468	
Volatility	187.1	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI MALT_MS_GARCH		
Regime 1		SE
intercept	0.0098	[0.0002]***
Beta (β)	0.421	[0.0091]***
nu_1	6.0382	[0.1633]***
xi_1	1.0793	[0.0033]***
posterior mean stable probability_1	0.6076	
Volatility	1.9578	
Regime 2		
intercept	0.0351	[0.0013]***
Beta (β)	0.4459	[0.0083]***
nu_2	7.774	[0.1654]***
xi_2	1.3302	[0.0222]***
p12	0.9323	
p21	0.1049	
posterior mean stable probability_2	0.3924	
Volatility	4.2847	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI INDI_MS_GARCH		
Regime 1		SE
intercept	0.0021	[0.0001]***
Beta (β)	0.1004	[0.0023]***
nu_1	69.23	[0.4938]***
xi_1	0.9579	[0.0040]***
posterior mean stable probability_1	0.575	
Volatility	1.1222	
Regime 2		
intercept	0.0142	[0.0003]***
Beta (β)	0.5887	[0.0056]***
nu_2	60.511	[0.5294]***
xi_2	0.936	[0.0046]***
p12	0.5457	
p21	0.6147	
posterior mean stable probability_2	0.425	
Volatility	4.2805	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI TAI_MS_GARCH		
Regime 1		SE
intercept	0.0127	[0.0001]***
Beta (β)	0.1111	[0.0013]***
nu_1	68.32	[0.4141]***
xi_1	1.2648	[0.0117]***
posterior mean stable probability_1	0.9663	
Volatility	3.2053	
Regime 2		
intercept	2.6288	[0.1156]***
Beta (β)	0.0019	[0.0005]***
nu_2	44.77	[0.6137]***
xi_2	7.3515	[0.1154]***
p12	0.98	
p21	0.5732	
posterior mean stable probability_2	0.0337	
Volatility	32.489	
cc.p-value	0.00816	
dq.p-value	0.00003	

MSCI KOR_MS_GARCH		
Regime 1		SE
intercept	0.0001	[0.0000]***
Beta (β)	0.767	[0.0033]***
nu_1	73.13	[0.4521]***
xi_1	0.1405	[0.0054]***
posterior mean stable probability_1	0.1475	
Volatility	0.2329	
Regime 2		
intercept	0.2625	[0.0023]***
Beta (β)	0.5083	[0.0035]***
nu_2	5.899	[0.0941]***
xi_2	0.9898	[0.0018]***
p12	0.1782	
p21	0.1422	
posterior mean stable probability_2	0.8525	
Volatility	3.3963	
cc.p-value	0.7175	
dq.p-value	0.9998	

MSCI HNGKNG_MS_GARCH		
Regime 1		SE
intercept	0.0023	[0.0001]***
Beta (β)	0.6739	[0.0053]***
nu_1	65.9	[0.5758]***
xi_1	4.0321	[0.0957]***
posterior mean stable probability_1	0.4715	
Volatility	1.6692	
Regime 2		
intercept	0.016	[0.0001]***
Beta (β)	0.0828	[0.0046]***
nu_2	33.1	[0.5766]***
xi_2	2.4808	[0.0561]***
p12	0.487	
p21	0.4577	
posterior mean stable probability_2	0.5285	
Volatility	4.4913	
cc.p-value	0.8133	
dq.p-value	0.9998	

MSCI SERB_MS_GARCH		
Regime 1		SE
intercept	0.0023	[0.0001]***
Beta (β)	0.5023	[0.0020]***
nu_1	57.39	[0.3387]***
xi_1	0.9078	[0.0029]***
posterior mean stable probability_1	0.7872	
Volatility	1.35508	
Regime 2		
intercept	0.0142	[0.0001]***
Beta (β)	0.9006	[0.0007]***
nu_2	99.22	[0.0102]***
xi_2	0.1545	[0.0023]***
p12	0.8586	
p21	0.5231	
posterior mean stable probability_2	0.2128	
Volatility	39.17	
cc.p-value	0.0392	
dq.p-value	0.0074	

MSCI UKR_MS_GARCH		
Regime 1		height SE
intercept	0.0155	[0.0003]***
Beta (β)	0.5357	[0.0043]***
nu_1	14.29	[0.4357]***
xi_1	0.8198	[0.0026]***
posterior mean stable probability_1	0.5365	
Volatility	2.8122	
Regime 2		
intercept	0.0181	[0.0003]***
Beta (β)	0.6671	[0.0035]***
nu_2	50.93	[0.7081]***
xi_2	0.8415	[0.0029]***
p12	0.947	
p21	0.0614	
posterior mean stable probability_2	0.4635	
Volatility	4.2827	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI BUL_MS_GARCH		
Regime 1		SE
intercept	0.0086	[0.0001]***
Beta (β)	0.3175	[0.0050]***
nu_1	99.98	[0.0010]***
xi_1	0.1049	[0.0041]***
posterior mean stable probability_1	0.273	
Volatility	1.7923	
Regime 2		
intercept	0.1308	[0.0017]***
Beta (β)	0.1388	[0.0017]***
nu_2	3.9007	[0.0298]***
xi_2	0.9822	[0.0020]***
p12	0.8913	
p21	0.0408	
posterior mean stable probability_2	0.727	
Volatility	14.4	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI ROM_MS_GARCH		
Regime 1		SE
intercept	0.0096	[0.0003]***
Beta (β)	0.3463	[0.0044]***
nu_1	13.32	[0.3193]***
xi_1	0.6105	[0.0065]***
posterior mean stable probability_1	0.5196	
Volatility	2.0349	
Regime 2		
intercept	0.0849	[0.0013]***
Beta (β)	0.3072	[0.0041]***
nu_2	13.61	[0.4512]***
xi_2	3.4099	[0.1038]***
p12	0.697	
p21	0.3276	
posterior mean stable probability_2	0.4804	
Volatility	4.8426	
cc.p-value	0.7175	
dq.p-value	0.9998	

MSCI POL_MS_GARCH		
Regime 1		SE
intercept	0.0534	[0.0010]***
Beta (β)	0.9365	[0.0013]***
nu_1	99.8	[0.0270]***
xi_1	3.9519	[0.0822]***
posterior mean stable probability_1	0.6481	
Volatility	1.2698	
Regime 2		
intercept	0.0242	[0.0002]***
Beta (β)	0.0483	[0.0015]***
nu_2	44.24	[0.5055]***
xi_2	0.5177	[0.0103]***
p12	0.5766	
p21	0.7798	
posterior mean stable probability_2	0.3519	
Volatility	4.7326	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI CZECH_MS_GARCH		
Regime 1		SE
intercept	0.0103	[0.0001]***
Beta (β)	0.1651	[0.0029]***
nu_1	35.22	[0.4474]***
xi_1	11.9435	[0.1350]***
posterior mean stable probability_1	0.3429	
Volatility	1.7706	
Regime 2		
intercept	0.0038	[0.0001]***
Beta (β)	0.4317	[0.0027]***
nu_2	46.39	[0.5918]***
xi_2	1.1538	[0.0524]***
p12	0.0196	
p21	0.5117	
posterior mean stable probability_2	0.6571	
Volatility	3.4982	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI BRA_MS_GARCH		
Regime 1		SE
intercept	0.0081	[0.0002]***
Beta (β)	0.4827	[0.0052]***
nu_1	47.56	[0.8788]***
xi_1	2.1339	[0.0563]***
posterior mean stable probability_1	0.6086	
Volatility	2.0993	
Regime 2		
intercept	0.4163	[0.0508]***
Beta (β)	0.3411	[0.0059]***
nu_2	61.63	[0.9352]***
xi_2	5.723	[0.1180]***
p12	0.7439	
p21	0.3981	
posterior mean stable probability_2	0.3914	
Volatility	13.86	
cc.p-value	0.8133	
dq.p-value	0.9998	

MSCI ARG_MS_GARCH		
Regime 1		SE
intercept	0.0746	[0.0013]***
Beta (β)	0.1407	[0.0060]***
nu_1	42.59	[0.5671]***
xi_1	2.3377	[0.0579]***
posterior mean stable probability_1	0.3641	
Volatility	9.3749	
Regime 2		
intercept	0.1043	[0.0043]***
Beta (β)	0.7609	[0.0072]***
nu_2	12.59	[0.5062]***
xi_2	1.7831	[0.0672]***
p12	0.8508	
p21	0.0854	
posterior mean stable probability_2	0.6359	
Volatility	15.15	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI COL_MS_GARCH		
Regime 1		SE
intercept	0.0037	[0.0002]***
Beta (β)	0.6897	[0.0028]***
nu_1	98.94	[0.0770]***
xi_1	1.0225	[0.0019]***
posterior mean stable probability_1	0.9459	
Volatility	2.4364	
Regime 2		
intercept	0.1144	[0.0034]***
Beta (β)	0.0414	[0.0013]***
nu_2	17.98	[0.2987]***
xi_2	6.1804	[0.1127]***
p12	0.9963	
p21	0.0647	
posterior mean stable probability_2	0.0541	
Volatility	116.3	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI BEL_MS_GARCH		
Regime 1		SE
intercept	0.0845	[0.0011]***
Beta (β)	0.8811	[0.0017]***
nu_1	45.53	[0.3822]***
xi_1	0.9218	[0.0028]***
posterior mean stable probability_1	0.907	
Volatility	1.1693	
Regime 2		
intercept	0.0183	[0.0005]***
Beta (β)	0.9741	[0.0005]***
nu_2	62.55	[0.4158]***
xi_2	0.8138	[0.0411]***
p12	0.9107	
p21	0.8701	
posterior mean stable probability_2	0.093	
Volatility	10.09	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI UAE_MS_GARCH		
Regime 1		SE
intercept	0.0002	[0.0004]
Beta (β)	0.7246	[0.0012]***
nu_1	3.3434	[0.0103]***
xi_1	1.1475	[0.0211]***
posterior mean stable probability_1	0.6309	
Volatility	1.1366	
Regime 2		
intercept	0.0121	[0.0002]***
Beta (β)	0.9311	[0.0009]***
nu_2	3.5332	[0.0169]***
xi_2	12.09	[0.1288***
p12	0.6406	
p21	0.6143	
posterior mean stable probability_2	0.3691	
Volatility	7.5209	
cc.p-value	0.0392	
dq.p-value	0.0074	

MSCI CHIL_MS_GARCH		
Regime 1		SE
intercept	0.0027	[0.0008]***
Beta (β)	0.3701	[0.0020]***
nu_1	46.18	[0.4538]***
xi_1	1.0775	[0.0025]***
posterior mean stable probability_1	0.9615	
Volatility	1.4642	
Regime 2		
intercept	0.5105	[0.0040]***
Beta (β)	0.22	[0.0033]***
nu_2	2.117	[0.0005]***
xi_2	6.8683	[0.1028]***
p12	0.9858	
p21	0.355	
posterior mean stable probability_2	0.0385	
Volatility	27.98	
cc.p-value	0.1483	
dq.p-value	0.0003	

MSCI MEX_MS_GARCH		
Regime 1		SE
intercept	0.0031	[0.0001]***
Beta (β)	0.5501	[0.0042]***
nu_1	6.6427	[0.1169]***
xi_1	0.893	[0.0019]***
posterior mean stable probability_1	0.6944	
Volatility	1.329	
Regime 2		
intercept	0.0293	[0.0002]***
Beta (β)	0.0036	[0.0002]***
nu_2	69.91	[0.2821]***
xi_2	0.9799	[0.0050]***
p12	0.9674	
p21	0.0741	
posterior mean stable probability_2	0.3056	
Volatility	3.1159	
cc.p-value	0.7175	
dq.p-value	0.3262	

MSCI QAT_MS_GARCH		
Regime 1		SE
intercept	0.0119	[0.0003]***
Beta (β)	0.2368	[0.0039]***
nu_1	3.436	[0.0630]***
xi_1	7.4993	[0.1268]***
posterior mean stable probability_1	0.3286	
Volatility	2.086	
Regime 2		
intercept	0.0567	[0.0020]***
Beta (β)	0.0892	[0.0037]***
nu_2	11.4	[0.1739]***
xi_2	3.2811	[0.1195]***
p12	0.4555	
p21	0.2664	
posterior mean stable probability_2	0.6714	
Volatility	5.1521	
cc.p-value	0.8133	
dq.p-value	0.9998	

MSCI LUX_MS_GARCH			MSCI TUN_MS_GARCH		
Regime 1		SE	Regime 1		SE
intercept	0,0217	[0.0002]***	intercept	0,1358	[0.0014]***
Beta ()	0,3598	[0.0039]***	Beta ()	0,085	[0.0023]***
nu_1	3,7802	[0.0251]***	nu_1	99,42	[0.0120]***
xi_1	0,9839	[0.0032]***	xi_1	1,0099	[0.0036]***
posterior mean stable probability_1	0,5141		posterior mean stable probability_1	0,6778	
Volatility	3,4573		Volatility	0,5758	
Regime 2			Regime 2		
intercept	0,0213	[0.0002]***	intercept	0,665	[0.0039]***
Beta ()	0,527	[0.0033]***	Beta ()	0,1296	[0.0017]***
nu_2	2,9543	[0.0312]***	nu_2	100	[0.0000]***
xi_2	1,0749	[0.0035]***	xi_2	1,9622	[0.0482]***
p12	0,9772		p12	0,5527	
p21	0,0241		p21	0,9408	
posterior mean stable probability_2	0,4859		posterior mean stable probability_2	0,3222	
Volatility	3,2952		Volatility	3,576	
cc.p-value	0,7175		cc.p-value	0,7175	
dq.p-value	0,1752		dq.p-value	0,9998	

MSCI OIL_MS_GARCH			MSCI GOLD_MS_GARCH			MSCI SILVER_MS_GARCH		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0063	[0.0001]***	**intercept**	0.006	[0.0001]***	**intercept**	0.0206	[0.0005]***
Beta (β)	0.6329	[0.0030]***	**Beta** (β)	0.3877	[0.0042]***	**Beta** (β)	0.3979	[0.0035]***
nu_1	51.029	[0.4939]***	nu_1	37.08	[0.3483]***	nu_1	8.4641	[0.2525]***
xi_1	0.2589	[0.0070]***	xi_1	1.135	[0.0031]***	xi_1	1.5206	[0.0536]***
posterior mean stable probability_1	0.4616		posterior mean stable probability_1	0.7935		posterior mean stable probability_1	0.813	
Volatility	2.1285		Volatility	1.8572		Volatility	4.838	
Regime 2			**Regime 2**			**Regime 2**		
intercept	0.0048	[0.0001]***	**intercept**	0.0014	[0.0001]***	**intercept**	0.4271	[0.0044]***
Beta (β)	0.5625	[0.0026]***	**Beta** (β)	0.9845	[0.0001]***	**Beta** (β)	0.2538	[0.0038]***
nu_2	23.93	[0.3775]***	nu_2	23.64	[0.3234]***	nu_2	54.15	[0.5598]***
xi_2	1.123	[0.0053]***	xi_2	14.61	[0.1257]***	xi_2	6.7181	[0.1193]***
p12	0.3737		p12	0.9653		p12	0.9151	
p21	0.5369		p21	0.1331		p21	0.3693	
posterior mean stable probability_2	0.5384		posterior mean stable probability_2	0.2065		posterior mean stable probability_2	0.187	
Volatility	4.13		Volatility	12.63		Volatility	52.28	
cc.p-value	0.5987		cc.p-value	0.5987		cc.p-value	0.5987	
dq.p-value	0.9998		dq.p-value	0.9998		dq.p-value	0.9998	

MSCI GAS_MS_GARCH			MSCI COPPER_MS_GARCH			MSCI Platinum_MS_GARCH		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0192	[0.0006]***	**intercept**	0.0045	[0.0001]***	**intercept**	0.1873	[0.0026]***
Beta (β)	0.4427	[0.0029]***	**Beta** (β)	0.4617	[0.0035]***	**Beta** (β)	0.7791	[0.0028]***
nu_1	11.18	[0.4455]***	nu_1	65.96	[0.4915]***	nu_1	95.34	[0.2335]***
xi_1	2.204	[0.0823]***	xi_1	1.689	[0.0111]***	xi_1	0.5643	[0.0071]***
posterior mean stable probability_1	0.8972		posterior mean stable probability_1	0.4809		posterior mean stable probability_1	0.4195	
Volatility	5.4432		Volatility	1.7101		Volatility	1.2108	
Regime 2			**Regime 2**			**Regime 2**		
intercept	0.2298	[0.0044]***	**intercept**	0.0049	[0.0003]***	**intercept**	0.1168	[0.0098]***
Beta (β)	0.1798	[0.0040]***	**Beta** (β)	0.6655	[0.0024]***	**Beta** (β)	0.0307	[0.0010]***
nu_2	80.53	[0.5688]***	nu_2	22.01	[0.4340]***	nu_2	3.116	[0.0423]***
xi_2	10.06	[0.1394]***	xi_2	0.9937	[0.0036]***	xi_2	1.1319	[0.0031]***
p12	0.9239		p12	0.9909		p12	0.5747	
p21	0.6639		p21	0.0084		p21	0.3074	
posterior mean stable probability_2	0.1028		posterior mean stable probability_2	0.5191		posterior mean stable probability_2	0.5805	
Volatility	57.6		Volatility	4.1555		Volatility	8.3061	
cc.p-value	0.5987		cc.p-value	0.0392		cc.p-value	0.5987	
dq.p-value	0.9998		dq.p-value	2.76E-06		dq.p-value	0.9998	

MSCI Palladium_MS_GARCH		
Regime 1		SE
intercept	0.0024	[0.0001]***
Beta (β)	0.1859	[0.0062]***
nu_1	66.19	[0.4744]***
xi_1	12.65	[0.1826***
posterior mean stable probability_1	0.3122	
Volatility	1.7234	
Regime 2		
intercept	0.0032	[0.0001]***
Beta (β)	0.499	[0.0065]***
nu_2	89.27	[0.3836]***
xi_2	1.5083	[0.0528]***
p12	0.549	
p21	0.2047	
posterior mean stable probability_2	0.6878	
Volatility	2.9641	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Nickel_MS_GARCH		
Regime 1		SE
intercept	0.0108	[0.0001]***
Beta (β)	0.268	[0.0029]***
nu_1	16.11	[0.1207]***
xi_1	0.9052	[0.0028]***
posterior mean stable probability_1	0.591	
Volatility	2.1687	
Regime 2		
intercept	0.067	[0.0009]***
Beta (β)	0.3505	[0.0017]***
nu_2	14.17	[0.2335]***
xi_2	1.0373	[0.0028]***
p12	0.9846	
p21	0.0222	
posterior mean stable probability_2	0.409	
Volatility	10.83	
cc.p-value	0.7175	
dq.p-value	0.0074	

MSCI Tin_MS_GARCH		
Regime 1		SE
intercept	0.0133	[0.0003]***
Beta (β)	0.2832	[0.0044]***
nu_1	15.78	[0.4855]***
xi_1	1.625	[0.0556]***
posterior mean stable probability_1	0.6445	
Volatility	2.7413	
Regime 2		
intercept	0.0875	[0.0030]***
Beta (β)	0.1975	[0.0038]***
nu_2	24.996	[0.6272]***
xi_2	3.9992	[0.1232]***
p12	0.7296	
p21	0.4902	
posterior mean stable probability_2	0.3555	
Volatility	6.8819	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Zinc_MS_GARCH		
Regime 1		SE
intercept	0.284	[0.0023]***
Beta (β)	0.7035	[0.0024]***
nu_1	41.32	[0.4921]***
xi_1	1.0102	[0.0028]***
posterior mean stable probability_1	0.6039	
Volatility	0.5341	
Regime 2		
intercept	0.1347	[0.0014]***
Beta (β)	0.0982	[0.0019]***
nu_2	2.3088	[0.0082]***
xi_2	3.7363	[0.1147]***
p12	0.7701	
p21	0.3505	
posterior mean stable probability_2	0.3961	
Volatility	5.8197	
cc.p-value	0.7175	
dq.p-value	0.0074	

MSCI Rhodium_MS_GARCH		
Regime 1		SE
intercept	0.0094	[0.0001]***
Beta (β)	0.4687	[0.0038]***
nu_1	10.29	[0.3267]***
xi_1	1.105	[0.0015]***
posterior mean stable probability_1	0.9935	
Volatility	5.1636	
Regime 2		
intercept	0.4255	[0.0056]***
Beta (β)	0.0296	[0.0012]***
nu_2	14.06	[0.2737]
xi_2	1.806	[0.0616]***
p12	0.9948	
p21	0.8012	
posterior mean stable probability_2	0.0065	
Volatility	163.8	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Ruthernium_MS_GARCH		
Regime 1		SE
intercept	0.0005	[0.0003]*
Beta (β)	0.9988	[0.0005]***
nu_1	12.51	[0.2408]***
xi_1	0.9902	[0.0022]***
posterior mean stable probability_1	0.3827	
Volatility	1.4593	
Regime 2		
intercept	0.0809	[0.0005]***
Beta (β)	0.1887	[0.0011]***
nu_2	19.59	[0.2585]***
xi_2	0.9673	[0.0027]***
p12	0.9817	
p21	0.0113	
posterior mean stable probability_2	0.6173	
Volatility	12.12	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Corn_MS_GARCH		
Regime 1		SE
intercept	0.0595	[0.0019]***
Beta (β)	0.8379	[0.0026]***
nu_1	99.91	[0.0014]***
xi_1	1.1383	[0.0029]***
posterior mean stable probability_1	0.7818	
Volatility	1.8948	
Regime 2		
intercept	0.1605	[0.0016]***
Beta (β)	0.2738	[0.0021]***
nu_2	62.36	[0.4566]***
xi_2	0.7306	[0.0046]***
p12	0.9441	
p21	0.2004	
posterior mean stable probability_2	0.2182	
Volatility	20.33	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Rubber_MS_GARCH		
Regime 1		SE
intercept	0.0034	[0.0009]***
Beta (β)	0.0075	[0.0004]***
nu_1	31.06	[0.5437]***
xi_1	1.2316	[0.0033]***
posterior mean stable probability_1	0.4688	
Volatility	1.2635	
Regime 2		
intercept	0.0131	[0.0131]***
Beta (β)	0.5178	[0.0027]***
nu_2	6.1099	[0.0596]***
xi_2	1.1837	[0.0041]***
p12	0.9921	
p21	0.007	
posterior mean stable probability_2	0.5312	
Volatility	3.2247	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Soyabean_MS_GARCH		
Regime 1		SE
intercept	0.001	[0.0008]***
Beta (β)	0.6632	[0.0031]***
nu_1	78.65	[0.3432]***
xi_1	1.3275	[0.0046]***
posterior mean stable probability_1	0.8704	
Volatility	1.2471	
Regime 2		
intercept	0.0484	[0.0003]***
Beta (β)	0.2944	[0.0035]***
nu_2	100	[0.0000]***
xi_2	11.56	[0.1251]***
p12	0.8811	
p21	0.799	
posterior mean stable probability_2	0.1296	
Volatility	9.7134	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Wool_MS_GARCH		
Regime 1		SE
intercept	0.0014	[0.0007]***
Beta (β)	0.7547	[0.0032]***
nu_1	9.7623	[0.1505]***
xi_1	7.6973	[0.0924]***
posterior mean stable probability_1	0.3844	
Volatility	1.3135	
Regime 2		
intercept	0.0034	[0.0001]***
Beta (β)	0.7465	[0.0039]***
nu_2	10.78	[0.1541]***
xi_2	2.7203	[0.0846]***
p12	0.6536	
p21	0.2163	
posterior mean stable probability_2	0.6156	
Volatility	2.3017	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Aluminium_MS_GARCH		
Regime 1		SE
intercept	0.0024	[0.0001]***
Beta (β)	0.9218	[0.0008]***
nu_1	5.6443	[0.0594]***
xi_1	0.9892	[0.0027]***
posterior mean stable probability_1	0.6055	
Volatility	1.3771	
Regime 2		
intercept	0.1012	[0.0010]***
Beta (β)	0.2242	[0.0022]***
nu_2	27.95	[0.4730]***
xi_2	0.9156	[0.0026]***
p12	0.9867	
p21	0.0204	
posterior mean stable probability_2	0.3945	
Volatility	10.41	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Lead_MS_GARCH		
Regime 1		SE
intercept	0.0017	[0.0008]***
Beta (β)	0.9981	[0.0008]***
nu_1	4.5562	[0.0139]***
xi_1	1.1497	[0.0025]***
posterior mean stable probability_1	0.6912	
Volatility	1.6446	
Regime 2		
intercept	0.1118	[0.0011]***
Beta (β)	0.2794	[0.0029]***
nu_2	46.35	[0.4735]***
xi_2	0.898	[0.0027]***
p12	0.9543	
p21	0.1023	
posterior mean stable probability_2	0.3088	
Volatility	12.1	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Wheat_MS_GARCH		
Regime 1		SE
intercept	0.1673	[0.0012]***
Beta (β)	0.7936	[0.0016]***
nu_1	64.79	[0.5892]***
xi_1	4.2024	[0.0793]***
posterior mean stable probability_1	0.6325	
Volatility	1.1785	
Regime 2		
intercept	0.0255	[0.0003]***
Beta (β)	0.0356	[0.0016]***
nu_2	88.13	[0.2769]***
xi_2	0.7131	[0.0057]***
p12	0.7975	
p21	0.3485	
posterior mean stable probability_2	0.3675	
Volatility	3.3071	
cc.p-value	0.1889	
dq.p-value	0.0074	

MSCI Cocoa_MS_GARCH		
Regime 1		SE
intercept	0.0034	[0.0003]***
Beta (β)	0.7322	[0.0042]***
nu_1	4.8824	[0.0498]***
xi_1	0.9808	[0.0024]***
posterior mean stable probability_1	0.599	
Volatility	1.9547	
Regime 2		
intercept	0.0977	[0.0007]***
Beta (β)	0.0687	[0.0013]***
nu_2	87.11	[0.2403]***
xi_2	0.9323	[0.0030]***
p12	0.9668	
p21	0.0496	
posterior mean stable probability_2	0.401	
Volatility	11.47	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Coffee_MS_GARCH		
Regime 1		SE
intercept	0.0015	[0.0008]***
Beta (β)	0.9979	[0.0010]***
nu_1	7.3977	[0.0341]***
xi_1	1.4034	[0.0031]***
posterior mean stable probability_1	0.726	
Volatility	2.1782	
Regime 2		
intercept	0.0566	[0.0005]***
Beta (β)	0.3275	[0.0012]***
nu_2	99.83	[0.0018]***
xi_2	0.8316	[0.0025]***
p12	0.9819	
p21	0.048	
posterior mean stable probability_2	0.274	
Volatility	14.57	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI Cotton_MS_GARCH		
Regime 1		SE
intercept	0.0058	[0.0002]***
Beta (β)	0.7806	[0.0019]***
nu_1	5.5234	[0.1112]***
xi_1	1.4926	[0.0050]***
posterior mean stable probability_1	0.7457	
Volatility	2.8921	
Regime 2		
intercept	0.0808	[0.0009]***
Beta (β)	0.1672	[0.0017]***
nu_2	44.99	[0.5238]***
xi_2	0.8435	[0.0029]***
p12	0.9812	
p21	0.0552	
posterior mean stable probability_2	0.2543	
Volatility	12.69	
cc.p-value	0.5987	
dq.p-value	0.9998	

MSCI WORLD_MS_GARCH			MSCI Europe_MS_GARCH			MSCI EM_MS_GARCH		
Regime 1		SE	Regime 1		SE	Regime 1		SE
intercept	0.0489	[0.0020]***	**intercept**	0.1842	[0.0009]***	**intercept**	0.3156	[0.0044]***
Beta (β)	0.3249	[0.0044]***	**Beta** (β)	0.7789	[0.0023]***	**Beta** (β)	0.4285	[0.0066]***
nu_1	4.1263	[0.0587]***	nu_1	84.82	[0.2312]***	nu_1	20.38	[0.4032]***
xi_1	1.1845	[0.0075]***	xi_1	1.0696	[0.0042]***	xi_1	1.8196	[0.0562]***
posterior mean stable probability_1	0.8022		posterior mean stable probability_1	0.9922		posterior mean stable probability_1	0.4897	
Volatility	4.4324		Volatility	1.9692		Volatility	1.0731	
Regime 2			**Regime 2**			**Regime 2**		
intercept	0.7318	[0.0028]***	**intercept**	0.3363	[0.0043]***	**intercept**	0.189	[0.0027]***
Beta (β)	0.121	[0.0023]***	**Beta** (β)	0.1875	[0.0023]***	**Beta** (β)	0.6559	[0.0049]***
nu_2	2.1591	[0.0077]***	nu_2	90.74	[0.2601]***	nu_2	20.93	[0.3663]***
xi_2	2.5491	[0.0606]***	xi_2	3.0898	[0.0660]***	xi_2	2.0555	[0.0567]***
p12	0.9598		p12	0.9967		p12	0.6298	
p21	0.1632		p21	0.4185		p21	0.3553	
posterior mean stable probability_2	0.1978		posterior mean stable probability_2	0.0078		posterior mean stable probability_2	0.5103	
Volatility	12.99		Volatility	131.04		Volatility	3.0296	
cc.p-value	0.5987		cc.p-value	0.7175		cc.p-value	0.7175	
dq.p-value	0.9998		dq.p-value	0.0074		dq.p-value	0.0074	

4.4 Volatility dynamics

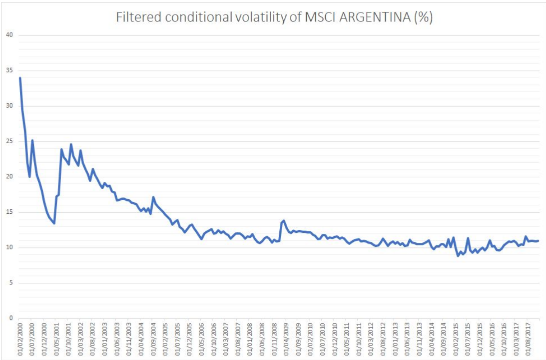
On volatility dynamics, Table 4 presents the mean filtered volatility from the MS-GARCH-CAPM for all the series. As can be seen, among the countries, the mean filtered volatility is highest in Turkey followed by Denmark and Argentina with a volatility of about 16.5, 14.9 and 13.4 respectively. In contrast, Tunisia, Portugal, and New Zealand exhibit the least mean filtered volatility of about 0.98, 1.67 and 1.85 respectively. Among the commodities, Rhodium and Gasoline possess the highest mean filtered volatility of 7.03 and 6.08 respectively whereas Wool and Palladium have the least mean filtered volatility of 2.07 and 2.14 respectively. Lastly, among the aggregate indices, the World aggregate stock has the highest mean filtered volatility whereas Emerging markets have the least with about 4.8 and 1.89 respectively. These results suggest that on the average, conventional asset classes exhibit higher volatility than the commodity securities as can be seen by the relatively larger values of the mean filtered volatility for countries compared to those of commodities.

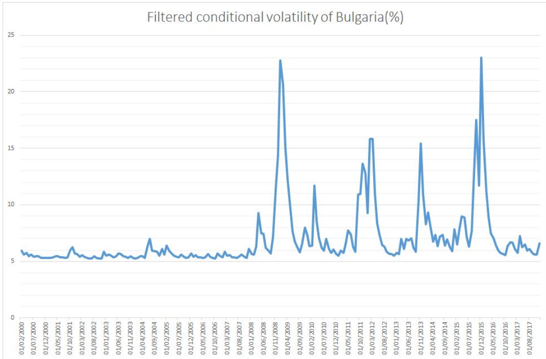
Figure 2 contains graphs of mean filtered volatility for 12 selected countries and commodities including Argentina, Bulgaria, China, Denmark, Gasoline, Crude Oil, Platinum, Rhodium, Silver, the USA, World, Zinc.

Table 4: Mean filtered MS-CAPM-GARCH volatility for all series

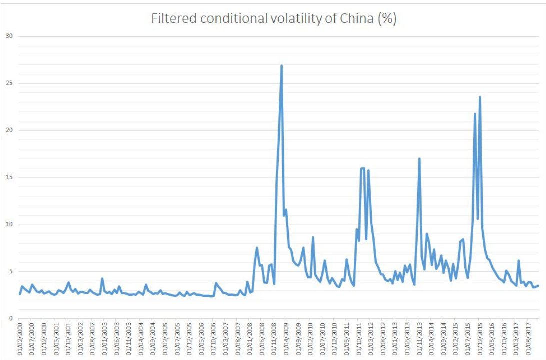
US S&P500	1.962619	**CRO-CROBEX**	5.015678
CAN TSX	2.554394	**LIT-OMXVILNIUS**	2.648331
GER DAX	4.802231	**HUN-BUX**	5.337474
AUS ASX	2.651945	**EGY-EGX30**	4.802231
DEN OMX	14.96079	**POR-PS-I20**	1.677671
FIN OMXHEX	4.802231	**CZECH-SEPX**	2.10555
SPNIBEX	1.967885	**BRA-BOVESPA**	2.794947
SLOVSBITOP	2.135627	**ARG-MERVAL25**	13.37952
UKFTSE100	4.828254	**COL-COLCAP**	4.809118
ITAFTSEMIB	7.406845	**BELG-BEL20**	2.17729
SWEOMX30	3.742947	**UAE-ADXGEN**	5.40287
SWTSMI	2.613581	**CHIL-IGPA**	5.298427
NZLNZX50	1.849826	**MEX-S&PBMVIPC**	1.901675
FRA-CAC	1.981416	**QAT-QE**	3.054392
NOR-OSEAX	1.932275	**LUX-LUXX**	3.481971
NETH-AEX	1.942495	**CRUDEOIL**	2.450924
JAP-NIKKEI225	1.928034	**GOLD**	2.962834
IRE-ISEQ	1.928034	**SILVER**	5.660347
TUN-TUNINDEX	0.981831	**GAS**	6.088891
THAI-SET50	1.851169	**COPPER**	2.332829
MYL-FTSEKLCI	1.851169	**PLATINUM**	5.019397
INDO-JCI	1.91567	**PALLADIUM**	2.135101
PHI-PSEI	1.91567	**NICKEL**	4.555906
SING-STI	2.236415	**TIN**	3.075775
CHIN-SSE	8.930896	**ZINC**	5.54257
INDI-SENSEX	2.572912	**RHODIUM**	7.026534
TAI-TWSE	2.003599	**RUTHENIUM**	4.528716
KOR-KOSPI	2.368377	**CORN**	4.902439
HNGKNG-HIS	2.381495	**RUBBER**	2.200272
SERB-BELEX15	6.445615	**SOYABEAN**	2.279543
UKR-PFTS	2.381495	**WOOL**	2.074668
BUL-SOFIX	7.443544	**ALUMINIUM**	4.334008
ROM-BET	5.62009	**LEAD**	4.407331
POL-WIG	2.616998	**WHEAT**	2.34754
ICE-SEICEX	4.447006	**COCOA**	4.532433
RUS-MICEX	3.948479	**COFFEE**	4.551753
MALT-MALTEX	2.52231	**COTTON**	4.800368
ISR-TA100	2.10099	**WORLD**	4.800368
LAT-OMXRIGA	1.896108	**EUROPE**	3.494552
EST-OMXTALLIN	5.67773	**EMERGING MARKETS**	1.890573
TUR-XU100	16.5353		

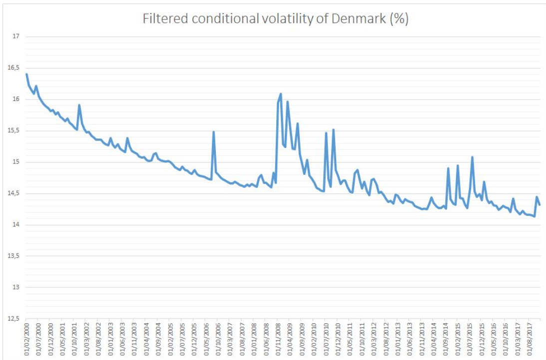
Note: Series names are given in Table 7.



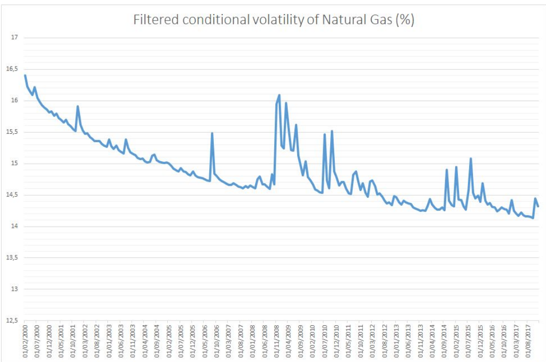


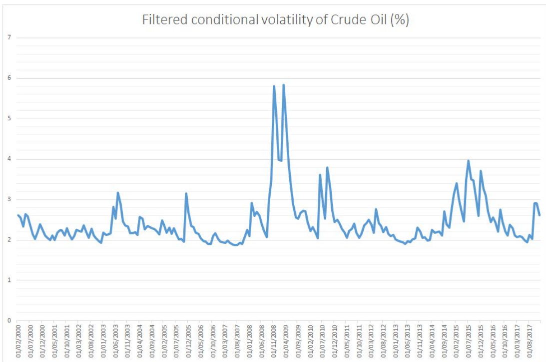
(a) Argentina (b) Bulgaria





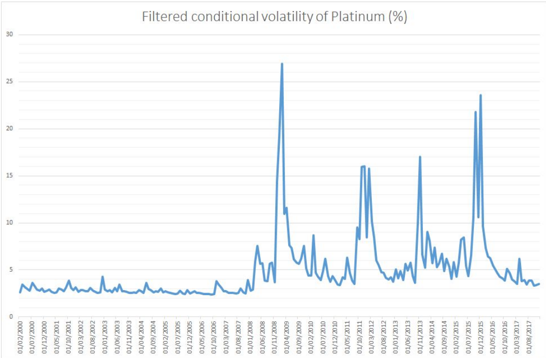
(c) China (d) Denmark



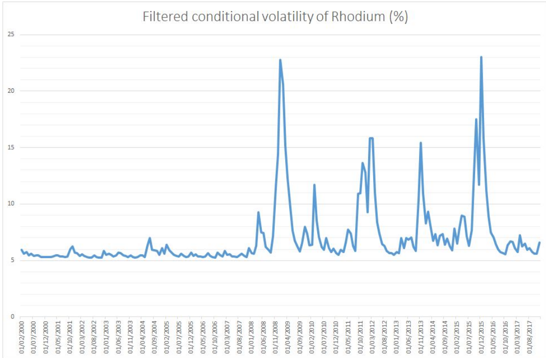


(e) Gasoline (f) Crude Oil

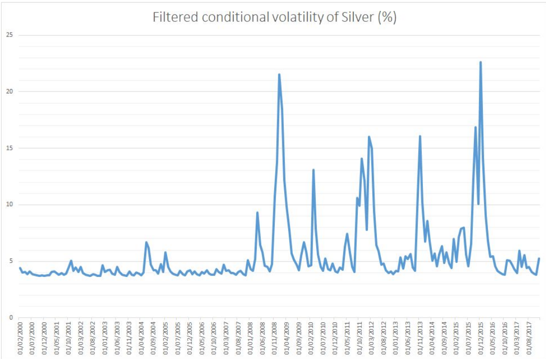
Figure 2: MS-CAPM selected plots of filtered volatilities



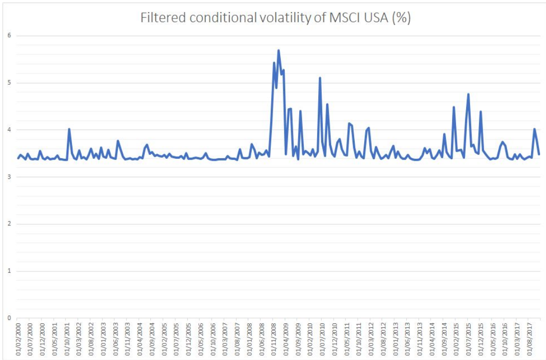
(g) Platinum



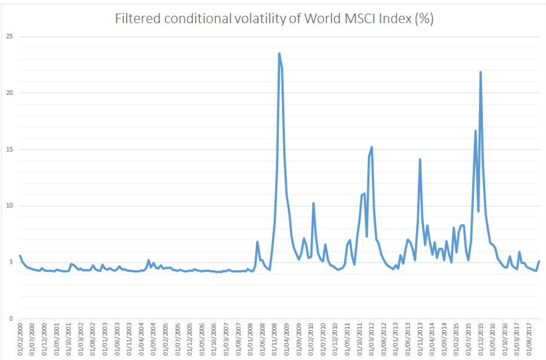
(h) Rhodium



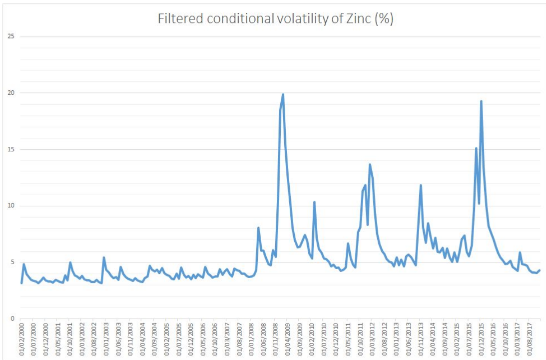
(i) Silver



(j) USA



(k) World



(l) Zinc

Figure 2: MS-CAPM selected plots of filtered volatilities (continued)

Looking at the graphs, some patterns can be discerned in most of the markets. For instance, periods of low volatility persisted throughout the beginning parts of the sample until the middle when periods of transitory high volatility clustered till the later part of the sample in Argentina, Bulgaria, China, Crude oil, Platinum, Rhodium, Silver, the USA, World, and Zinc. In contrast, the pattern changes for both Denmark and Natural Gas in which the beginning part of the sample exhibit high volatility levels which decline continuously but with brief increases in volatility until the middle of the sample during which high volatility levels appear though short-lived. Lastly, the last few months in the sample exhibit low volatility levels except in Natural Gas, Crude oil and Denmark in which volatility levels seems to build up. As observed earlier, the middle of our sample coincides with the period of the past financial crisis which triggered significant turbulence in assets prices and returns whereas the immediate period after this event witnessed a series of unconventional macroeconomic policies such as the US Quantitative easing which altered investors' risk appetite.

4.5 Quantitative risk-management

The importance of modeling and forecasting financial risk in stock markets for useful risk measurement has never been more significant given the recent global financial disasters. VaR remains the standard method of measuring financial risks as it yields forecasts for the likely losses which may arise following changes in price over a pre-defined time horizon and a given confidence level (Sajjad et al. 2008). In this section, we present and compare the performance of risk metrics such as the Expected Shortfall and Out-of-Sample forecasts from the GARCH and MS-GARCH models. Besides, we show which model brings about considerable improvements in correctly forecasting one-day-ahead VaR using an innovative back-testing procedure for 12 selected stock markets including Bulgaria, Columbia, China, Japan, Latvia, Korea, Portugal, Qatar, Turkey, Wool, Cocoa, and World. We wish to stress that although the expected shortfall is not a conventional tool for validating the VaR forecasts or evaluating models' performance, it remains an acceptable tool for risk managers as it is a good candidate for quantifying how much is likely to be lost in case of a failed model.

We use the innovative GAS models proposed by Ardia et al. (2016) for VaR evaluation, prediction and back-testing under a rolling window on a 95% confidence interval with the assumption that the distribution of returns is left skewed and fat-tailed, and its variance is time-varying. The GAS models have found broad application in financial econometrics given their ability to link many volatility modeling frameworks especially the GARCH models. The Conditional Coverage (CC) first proposed by Christoffersen (1998) evaluates the correct coverage of the conditional left-tail distribution of log returns while the Dynamic Quantile (DQ) of Engle and Manganelli (2004) tests some linear restrictions in a linear model that links the violations to a set of explanatory variables. Ardia et al. (2016) note that the DQ has more power and provides a holistic testing procedure for identifying when VaR backtesting model is misspecified.

The p-values for the CC and DQ tests of parameter restrictions on the transition probabilities matrix for the regime switching process in our MS-GARCH-CAPM is presented in Table 3. The null hypothesis for the CC test is that the hits variable is uncorrelated with its own lagged values and with the lag of any other variable including past log returns. Past VaR and its expected value must be equal to zero whereas that of the DQ test is that of the correct model specification at our chosen confidence level $\alpha = 5\%$ for the VaR model. As can be seen the table, the p-value for the CC test is more significant than the conventional significance level for most of the markets. These results suggest that the assumptions of the CC test hold for most of the markets in our sample. However, this is not the case for Canada, Italy, Taiwan, Serbia, Argentina, UAE and Copper where the p-value is less than 5% suggesting that this assumption is violated and we can reject the null hypothesis for these markets. Similarly, The large p-values of DQ for most of the markets is an indication that the null hypothesis of the correct model specification for the 5% significant level. In contrast, the p-values for DQ test in Canada, Spain, Italy, Sweden, Taiwan, Serbia, UEA, Chile, Nickel, Zinc, Wheat, Europe, and Emerging markets are smaller than 5% and in this case, against the assumption of the correct model specification for the 5% VaR level.

Figure 3 is composed of two panels for each series: the upper panel contains the Out-of-Sample returns, whereas the lower panel contrasts the VaR computed at 5% level for the GARCH and MS-GARCH models respectively while Table 5 contains the remaining expected shortfall (ES) estimates. Looking at the upper panel, it can be seen that among our twelve selected markets, the out-of-sample returns forecasts is highest in Bulgaria with about 0.43 while it is least in Turkey with about -0.76. The highest mean out-of-sample returns forecast is 0.09 for Korea and Japan followed by 0.08 for China whereas the least is -0.69 and -0.04 for Turkey and Latvia respectively. More so, this panel reveals that out-of-sample returns forecasts are less than zero for Turkey most of the periods for Portugal and Latvia whereas it is almost positive in all the periods for Korea, Columbia, Japan, and Wool. It has been noted that it is unclear how much weight to place on the ability of out-of-sample forecasts on predicting stock returns, Campbell and Thompson (2007) note however that out-of-sample forecasts do have some ability to predict stock returns and are economically important especially to mean-variance investors, because they can generate significant improvements in portfolio performance.

Regarding the lower panel, the VaR at 5% level for the GARCH model is represented by the blue color while the orange color represents that of the MS-GARCH. From the VaR plots in this panel, it can be seen that backtesting test discriminated between the VaR for the GARCH and MS-GARCH especially in Bulgaria where the plots never met at the point throughout the sample period. Here, the critical finding is that in all the markets considered, the mean VaR at 5% for the MS- GARCH model is either higher or equal to VaR at 5% from the GARCH model except in Turkey. Specifically, the mean VaR from the GARCH model is greatest in Columbia while it is least in China. Similarly, the mean from the MS-GARCH model is most significant in Columbia and Wool but least in China.

There were some sections of the sample where the plot of VaR at 5% forecasts from the GARCH model was identical with those from MS-GARCH model. For instance, the backtesting test failed to discriminate between the plots from both models until after the first half of the sample in the following markets: China, Columbia, Cocoa, Japan, Latvia, Portugal, Qatar, and World. However, in Korea, backtesting distinguished between plots from both models most of the periods from the beginning of the sample until the end of the first half after which it failed till the end of the sample period. In most of the markets, the plot for the MS-GARCH was over that of the GARCH model in most periods especially in China, Latvia whereas the plot for the GARCH model was over that of the MS-GARCH model throughout the sample period in Bulgaria and at some point in Columbia, Turkey, and World.

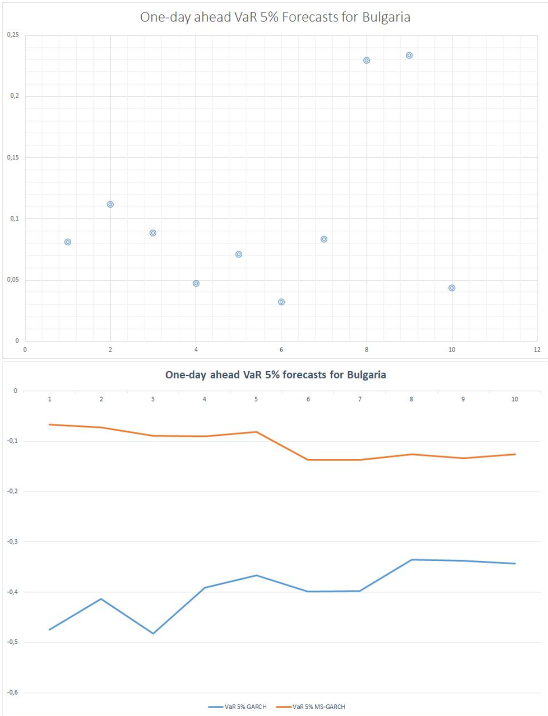
Concerning the backtesting estimates for Expected Shortfalls (ES) as presented in Table 5, the last line of the table reports the average expected shortfall estimates. ES as a financial risk measurement tool estimates the average of $100p\%$ worst losses where p is a chosen confidence level (Acerbi and Tasche, 2002a). ES is widely applicable in stocks returns evaluation despite the underlying sources of risks thereby offering a uniquely global approach to portfolio selection when assets are exposed to different sources of risk to, and it offers. Given these, the ES has been variously modified and offered as an alternative to the VaR approach to stocks returns evaluation given that it can give more reliable estimates even when the VaR estimators fail (Acerbi and Tasche, 2002b). Further, Taylor (2008) notes that there is no significant difference between the two approaches but that ES is an appropriate approach for GARCH models estimated through the skewed-t distribution. In our results, it can be seen that the average ES is highest in China followed by Bulgaria with about -1.61 whereas the least is Latvia is -0.17. These results suggest that stocks from the Chinese market seem riskier, whereas securities from the Latvian market appear as the least risky among the selected markets.

Overall, the performance of the MS-GARCH model compared to the GARCH in the above RiskMetrics lends credence to the claim that regime-switching models bring about more significant improvement in forecasting stock returns, especially in backtesting the one-day-ahead VaR at 5% level for the selected markets as shown earlier. For instance, our results suggest that the single regime GARCH specification mostly underestimates the returns (risk) as shown by the plots of VaR at 5% from both models. These results are complemented by the findings of Kuester et al. (2006), Sajjad et al. (2008) and Taylor (2008) who favor the use of switching models especially in backtesting VaR and Expected Shortfall as it has been argued that systematic risks may vary depending on the volatility regime.

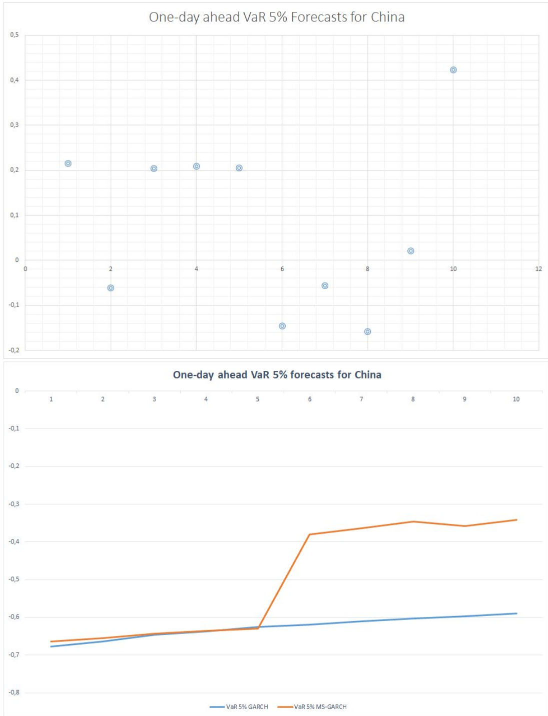
Table 5: Backtests: Expected Shortfall (ES) estimates

BULGARIA	**CHINA**	**COCOA**	**COLUMBIA**	**JAPAN**	**KOREA**	**LATVIA**	**PORTUGAL**	**QATAR**	**TURKEY**	**WOOL**	**WORLD**
-0.3696935	-1.59896481	-0.34339205	-0.28504994	-0.22241096	-0.2939785	-0.1342876	-0.23577201	-0.40365985	-0.23577201	-0.20240418	-0.20894887
-0.43337183	-1.67769711	-0.35420113	-0.2933303	-0.22812045	-0.30578616	-0.15315286	-0.23428059	-0.45654336	-0.23428059	-0.21547615	-0.22150739
-0.53007848	-1.60642624	-0.3701448	-0.30702414	-0.23707951	-0.3067333	-0.16160187	-0.2390468	-0.47023146	-0.2390468	-0.22253285	-0.2306819
-0.61036632	-1.44400855	-0.35833353	-0.30345896	-0.25069577	-0.31563426	-0.16564428	-0.23918478	-0.48149671	-0.23918478	-0.23316302	-0.2380991
-0.6900595	-1.5166263	-0.37778933	-0.30160493	-0.25903908	-0.31825599	-0.18481907	-0.24140153	-0.5168024	-0.24140153	-0.24519744	-0.26974967
-0.65571115	-1.58169698	-0.38602474	-0.29859613	-0.26478727	-0.32096735	-0.17300207	-0.23705698	-0.508046	-0.23705698	-0.23973005	-0.26329892
-0.73043507	-1.76632596	-0.40561767	-0.3097635	-0.270502	-0.3329765	-0.18535075	-0.24114021	-0.53040442	-0.24114021	-0.25219612	-0.2678908
-0.7859926	-1.75388221	-0.44246984	-0.31257195	-0.2800636	-0.33564166	-0.19322463	-0.23907795	-0.53696968	-0.23907795	-0.25639462	-0.26651705
-0.85848732	-1.5137559	-0.45070069	-0.318138	-0.28029283	-0.33197371	-0.20509865	-0.23770699	-0.58598317	-0.23770699	-0.26242186	-0.30719896
-0.85124058	-1.67578901	-0.47499313	-0.31710507	-0.28898245	-0.32554309	-0.20926281	-0.23596116	-0.54152891	-0.23596116	-0.25136108	-0.29112545
-0.65154364	-1.61351731	-0.39636669	-0.30466429	-0.25819739	-0.31874905	-0.17654446	-0.2380629	-0.5031666	-0.2380629	-0.23808774	-0.25650181

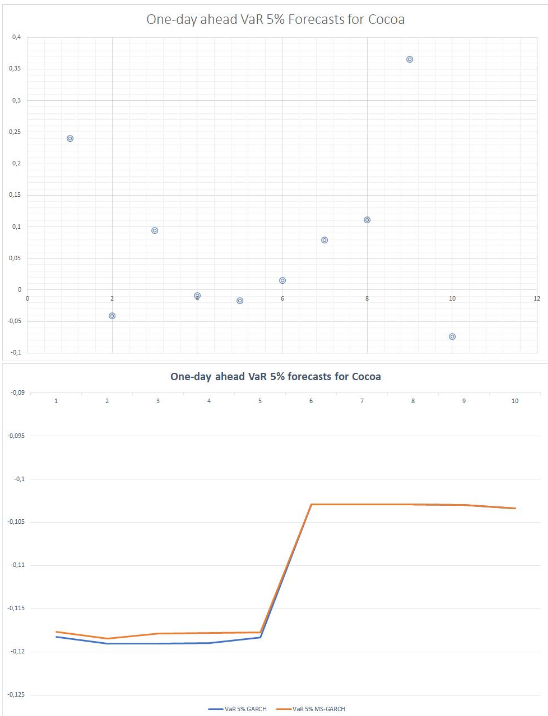
Note: The last line of the Table reports the average Expected Shortfall estimates.



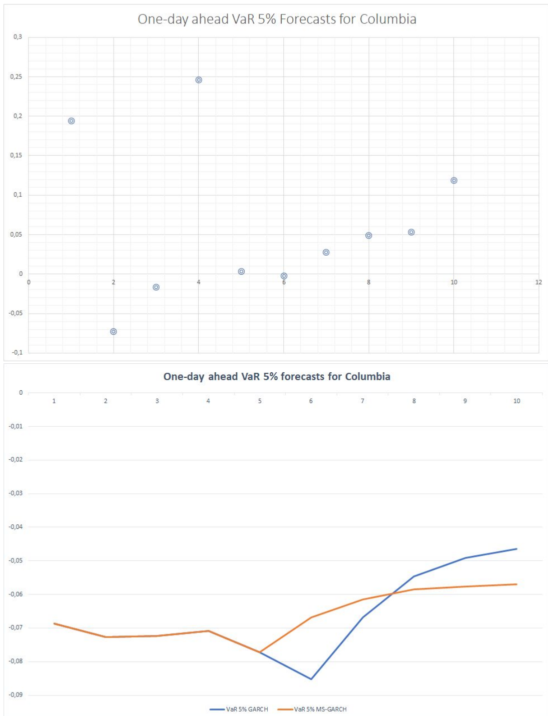
(a) Bulgaria



(b) China



(c) Cocoa

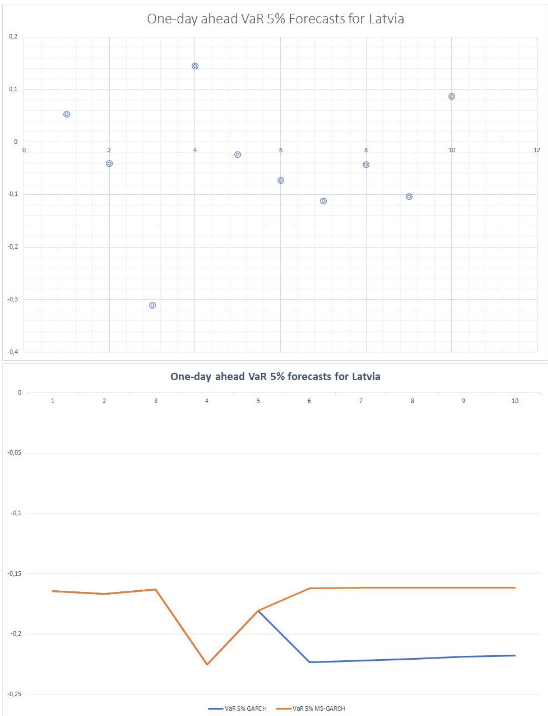


(d) Columbia

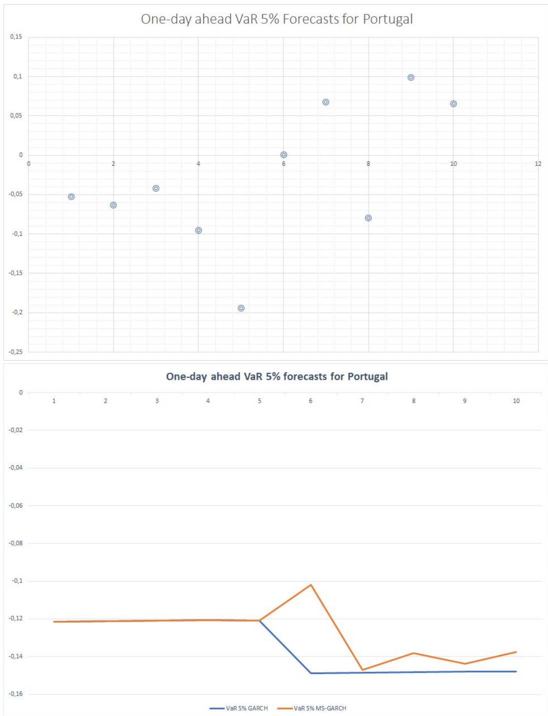
Figure 3: Backtests: Out-of-Sample returns (top), GARCH *vs.* MS-GARCH VaR 5% Forecasts (bottom) for selected markets

(e) Japan

(f) Korea



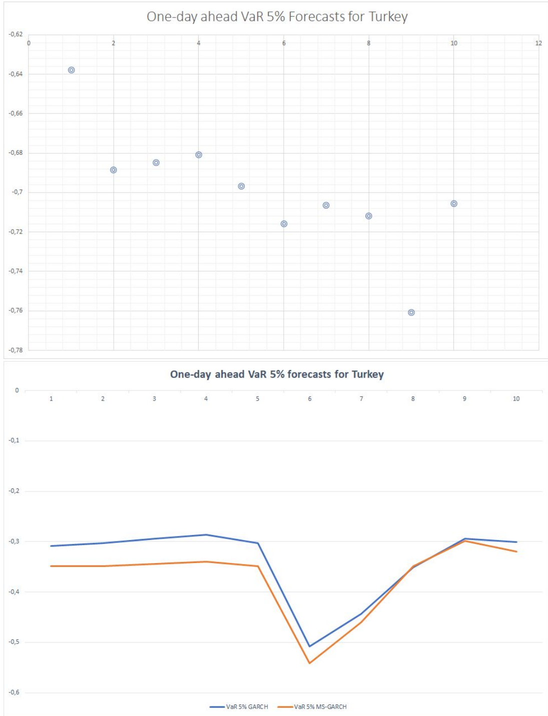
(g) Latvia



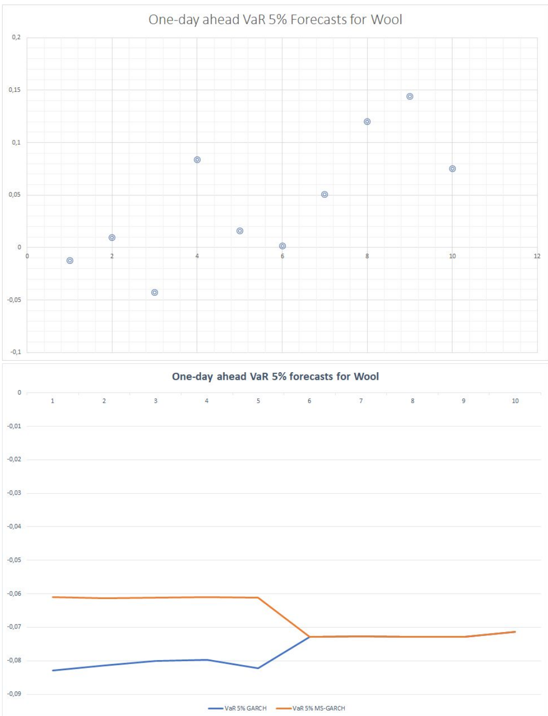
(h) Portugal

Figure 3: Backtests: Out-of-Sample returns (top), GARCH *vs.* MS-GARCH VaR 5% Forecasts (bottom) for selected markets (continued)

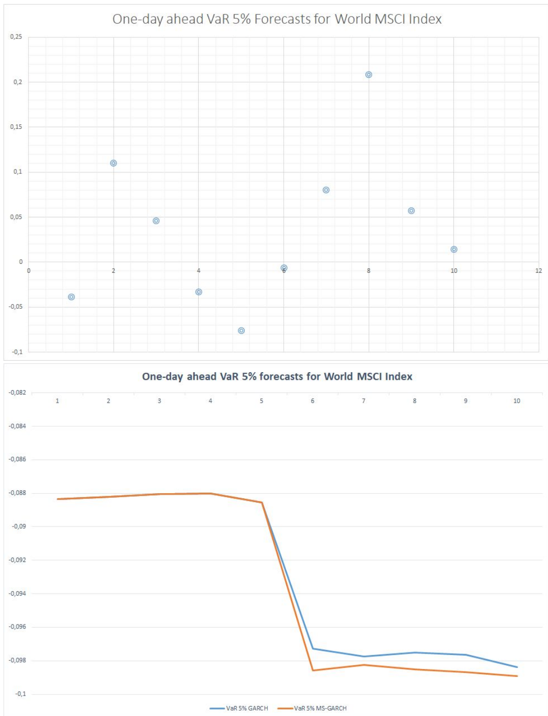
(i) Qatar



(j) Turkey



(k) Wool



(l) World

Figure 3: Backtests: Out-of-Sample returns (top), GARCH *vs.* MS-GARCH VaR 5% Forecasts (bottom) for selected markets (continued)

5 Conclusion

The conditional regime-switching GARCH CAPM accommodates the essential characteristics of time-varying conditional variances and covariances in financial time series. It captures predictable time-variation in both the conditional mean and the conditional volatility of the market excess return. An additional advantage of this framework lies in decomposing the series into two distinct economic regimes. It has been applied to study substantial time variations in the conditional betas. In this paper, we propose and directly estimate a conditional regime-switching GARCH CAPM from where we studied the instability of β across three models. Our estimation approach is through the MCMC/Bayesian, and our conditional distribution is the skewed Student-t. Also, because volatility may be heterogeneous and vary across different regimes, we studied the evolution of volatility using the mean filtered volatility from the regime switching GARCH-CAPM model. Even more, given the increasing need for effective risk management, we computed risk management metrics from the regime switching GARCH, and we compare the risk forecasting performance with that of the single regime GARCH using the backtesting technique. This we did for a large dataset comprising a total of 81 markets.

Our findings can be summarized as follows. First, results from the conditional regime switching GARCH CAPM offer convincing evidence against the prediction of the traditional model given that CAPM beta varies across the three models and different regimes and this is even more pronounced in frontline stocks and commodities. Specifically, among the stocks such as the USA, the UK, Germany, France, China, and Malaysia we find significant variations not only in the size of beta from one model to another and across regimes but changes in the direction of the relation between risks and market returns. For instance, beta parameter estimates from the unconditional CAPM model suggest that stocks in the US, Germany, France, and Malaysia move together with the market. Beta estimates from the MS-CAPM model only confirm these results for stocks in France in both regimes, in regime 1 for Germany and regime 2 for Malaysia. They, however, suggest that in regime 1, stocks in Malaysia move in the opposite direction with the market whereas stocks in Germany, US have no relation with the market in regime two and both regimes respectively.

Further, beta estimates from the regime switching GARCH-CAPM agrees with the result of the unconditional CAPM in both regimes for US and Malaysia but suggests the opposite of these results for Germany and France in both regimes. In the UK and China, beta estimates from the CAPM model suggests these stocks move in the opposite direction. This result is validated by the MS-GARCH model in both regimes for the UK and only in regime 1 in China. The estimates of beta from the regime switching GARCH-CAPM only agrees with that of MS-CAPM for China but suggests no relation exists between returns on UK stocks and the market.

Regarding commodities indices, we also find that these variations exist but not in equal magnitude with stocks. We are considering prominent commodities such as Crude Oil, Gold, Copper, Tin, Rubber, Aluminum, Gasoline and Platinum. Beta parameter estimates from the regime switching GARCH-CAPM model suggest that all the commodity indices move in the same direction with the market during both volatility regimes. This is similar to the results from the simple CAPM model except for Gasoline and Platinum where this model suggest that these commodities have no relation with the market. Beta estimates from the MS-GARCH model suggest that Crude oil, Gold and Gasoline do not have relations with the market in both regimes whereas in Aluminum and Platinum move in the same direction with the market in regime 1 but have no relation in regime 2. Also, Tin and Copper move in the opposite direction with the market respectively in regime 1 and 2 whereas Rubber moves in the same direction with the market. These commodities are however not related to the market in the other regimes. Concerning the aggregate markets, both the simple CAPM and the regime switching GARCH-CAPM models suggest that these markets move together with the market in all regimes whereas, in the MS-GARCH model, the World aggregate stock moves together with the market only in regime 2 while Europe and Emerging markets aggregate stocks do not have relation with the market in both regimes.

Results from the volatility dynamics using the mean filtered volatility from the regime switching GARCH-CAPM suggest that among stocks, Turkey is the most volatile with about 16.53; among commodities, Rhodium is the most volatile with about 7.02 whereas the World is the most volatile with about 4.8 among aggregates. This implies that stocks are the most volatile asset class with the most volatile stock being more than twice and thrice as volatile as the most volatile commodity and aggregate respectively. Lastly, results from the quantitative risk management tests suggest that the regime-switching model delivers better estimates of one-day-ahead VaR at 5% forecasts than the single regime GARCH model whereas ES is highest in China but least in Latvia.

At this stage, policy implications and some extensions to this paper can be considered. First, given the success of Markov switching models in capturing the switching behavior of risks and returns volatility across regimes as well as its superior forecast of RiskMetrics, this paper recommends that risk managers can improve on their risk management strategy by extending their single-regime-type models with a regime switching mechanism to better manage portfolio risks. Although this paper employs a large dataset, it only considers the risks dynamics and monitoring process for individually traded stocks. This paper could, therefore, be extended by considering exceptions and regulatory-based tests such as the Basel traffic light regulation to compute capital requirements for banks and other financial institutions. Lastly, given that it has become a widespread practice to separately assess the VaR for the left and right tails of the returns distributions, our paper could also be extended by using our nested model to assess and compare the VaR for the long and short positions to equip risk managers and traders depending on their position.

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Appendix

Table 6: Return Series Descriptive Statistics

Countries	**Mean**	**Std. Dev**	**Skewness**	**Ex. Kurtosis**	**JB**	**LM ARCH (5)**
ESTONIA	0.0064	0.0679	-0.7785	3.447	131.14	42.509
					[0.000]	[0.000]
TURKEY	0.0132	0.1138	0.0614	1.2233	95.765	22.931
					[0.000]	[0.000]
CROTIA	0.0046	0.0759	-0.5607	5.8042	32.346	42.334
					[0.000]	[0.000]
LITUANIA	0.0086	0.0681	-0.8171	7.0969	49.754	21.493
					[0.000]	[0.001]
HUNGARY	0.0075	0.0661	-0.4716	1.5901	31.336	9.616
					[0.000]	[0.008]
EGYPT	0.0122	0.0947	-0.1093	0.825	6.677	10.572
					[0.035]	[0.061]
PORTUGAL	-0.0027	0.0556	-0.5994	1.4686	32.945	61.897
					[0.000]	[0.022]
CZECH REPUBLIC	0.0034	0.0634	-0.9317	3.735	59.713	43.224
					[0.000]	[0.000]
BRAZIL	0.0089	0.073	-0.3023	0.7116	7.993	6.209
					[0.018]	[0.028]
ARGENTINA	0.0184	0.1054	-0.0611	1.0401	10.053	11.383
					[0.006]	[0.044]
COLUMBIA	0.0108	0.0633	0.1285	1.3558	17.457	10.411
					[0.001]	[0.064]
BELGIUM	0.0012	0.0519	-0.346	3.3225	67.622	57.899
					[0.000]	[0.000]
UAE	0.0077	0.0625	0.3206	3.8689	140.98	40.78
					[0.000]	[0.000]
CHILE	0.0076	0.0397	0.0967	1.0918	11.269	20.848
					[0.003]	[0.072]
MEXICO	0.0021	0.0881	-0.476	2.0912	61.237	35.408
					[0.000]	[0.000]
QATAR	0.0101	0.0581	-0.396	1.0943	16.729	40.807
					[0.000]	[0.000]
LUXEMBOURG	0.0018	0.063	-0.8922	2.7717	99.612	15.929
					[0.000]	[0.007]
ISRAEL	0.0056	0.0569	-1.2835	3.3747	164.79	20.783
					[0.000]	[0.000]
MALTEX	0.0039	0.0497	1.0272	4.5366	227.34	22.746
					[0.000]	[0.000]
TUNISIA	0.0077	0.0355	-0.0506	2.2332	45.809	16.522
					[0.000]	[0.005]

Note: Std. Dev. stands for standard deviation, Ex. Kurtosis for excess kurtosis, JB for Jarque-Bera statistics, and LM ARCH for Lagrange Multiplier ARCH test.

Countries	Mean	Std. Dev	Skewness	Ex. Kurtosis	JB	LM ARCH (5)
USA	0.0032	0.0518	-1.5932	6.0584	429.52	54.985
					[0.000]	[0.000]
CANADA	0.0038	0.0404	-1.0552	3.1994	134.65	21.292
					[0.000]	[0.000]
GERMANY	0.0041	0.0623	-0.8671	3.0538	113.06	13.819
					[0.000]	[0.016]
AUSTRALIA	0.0033	0.0413	-0.4041	1.1743	18.621	47.666
					[0.000]	[0.000]
DENMARK	0.0071	0.0544	-0.5504	1.8793	43.485	36.067
					[0.000]	[0.000]
FINLAND	0.0011	0.0797	-0.2628	2.0447	40.857	45.586
					[0.000]	[0.000]
SPAIN	0.0005	0.0633	-0.4596	0.5081	10.115	22.611
					[0.000]	[0.000]
FRANCE	0.001	0.0595	-0.7812	2.1792	65.912	21.227
					[0.000]	[0.000]
UK	0.0008	0.0413	-0.6388	1.0478	25.027	15.128
					[0.000]	[0.009]
ITALY	-0.0022	0.0609	-0.3265	0.8052	9.851	5.855
					[0.007]	[0.032]
SWEDEN	0.0031	0.0587	-0.2977	0.681	7.5028	26.114
					[0.023]	[0.000]
SWITZERLAND	0.0013	0.0392	-0.7277	0.8563	28.139	21.115
					[0.000]	[0.000]
NEW ZEALAND	0.0044	0.0354	-0.5696	2.104	52.476	36.106
					[0.000]	[0.000]
NORWAY	0.0081	0.0592	-0.7901	1.5799	45.768	39.405
					[0.000]	[0.000]
NETHERLAND	0.0003	0.0574	-10723	2.2708	89.431	44.214
					[0.000]	[0.000]
JAPAN	0.0011	0.059	-0.4712	1.0824	18.882	17.889
					[0.000]	[0.003]
IRELAND	0.0041	0.0629	-0.8876	2.5519	88.586	62.801
					[0.000]	[0.000]
THAILAND	0.0062	0.0668	-1.1079	4.6719	24.508	59.109
					[0.000]	[0.000]
MYLASIA	0.0038	0.0432	-0.4117	1.6887	32.357	10.199
					[0.000]	[0.069]
INDONESIA	0.0109	0.0643	-1.0897	3.5015	35.059	16.67
					[0.000]	[0.002]
PHILIPPINES	0.0056	0.0591	-0.4426	1.6858	33.233	19.624
					[0.000]	[0.008]
SINGAPORE	0.002	0.0544	-0.9535	2.0021	80.16	61.908
					[0.000]	[0.000]
CHINA	0.0032	0.0824	-0.667	1.8309	47.043	32.67
					[0.000]	[0.000]
INDIA	0.0098	0.0738	-0.6006	2.0889	53.227	12.843
					[0.000]	0.0248
TAIWAN	0.0012	0.0647	-0.1855	1.6735	26.932	31.461
					[0.000]	[0.000]
KOREA	0.0046	0.0642	-0.0967	0.752	5.527	33.064
					[0.063]	[0.000]
HONG KONG	0.0036	0.0618	-0.555	1.2433	25.463	16.839
					[0.000]	[0.004]
SERBIA	0.0002	0.0815	-2.0224	15.449	111.21	30.031
					[0.000]	[0.000]
UKRAINE	0.0024	0.0508	-0.5851	2.6786	76.321	70.932
					[0.000]	[0.000]
BULGARIA	0.0084	0.0905	-1.9048	15.15	122.51	25.71
					[0.000]	[0.000]
ROMANIA	0.012	0.0804	-0.4141	2.2836	54.09	22.652
					[0.000]	[0.000]
SLOVANIA	0.0006	0.056	-0.3511	0.961	12.986	11.508
					[0.001]	[0.042]
POLAND	0.0059	0.0638	-0.546	1.2584	25.449	12.324
					[0.000]	[0.030]
ICELAND	0.0001	0.1044	-8.3349	2.644	84.658	7.05
					[0.000]	[0.005]
RUSSIA	0.0134	0.1017	-0.8937	4.6675	228.99	16.973
					[0.000]	[0.004]
LATVIA	-0.0001	0.0789	-0.3563	3.9627	148.59	75.24
					[0.000]	[0.000]

COMMODITIES	Mean	Std. Dev	Skewness	Ex. Kurtosis	JB	LM ARCH (5)
CRUDE OIL	0.0052	0.1144	-0.6037	1.0278	23.051	33.972
					[0.000]	[0.000]
GOLD	0.0072	0.049	0.0799	1.6769	26.012	13.122
					[0.000]	[0.022]
SILVER	0.0051	0.0842	-0.3747	2.0796	44.791	19.753
					[0.000]	[0.001]
NATURAL GAS	0.0003	0.1388	-0.32151	1.7985	33.439	46.064
					[0.000]	[0.004]
COPPER	0.0066	0.0778	-0.8704	4.3231	199.1	25.678
					[0.000]	[0.000]
PLATINUM	0.0042	0.0697	-0.5932	3.1535	104.06	27.119
					[0.000]	[0.000]
PALLEDIUM	0.0049	0.1067	-0.6819	2.7276	85.251	7.044
					[0.000]	[0.054]
NICKEL	0.0027	0.1053	-0.6051	2.4071	66.541	6.311
					[0.000]	[0.037]
TIN	0.0059	0.0731	-0.3861	1.494	25.928	186.272
					[0.000]	[0.000]
ZINC	0.0046	0.0775	-0.9029	4.1319	186.39	8.1738
					[0.000]	[0.005]
RHODIUM	0.0024	0.1441	-1.6576	14.075	149.34	179.45
					[0.000]	[0.000]
RUTHERNIUM	0.0071	0.1417	0.8763	5.0058	257.85	187.68
					[0.000]	[0.000]
CORN	0.0026	0.0864	-0.3647	1.9197	38.66	181.18
					[0.000]	[0.000]
RUBBER	0.0045	0.0884	-1.2396	6.3796	429.42	178.78
					[0.000]	[0.000]
SOYABEAN	0.0032	0.0712	-0.184	0.8392	7.697	10.566
					[0.021]	[0.060]
WOOL	0.005	0.0495	0.0212	2.6458	64.186	194.85
					[0.000]	[0.000]
ALLUMINIUM	0.0017	0.0538	-1.0768	5.457	315.48	49.08
					[0.000]	[0.000]
LEAD	0.0072	0.0955	-0.3254	2.2701	51.122	37.475
					[0.000]	[0.000]
WHEAT	0.003	0.0959	0.0282	1.376	17.384	13.852
					[0.000]	[0.016]
COCOA	0.0027	0.0739	0.2582	1.1666	14.921	7.183
					[0.000]	[0.0207]
COFFEE	0.0013	0.0887	0.0474	1.9878	36.302	6.322
					[0.000]	[0.041]
COTTON	0.0016	0.0806	0.1724	0.9626	9.584	18.783
					[0.008]	[0.002]

Table 7: Series names

	Countries	CAPM	MS-CAPM	MS-GARCH-CAPM
1	USA	US S&P500	MSCI USA_	MSCI USA_MS_GARCH
2	CANADA	CAN TSX	MSCI CAN_	MSCI CAN_MS_GARCH
3	GERMANY	GER DAX	MSCI GER_	MSCI GER_MS_GARCH
4	AUSTRALIA	AUS ASX	MSCI AUS_	MSCI AUS_MS_GARCH
5	DENMARK	DEN OMX	MSCI DEN_	MSCI DEN_MS_GARCH
6	FINLAND	FIN OMXHEX	MSCI FIN_	MSCI FIN_MS_GARCH
7	SPAIN	SPNIBEX	MSCI SPN_	MSCI SPN_MS_GARCH
8	FRANCE	FRA-CAC	MSCI FRA_	MSCI FRA_MS_GARCH
9	UK	UKFTSE100	MSCI UK_	MSCI UK_MS_GARCH
10	ITALY	ITAFTSEMIB	MSCI ITA_	MSCI ITA_MS_GARCH
11	SWEDEN	SWEOMX30	MSCI SWE_	MSCI SWE_MS_GARCH
12	SWITZERLAND	SWTSMI	MSCI SWT_	MSCI SWT_MS_GARCH
13	NEW ZEALAND	NZLNZX50	MSCI NZL_	MSCI NZL_MS_GARCH
14	NORWAY	NOR-OSEAX	MSCI NOR_	MSCI NOR_MS_GARCH
15	NETHERLAND	NETH-AEX	MSCI NLD_	MSCI NLD_MS_GARCH
16	JAPAN	JAP-NIKKEI225	MSCI JAP_	MSCI JAP_MS_GARCH
17	IRELAND	IRE-ISEQ	MSCI IRE_	MSCI IRE_MS_GARCH
18	THAILAND	THAI-SET50	MSCI THAI_	MSCI THAI_MS_GARCH
19	MYLASIA	MYL-FTSEKLCI	MSCI MYL_	MSCI ,MYL_MS_GARCH
20	INDONESIA	INDO-JCI	MSCI INDO_	MSCI INDO_MS_GARCH
21	PHILIPPINES	PHI-PSEI	MSCI PHI_	MSCI PHI_MS_GARCH
22	SINGAPORE	SING-STI	MSCI SING_	MSCI SING_MS_GARCH
23	CHINA	CHIN-SSE	MSCI CHIN_	MSCI CHIN_MS_GARCH
24	INDIA	INDI-SENSEX	MSCI INDI_	MSCI INDI_MS_GARCH
25	TAIWAN	TAI-TWSE	MSCI TAI_	MSCI TAI_MS_GARCH
26	KOREA	KOR-KOSPI	MSCI KOR_	MSCI KOR_MS_GARCH
27	HONG KONG	HNGKNG-HIS	MSCI HNGKNG_	MSCIHNGKNG_MS_GARCH
28	SERBIA	SERB-BELEX15	MSCI SERB_	MSCI SERB_MS_GARCH
29	UKRAINE	UKR-PFTS	MSCI UKR_	MSCI UKR_MS_GARCH
30	BULGARIA	BUL-SOFIX	MSCI BUL_	MSCI BUL_MS_GARCH
31	ROMANIA	ROM-BET	MSCI ROM_	MSCI ROM_MS_GARCH
32	SLOVANIA	SLOVSBITOP	MSCISLOV_	MSCI SLOV_MS_GARCH
33	POLAND	POL-WIG	MSCI POL_	MSCI POL_MS_GARCH
34	ICELAND	ICE-SEICEX	MSCI ICE_	MSCI ICE_MS_GARCH
35	RUSSIA	RUS-MICEX	MSCI RUS_	MSCI RUS_MS_GARCH
36	LATVIA	LAT-OMXRIGA	MSCI LAT_	MSCI LAT_MS_GARCH
37	ESTONIA	EST-OMXTALLIN	MSCI EST_	MSCI EST_MS_GARCH
38	TURKEY	TUR-XU100	MSCI TUR_	MSCI TUR_MS_GARCH
39	CROTIA	CRO-CROBEX	MSCI CRO_	MSCI CRO_MS_GARCH
40	LITUANIA	LIT-OMXVILNIUS	MSCI LIT_	MSCI LIT_MS_GARCH
41	HUNGARY	HUN-BUX	MSCI HUN_	MSCI HUN_MS_GARCH
42	EGYPT	EGY-EGX30	MSCI EGY_	MSCI EGY_MS_GARCH
43	PORTUGAL	POR-PS-I20	MSCI POR_	MSCI POR_MS_GARCH
44	CZECH REPUBLIC	CZECH-SEPX	MSCI CZECH_	MSCI CZECH_MS_GARCH
45	BRAZIL	BRA-BOVESPA	MSCI BRA_	MSCI BRA_MS_GARCH
46	ARGENTINA	ARG-MERVAL25	MSCI ARG_	MSCI ARG_MS_GARCH
47	COLUMBIA	COL-COLCAP	MSCI COL_	MSCI COL_MS_GARCH
48	BELGIUM	BELG-BEL20	MSCI BEL_	MSCI BEL_MS_GARCH
49	UAE	UAE-ADXGEN	MSCI UAE_	MSCI UAE_MS_GARCH
50	CHILE	CHIL-IGPA	MSCI CHIL_	MSCI CHIL_MS_GARCH
51	MEXICO	MEX-S&PBMVIPC	MSCI MEX_	MSCI MEX_MS_GARCH
52	QATAR	QAT-QE	MSCI QAT_	MSCI QAT_MS_GARCH
53	LUXEMBOURG	LUX-LUXX	MSCI LUX_	MSCI LUX_MS_GARCH
54	ISRAEL	ISR-TA100	MSCI ISR_	MSCI ISR_MS_GARCH
55	MALTEX	MALT-MALTEX	MSCI MALT_	MSCI MALT_MS_GARCH
56	TUNISIA	TUN-TUNINDEX	MSCI TUN_	MSCI TUN_MS_GARCH

	Commodities			
57	CRUDEOIL	CRUDEOIL	MSCI OIL_	MSCI OIL_MS_GARCH
58	GOLD	GOLD	MSCI GOLD_	MSCI GOLD_MS_GARCH
59	SILVER	SILVER	MSCI SILVER_	MSCI SILVER_MS_GARCH
60	GAS	GAS	MSCI GAS_	MSCI GAS_MS_GARCH
61	COPPER	COPPER	MSCI Copper_	MSCI COPPER_MS_GARCH
62	PLATINUM	PLATINUM	MSCI Platinum_	MSCI Platinum_MS_GARCH
63	PALLADIUM	PALLADIUM	MSCI Palledium_	MSCI Palledium_MS_GARCH
64	NICKEL	NICKEL	MSCI Nickel_	MSCI Nickel_MS_GARCH
65	TIN	TIN	MSCI Tin_	MSCI Tin_MS_GARCH
66	ZINC	ZINC	MSCI Zinc_	MSCI Zinc_MS_GARCH
67	RHODIUM	RHODIUM	MSCI Rhodium_	MSCI Rhodium_MS_GARCH
68	RUTHENIUM	RUTHENIUM	MSCI Ruthernium_	MSCI Ruthernium_MS_GARCH
69	CORN	CORN	MSCI Corn_	MSCI Corn_MS_GARCH
70	RUBBER	RUBBER	MSCI Rubber_	MSCI Rubber_MS_GARCH
71	SOYABEAN	SOYABEAN	MSCI Soyabean_	MSCI Soyabean_MS_GARCH
72	WOOL	WOOL	MSCI Wool_	MSCI Wool_MS_GARCH
73	ALUMINIUM	ALUMINIUM	MSCI Aluminium_	MSCI Aluminium_MS_GARCH
74	LEAD	LEAD	MSCI Lead_	MSCI Lead_MS_GARCH
75	WHEAT	WHEAT	MSCI Wheat_	MSCI Wheat_MS_GARCH
76	COCOA	COCOA	MSCI Cocoa_	MSCI Cocoa_MS_GARCH
77	COFFEE	COFFEE	MSCI Coffee_	MSCI Coffee_MS_GARCH
78	COTTON	COTTON	MSCICotton_	MSCI Cotton_MS_GARCH
	Aggregates			
79	WORLD	WORLD	MSCI WORLD_	MSCI WORLD_MS_GARCH
80	EUROPE	EUROPE	MSCI Europe_	MSCI Europe_MS_GARCH
81	EMERGING MARKETS	EMERGING MARKETS	MSCI EM_	MSCI EM_MS_GARCH

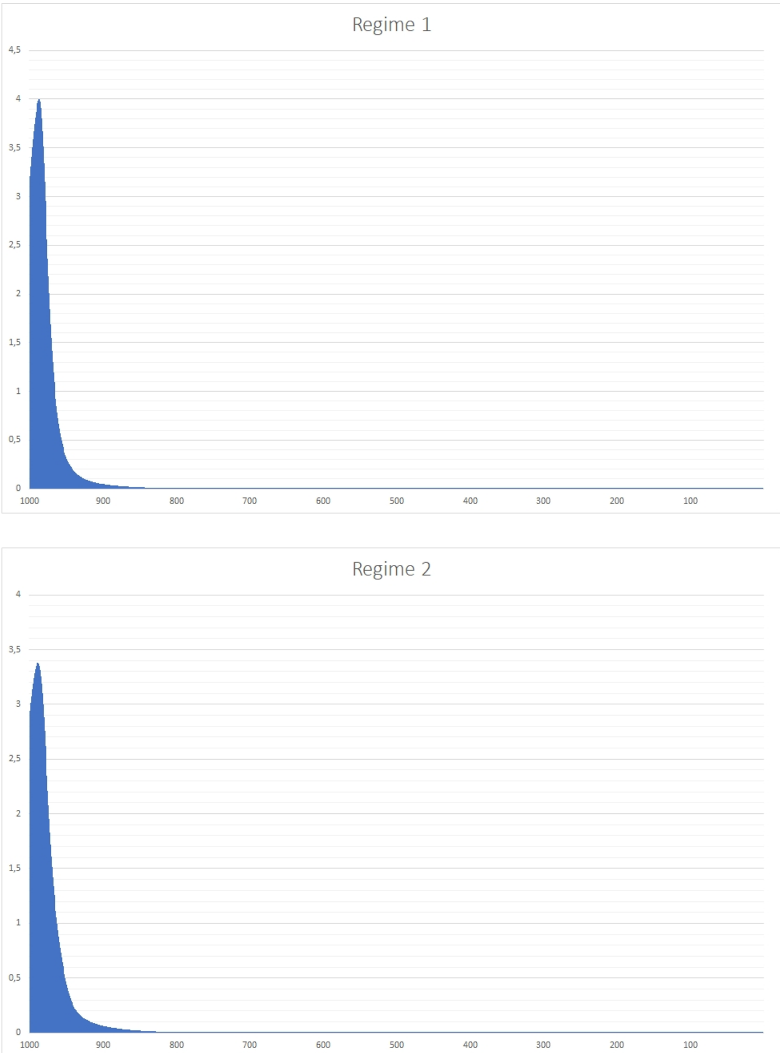

Figure 4: Histogram of the predictive distribution in each regime of the MS-GARCH-CAPM for MSCI USA